Exercise Session
Distributed Edge AI (and TinyML) Systems

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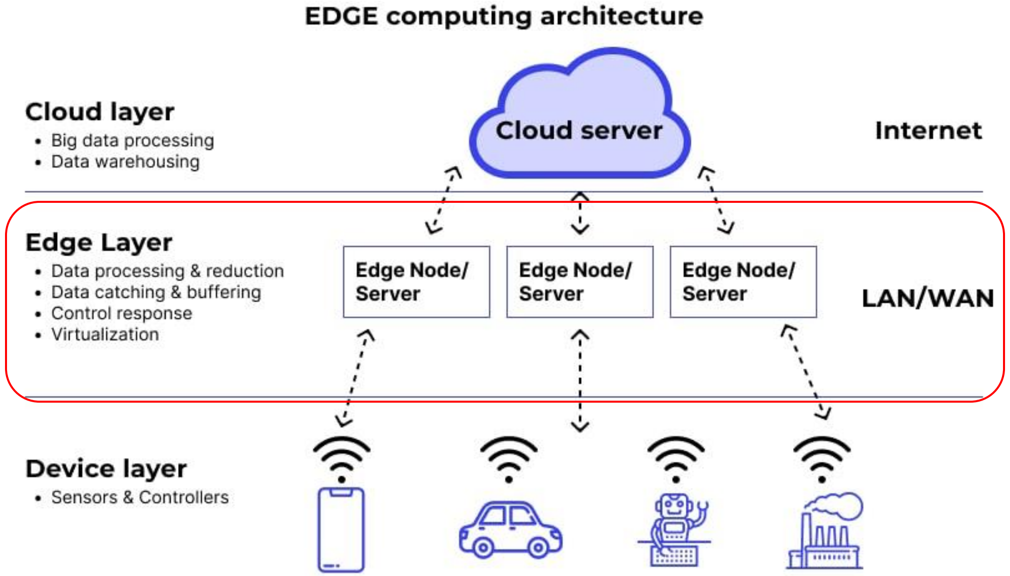
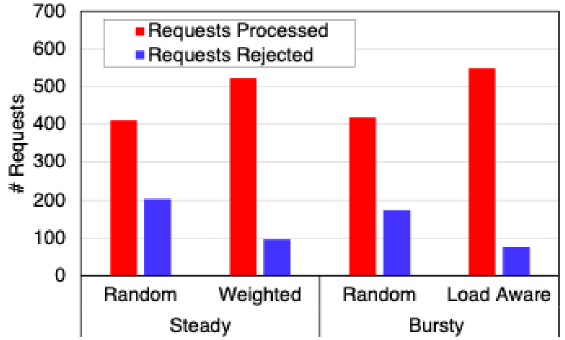
Recap From the Morning



Edge AI **challenges**:

- **Performance vs Latency**
- **Energy vs Accuracy**
- **Cost vs Autonomy**

The Edge–Cloud continuum: Device → Edge → Cloud.



Generative AI at the edge: why it matters

Goal of The Session

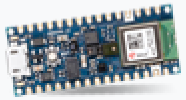
Explore TinyML in practice (training + quantization).

Experiment with computing continuum offloading trade-offs.

Work in groups to extend the simulator with new research ideas.

Instructions: https://github.com/robertmora/distributed-edge-ai-lab

TinyML Primer

	Micro**processor**	>	Micro**controller**
Platform			
Compute	1GHz–4GHz	**~10X**	1MHz–400MHz
Memory	512MB–64GB	**~10000X**	2KB–512KB
Storage	64GB–4TB	**~100000X**	32KB–2MB
Power	30W–100W	**~1000X**	150µW–23.5mW

Source: Content on these slides is sourced from https://github.com/edgeimpulse/courseware-embedded-machine-learning and https://github.com/tinyMLx/courseware/tree/master/edX

How to Deal with This?

Machine Learning Models → Pruning, Quantization, Knowledge Distillation, ...

Machine Learning Runtimes

Machine Learning Hardware

- Pruning
- Quantization
- Knowledge Distillation
- ...

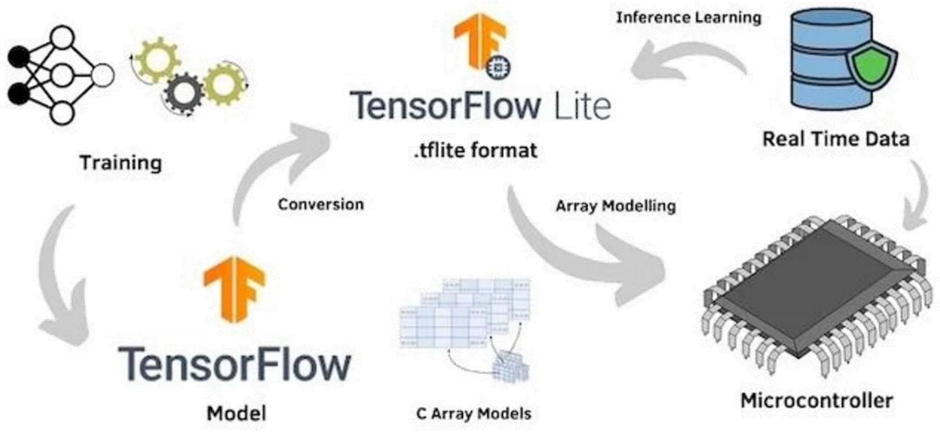
Source: S. Bianco, R. Cadene, L. Celