Adapting Swarm Application

A Systematic and Quantitative Approach

Ben Zhang
June 5, 2018

TerraSwarm Research Center
https://github.com/nebgnahz/dissertation-talk
1. Introduction to the Swarm

2. Network Resource Adaptation

3. Compute Resource Adaptation

4. Conclusion and Acknowledgement
Introduction to the Swarm
The Swarm at the Edge of the Cloud

J. Rabaey, ASPDAC’08
The Swarm at the Edge of the Cloud

Swarm, or
- Internet of Things (IoT)
- Internet of Everything (IoE)
- Industry 4.0
- The Industrial Internet
- TSensors (Trillion Sensors)
- Machine to Machine (M2M)
- Smarter Planet

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J. Rabaey, ASPDAC’08
A Cloud-centric Approach

(a) Electric Imp

(b) Samsung SAMI

(c) Ninja Sphere
“The Cloud”: Model vs. Reality
“The Cloud”: Model vs. Reality
The Cloud is Not Enough

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Privacy &amp; Security</td>
<td>Open for access</td>
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</tr>
<tr>
<td>Scarcity</td>
<td>Power law</td>
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</tr>
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<td>Interaction Model</td>
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</tr>
<tr>
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Pitfalls with Today’s Approach to IoT [Zhang et al., 2015]
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Bandwidth: Downstream vs. Upstream

Users
Web/IT

Users
Swarm/IoT
Network Resource Adaptation
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### Limited Network Resource

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- Video surveillance, 3 mbps per camera [Amerasinghe, 2009]
- Electrical grid monitoring, 1.4 million data points per second [Andersen and Culler, 2016]
### Limited Network Resource

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... *Dropcam*, a WiFi video-streaming camera and associated cloud backend service for storing and watching the resulting video. *Dropcam has the fewest clients* (2,940) ... Yet, each client uses roughly *2.8 GB* a week and uploads *nearly 19 times more* than they download, implying that *Dropcam users do not often watch what they record.*

Large-scale Measurements of Wireless Network Behavior [Biswas et al., 2015]
Limited Network Resource

Demand
Huge Data Volume at the Edge

Resource
Insufficient WAN Bandwidth

Bandwidth variations throughout the day between Amazon EC2 sites. Similar scarcity and variation for wireless networks, broadband access networks and cellular networks (backup slides).
Limited Network Resource

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What about edge processing? (I will cover in the second half of this talk).

But communication is not avoidable.

- Large performance gap between the cloud and the edge (GPU/TPU/ASIC).
- Aggregation is sometimes necessary in applications.
- Last-hop wireless may become the bottleneck.
Fidelity vs. Freshness

When the network resource is not sufficient:

- TCP ensures data delivery, but hurts latency
- UDP sends as fast as possible, uncontrolled packet loss
Fidelity vs. Freshness

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Fidelity vs. Freshness

When the network resource is not sufficient:

- TCP ensures data delivery, but hurts latency
- UDP sends as fast as possible, uncontrolled packet loss
- Manual policies (developer heuristics) are sub-optimal
  - JetStream [Rabkin et al., 2014] uses manual policy
  - “if bandwidth is insufficient, switch to sending images at 75% fidelity, then 50% if still not enough”
When the network resource is not sufficient:

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- Application-specific optimizations don’t generalize
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- TCP ensures data delivery, but hurts latency
- UDP sends as fast as possible, uncontrolled packet loss
- Manual policies (developer heuristics) are sub-optimal
- Application-specific optimizations don't generalize
  - Video streaming often aims at Quality of Experience (limited degradation dimension, e.g. maintain 25FPS)
  - For object detection, resolution matters more than FPS
Fidelity vs. Freshness

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![Graph showing fidelity vs. freshness](image-url)
Fidelity vs. Freshness

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Application-specific Optimizations Don’t Generalize

$\text{t=0s, small target in far-field views}$

$\text{t=1s, small difference}$
Application-specific Optimizations Don’t Generalize

Positive if intersection over union (IOU) larger than 0.5.

\[ \text{IOU} = \frac{\text{Area of Intersection}}{\text{Area of Union}} \]

- (a) IOU = 0.14
- (b) IOU = 0.57
- (c) IOU = 0.82
Application-specific Optimizations Don’t Generalize

F1 score is the harmonic mean of precision and recall, ranging from 0 to 1:

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<th>N</th>
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<tr>
<td>Y</td>
<td>True Positive</td>
<td>False Positive</td>
</tr>
<tr>
<td>N</td>
<td>False Negative</td>
<td>True Negative</td>
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Precision = \( \frac{\text{true positive}}{\text{all positive}} \)

Recall = \( \frac{\text{true positive}}{\text{all detection}} \)

\[ F1 = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}} \]
Application-specific Optimizations Don’t Generalize

t=0s, small target in far-field views

t=1s, small difference

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<th>Accuracy</th>
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<td></td>
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<td></td>
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<tr>
<td>360p</td>
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Frame Rate

0  30  10  5  3  2
Application-specific Optimizations Don’t Generalize

$t=0s$, small target in far-field views

$t=1s$, small difference

![Graph showing Bandwidth (normalized) vs. Accuracy against Frame Rate (30, 10, 5, 3, 2)]

- 30: 100, 92, 90
- 10: 92, 90, 87
- 5: 90, 87, 84
- 3: 87, 84
- 2: 84
Application-specific Optimizations Don’t Generalize

$t=0s$, small target in far-field views

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Application-specific Optimizations Don’t Generalize

- t=0s, small target in far-field views
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Graph showing bandwidth (normalized) and accuracy for different frame rates:
- Frame Rate: 30, 10, 5, 3, 2
- Accuracy: 100, 92, 90, 87, 84

Graph showing bandwidth (normalized) and accuracy for different resolutions:
- Resolution: 1080p, 900p, 720p, 540p, 360p
- Accuracy: 100, 79, 87, 84, 71, 17, 11
Application-specific Optimizations Don’t Generalize

t=0s, nearby and large targets

\( \begin{align*}
&1080p & 900p & 720p & 540p & 360p \\
100 & 100 & 99 & 97 & 93 & 87
\end{align*} \)

Frame Rate vs. Bandwidth (normalized) and Accuracy

Resolution vs. Accuracy
**Goal**

Minimize bandwidth while maximizing application accuracy
Making Adaptation Practical is Challenging

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Minimize bandwidth while maximizing application accuracy

**Challenges:**

1. Application-specific optimizations don’t generalize.
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**Challenges:**

1. Application-specific optimizations don’t generalize.

2. It requires expertise and manual work to explore multidimensional adaptation.
Making Adaptation Practical is Challenging

**Goal**

Minimize bandwidth while maximizing application accuracy

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3. The adaptation happens at the runtime.
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Minimize bandwidth while maximizing application accuracy

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   - APIs: maybe operators to express adaptation.

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   - Profiling: automatically learn Pareto-optimal strategy with multi-dimensional exploration.
3. The adaptation happens at the runtime.
   - Engineering an adaptation system to balance latency and accuracy.
Goal

Minimize bandwidth while maximizing application accuracy
(1) Stream Processing APIs

Data Stream → Operator → Data Stream
### (1) Stream Processing APIs

**Data Stream** → **Operator** → **Data Stream**

\[
\{x_1, x_2, x_3, x_4, \ldots\} \xrightarrow{\text{map}(f)} \{f(x_1), f(x_2), f(x_3), f(x_4), \ldots\}
\]

\[
\{x_1, x_2, x_3, x_4, \ldots\} \xrightarrow{\text{window}(2, f)} \{f(x_1, x_2), f(x_3, x_4), \ldots\}
\]
Stream Processing APIs

**Diagram:**
- Data Stream → Operator → Data Stream
- \{x_1, x_2, x_3, x_4, \ldots\} → map(f) → \{f(x_1), f(x_2), f(x_3), f(x_4), \ldots\}
- \{x_1, x_2, x_3, x_4, \ldots\} → window(2, f) → \{f(x_1, x_2), f(x_3, x_4), \ldots\}

**Normal Operations:**
- `map (f: I \Rightarrow O)` Stream\(<I>\) \Rightarrow Stream\(<O>\)
- `skip (i: Integer)` Stream\(<I>\) \Rightarrow Stream\(<I>\)
- `window (count: Integer, f: Vec<I> \Rightarrow O)` Stream\(<I>\) \Rightarrow Stream\(<O>\)
- `...` ...

---

13/37
Stream Processing APIs

\[ \{x_1, x_2, x_3, x_4, \ldots \} \xrightarrow{\text{map}(f)} \{f(x_1), f(x_2), f(x_3), f(x_4), \ldots \} \]

\[ \{x_1, x_2, x_3, x_4, \ldots \} \xrightarrow{\text{window}(2, f)} \{f(x_1, x_2), f(x_3, x_4), \ldots \} \]

\[ \{x_1, x_2, x_3, x_4, \ldots \} \xrightarrow{\text{maybe}(\vec{k}, f)} \{f(x_1, k_{i_1}), f(x_2, k_{i_2}), f(x_3, k_{i_3}), f(x_4, k_{i_4}), \ldots \} \]

Normal

\[
\begin{align*}
\text{map} & \quad (f: I \Rightarrow O) \quad \text{Stream}<I> \Rightarrow \text{Stream}<O> \\
\text{skip} & \quad (i: \text{Integer}) \quad \text{Stream}<I> \Rightarrow \text{Stream}<I> \\
\text{window} & \quad (\text{count: Integer, } f: \text{Vec}<I> \Rightarrow O) \quad \text{Stream}<I> \Rightarrow \text{Stream}<O> \\
\end{align*}
\]
**1. Stream Processing APIs**

![Diagram of data stream processing](image)

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<td><code>map (knobs: Vec&lt;T&gt;, f: (T, I) ⇒ I)</code></td>
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<td><code>skip (i: Integer)</code></td>
<td><code>maybe_skip (knobs: Vec&lt;Integer&gt;)</code></td>
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```rust
maybe(knobs: Vec<T>, f: (T, I) => I)
```

```rust
def maybe(n: int): int
    if n > 0:
        return n
    return 0
```

```rust
let quantized_stream = vec![1, 2, 3, 4].into_stream()
    .maybe(vec![2, 4], |k, val| val / k)
    .collect();
```

```
[1, 2, 3, 4]
```

```
[0, 1, 1, 2]
k = 2
```

```
[0, 0, 0, 1]
k = 4
```

We rewrite the video streaming application as follows,
```
let app = Camera::new((1920, 1080), 30).
    maybe_downsample(vec![1600, 900, 1280, 720]).
    maybe_skip(vec![2, 5]).
    map(|frame| pedestrian_detect(frame)).
    compose();
```

Example code in Rust, simplified for presentation.
maybe(knobs: Vec<T>, f: (T, I) => I)

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## Training Data

### Accuracy Function

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15/37
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...
Profile: Pareto-optimal Strategy

Symbol | Description
---|---
$n$ | number of degradation operations
$k_i$ | the $i$-th degradation knob
$c = [k_1, k_2, ... k_n]$ | one specific configuration
$C$ | the set of all configurations
$B(c)$ | bandwidth requirement for $c$
$A(c)$ | accuracy measure for $c$
$\mathbb{P}$ | Pareto-optimal set

See red markers in the figure.
**Profile: Pareto-optimal Strategy**

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**Profile: Pareto-optimal Strategy**

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the set of all configurations

\( B(c) \)
bandwidth requirement for \( c \)

\( A(c) \)
accuracy measure for \( c \)

\( \mathbb{P} \)
Pareto-optimal set

\[
\mathbb{P} = \{ c \in \mathcal{C} : \{ c' \in \mathcal{C} : B(c') < B(c), A(c') > A(c) \} = \emptyset \} 
\]

See red markers in the figure.
(3) Runtime Adaptation

Adaptation Controller State Machine. We introduce the Probe phase to conservatively change the adaptation level. For details, please see the paper/thesis.
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# Applications

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<th>Knobs</th>
<th>Accuracy</th>
<th>Dataset</th>
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<tr>
<td>Augmented Reality</td>
<td>resolution, frame rate, quantization</td>
<td>F1 score</td>
<td>iPhone video clips training: office (24s) testing: home (246s)</td>
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<tr>
<td>Pedestrian Detection</td>
<td>resolution, frame rate, quantization</td>
<td>F1 score</td>
<td>MOT16 [Milan et al., 2016] training: MOT16-04 testing: MOT16-03</td>
</tr>
<tr>
<td>Log Analysis (Top-K, K=50)</td>
<td>head (N), threshold (T)</td>
<td>Kendall’s τ</td>
<td>SEC.gov logs [DERA, 2016] training: 4 days testing: 16 days</td>
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A distributed Top-K application with two degradation operations: head and threshold. In this example, f2, which is not in Top-1 for either client, becomes the global Top-1 after the merge. It would have been purged if the clients use threshold T=3, demonstrating degradation that reduces data sizes affects fidelity.
Evaluation: Generated Profiles

(a) Augmented Reality (AR)

- ● Pareto boundary
- - tune quantizer
- ▲ tune framerate
- + tune resolution

(b) Pedestrian Detection (PD)

- ● Pareto boundary
- - tune quantizer
- ▲ tune framerate
- + tune resolution

Optimal strategy is achieved with multiple dimensions; tuning one dimension leads to suboptimal performance.

For the same application, different dimensions have different impact.

For different applications, the same dimension has different impact.
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The effect of each dimension is not significantly different. The profile offers quantified effects of degradation.
Evaluation: Generated Profiles (Top-K)

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### Evaluation: Runtime Experiment Baselines

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JetStream++

Uses adaptation policy generated by A WStream. JetStream runtime does not probe (hence may oscillate between policies).

HLS

[2047][Pantos and May, 2016]

HTTP Live Streaming represents popular adaptive video streaming techniques; used for Periscope video stream.

[Wang et al., 2016]
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HTTP Live Streaming (HLS) architecture: designed for live video viewing and relying on buffering at the viewing side.
Evaluation: Runtime Performance

- AWStream
- JetStream++
- JetStream
- HLS
- Streaming over TCP
- Streaming over UDP

Throughput (mbps)

Latency (seconds)

Accuracy (F1 Score)

Time (seconds)
Evaluation: Runtime Performance

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Evaluation: Runtime Performance

Throughput (Mbps)

Latency (seconds)

Accuracy (F1 Score)
Evaluation: Runtime Performance

- Latency (ms)
- Accuracy (F1 score)

- Streaming over UDP
- Streaming over TCP
- HLS
- JetStream
- JetStream++
- AWStream

- Freshness, latency reversed (seconds)
- Fidelity, accuracy (%)

23/37
Evaluation: Runtime Performance

Latency (ms) vs. Accuracy (F1 score)

- AWStream
- JetStream++
- JetStream
- HLS
- Streaming over TCP
- Streaming over UDP

Fidelity, accuracy (%) vs. Freshness, latency reversed (seconds)

- Streaming over TCP
- Manual Policies
- App-specific
- AWStream
- Streaming over UDP

Better
Compute Resource Adaptation
Edge Computing: Fog/Cloudlet/Swarmbox & New Infrastructure

- Philips Hue Hub
- SmartThings
- Smartphones
- Google onHub
- SwarmBox
- Intel NUC
- Many Gateways
Edge Computing: Fog/Cloudlet/Swarmbox & New Infrastructure

Cisco Fog Computing [Bonomi et al., 2012]

Cloudlet [Satyanarayanan et al., 2009]
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Heterogeneous Environment

IoT / Mobile Devices
- Limited Resources
- Less workload
- Lower latency

Edge Computers (Cloudlet)
- Compute Power
- Workload
- Latency

Cloud
- More Available Resources
- More workload
- Higher latency

Characteristics of IoT/mobile, edge and cloud
Heterogeneous Environment

IoT / Mobile Devices

Edge Computers (Cloudlet)

Cloud

More Available Resources

Compute Power

Limited Resources

Less workload

Workload

More workload

Less resource guarantee

Higher latency

Less stable connections

Latency

Lower latency

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<tr>
<th>Platform</th>
<th>RPi Model B</th>
<th>Macbook Model A1502</th>
<th>Workstation Xeon E5-1620</th>
</tr>
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<tbody>
<tr>
<td>Processing times (ms)</td>
<td>4105</td>
<td>544</td>
<td>346</td>
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Processing times (ms) on different platforms.
Accuracy and Processing Times Tradeoff

Adaptation

Different algorithm and parameters affect the accuracy and processing times.

Within the tradeoff space, select appropriate algorithm and parameters to meet bounded response time goal.
Accuracy and Processing Times Tradeoff


(b) Benchmarks for Viola Jones face detection when changing different parameters (see explanation on the next slide).
Accuracy and Processing Times Tradeoff


(b) Benchmarks for Viola Jones face detection when changing different parameters (see explanation on the next slide).
The OpenCV implementation of Viola-Jones [Viola and Jones, 2001] has three parameters:

- **scale**: how much the image size is reduced at each image scale.
- **min_size**: minimum detectable object size.
- **min_neighbors**: how many neighbors each candidate rectangle should have to retain it.

Image Source: pyimagesearch.
detectMultiScale in Viola-Jones (or CascadeClassifier)

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Exhaustive Search is Too Expensive

- **scale**: how much image size is reduced at each image scale.
- **min_size**: minimum detectable object size.
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Best accuracy:
(22.1 ms, 80.2%)
pub struct HogParams {
    pub win_size: Size2i,
    pub block_size: Size2i,
    pub block_stride: Size2i,
    pub cell_size: Size2i,
    pub nbins: c_int,
    pub win_sigma: f64,
    pub l2hys_threshold: f64,
    pub gamma_correction: bool,
    pub nlevels: usize,
    pub hit_threshold: f64,
    pub win_stride: Size2i,
    pub padding: Size2i,
    pub scale: f64,
    pub group_threshold: c_int,
    pub use_meanshift_grouping: bool,
    pub final_threshold: f64,
}
## Challenges in Adapting Computation

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### Challenges

1. **Large parameter space**
   - Previous approaches use random search or coordinate/greedy approach
   - We propose Bayesian Optimization (BO) for profiling

2. **Heterogeneous capabilities (and not available when profiling)**
   - Profile transfer: refine existing Pareto-optimal points
Challenges in Adapting Computation

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## Challenges in Adapting Computation

### Goal
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   - **Profile transfer**: refine existing Pareto-optimal points
Bayesian optimization approximate black-box functions with proxy functions and iteratively proposes new sample point in the large parameter space. Effective for,

• Evaluating each sample is expensive.
• The objective is a black-box.
• The evaluation can be noisy.

Gaining attraction beyond ML scope:
• CherryPick [Alipourfard et al., 2017] finds the best cloud configurations for big data analytics.
• Google optimize chocolate chip cookies recipes [Solnik et al., 2017].
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Bayesian Optimization 101

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Bayesian Optimization (Illustrated)

Acquisition function evaluates the utility of candidate points for the next evaluation of \( f \), balancing a high objective (exploitation) and high uncertainty (exploration) [Shahriari et al., 2016]
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For two-objective optimization, utility gain is based on additive-epsilon (top) or hypervolume (bottom) [Binois and Picheny, 2018]
We use PESMO\textsuperscript{2} [Hernández-Lobato et al., 2016] and compare it with two baselines: (1) greedy/coordinate search; (2) random search.

\textsuperscript{2}A Python package based on Spearmint. It chooses evaluation points to maximally reduce the entropy of the posterior distribution over the Pareto set.
We use PESMO\textsuperscript{2} [Hernández-Lobato et al., 2016] and compare it with two baselines: (1) greedy/coordinate search; (2) random search.

\begin{figure}
\centering
\begin{tikzpicture}
\begin{axis}[
    xlabel=Processing Time (ms),
    ylabel=Accuracy (F1 score),
    xmin=0, xmax=10,
    ymin=0, ymax=0.8,
    xtick={1,10},
    ytick={0,0.2,0.4,0.6,0.8},
    legend style={at={(0.5,0.8)},anchor=north}
]
\addplot coordinates {
    (1,0.0) (10,0.2) (1,0.4) (10,0.6) (1,0.8) (10,0.2)
};
\addplot coordinates {
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};
\addplot coordinates {
    (1,0.4) (10,0.6) (1,0.8) (10,0.2) (1,0.6) (10,0.4)
};
\end{axis}
\end{tikzpicture}
\caption{Comparison of BO, Greedy, and Random search strategies.}
\end{figure}

BO evaluates 50 configurations and recommends 29 configurations as the Pareto-optimal boundary (the blue line). Greedy and Random find sub-optimal Pareto configurations with a budget of 80 evaluations (the yellow line in each figure).

\textsuperscript{2}A Python package based on Spearmint. It chooses evaluation points to maximally reduce the entropy of the posterior distribution over the Pareto set.
Profile Transfer (without re-running the entire BO)

We make the following observations:

- Accuracy remains for a given algorithm/parameter.
- Processing time order is preserved.
- More expensive algorithms/parameters remain the same across platforms.
- The "Pareto-optimal" is horizontally stretched/compressed.

Empirically, processing times follow a linear approximation. See paper for details.
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![Graphs showing time vs. accuracy for algorithms m1 and m2, and reference.](Left) Empirically, processing times follows a linear approximation. (Right) Stretched/compressed profile. See paper for details.
Conclusion and Acknowledgement
Summary and Contributions

• Swarm/IoT has huge potentials but also challenges
  • Network resource adaptation
    • Addresses scarce and variable WAN bandwidth
  • Compute resource adaptation
    • Addresses heterogeneous platforms and large parameter space
• Overall, a systematic and quantitative approach for adaptation
Summary and Contributions

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TerraSwarm Vision

TerraSwarm applications are characterized by their ability to dynamically recruit resources such as sensors and data from the cloud, aggregate and use that information to make or aid decisions.
TerraSwarm Vision

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(a) Accessor in a network of actors. (b) Instantiate accessors on another host.
TerraSwarm applications are characterized by their ability to **dynamically recruit** resources such as sensors and data from the cloud, aggregate and use that information to make or aid decisions.

![Diagram of TerraSwarm Vision](image)

(a) Accessor in a network of actors.  
(b) Instantiate accessors on another host.

Work in progress with Marten and Andrés. Maybe checkout Marten's dissertation talk in the future :)
Acknowledgment
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Prof. Edward Lee  Prof. John Wawrzynek  Prof. John Chuang  Prof. Sylvia Ratnasamy  Prof. Björn Hartmann  Prof. Xin Jin  Prof. John Kubiatowicz

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1N73LL1G3NC3
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Image Source: Ostees.com
Google Network Infrastructure

Figure 4: Bandwidth Sharing on a Bottleneck Link.

Figure 5: BwE Architecture.

BwE: Flexible, Hierarchical Bandwidth Allocation for WAN Distributed Computing [Kumar et al., 2015]
Twitter, Pub/Sub, Stream Processing
Backup Slides.
- **I-frames** are the least compressible but don’t require other video frames to decode. I-frames are further compressed with quantization.

- **P-frames** can use data from previous frames to decompress and are more compressible than I-frames.

- **B-frames** can use both previous and forward frames for data reference to get the highest amount of data compression (not an option in live streaming).
Evaluation: Resource Allocation for Multiple Applications

(a) Resource Fairness

(b) Utility Fairness
3. RESULTS AND ANALYSIS

In this section, we present our results. In particular, we look at 1) the achieved segment quality along the routes actually watching the video in every test, and registering the information we need to plot the quality level as a function of geographical location. 2) the amount of video data presented according to time, and 3) the stability or safety margins. As a result, the users' quality of experience suffers due to buffer underruns and too frequent buffer underruns, and 3) the corresponding bandwidths are shown in figure 2. We can see nearly as realistic as a field trial.

Comparing Adobe's quality level plots in figure 3 with the bandwidth plots, one can clearly see that their shapes indicate of the quality switching pattern. These properties are plotted in figures 3, 4 and 5, respectively, for all four streaming environments were used extensively in our experiments, while at the same time being fairly deterministic, this study requires identical results on the bandwidth (as a function of geographical location) to be reproducible in our experiments, while at the same time being nearly as realistic as a field trial.

We selected four representative bandwidth logs from our database of measurements and measured in our real wireless 3G network. This approach means that each media player can get exactly the same bandwidth plots as shown in the figures.

We considered two types of clients, one acting as server and the other as a client, with the former in the role of a client (server) and the latter in the role of a client (server). The former type of client is used to simulate the average round-trip latency experienced by the latter type of client, and the latter type of client is used to simulate the average round-trip latency experienced by the former type of client.

While streaming, we used our Apache module also adds a small one-way delay of 40 ms. After loading the session starts, the web server's maximum achieved rates and outages. This approach means that each media player can get exactly the same bandwidth plots as shown in the figures.

Bandwidth Fluctuations (WiFi)

Figure 4: Delivery ratio variation over a week for two randomly chosen 2.4 GHz links.

Figure 5: Delivery ratio variation over a week for two randomly chosen 5 GHz links.

Biswa et al, Cisco Meraki, Large-scale Measurements of Wireless Network Behavior, SIGCOMM’15. Two randomly chosen links.

Continue with the main slides.
Augmented Reality

- Training and testing data characteristics
  - 1920x1080 resolution with 30 FPS
  - training: 707 frames (23.5 seconds), testing: 1384 frames (46 seconds)

- Object Recognition
  - Darknet: Open Source Neural Networks in C
  - Developed by Joseph Redmon, ”Do whatever you want with it” license
  - It supports CPU/GPU
  - In this work, I am using a pre-trained model with Coco dataset

- Other systems such as TensorFlow, Caffe would also work
IOU and F1

Positive if intersection over union (IOU) larger than 0.5.

\[
\text{IOU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}
\]

(a) IOU = 0.14  (b) IOU = 0.57  (c) IOU = 0.82

F1 is the harmonic mean of precision and recall:

<table>
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<th>P</th>
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<tbody>
<tr>
<td>Y (True)</td>
<td>False Positive</td>
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<tr>
<td>N (True)</td>
<td>False Positive</td>
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Precision = \(\frac{\text{true positive}}{\text{all positive}}\)

Recall = \(\frac{\text{true positive}}{\text{all detection}}\)

\[
F1 = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}
\]


**Rapid Object Detection Using a Boosted Cascade of Simple Features.**

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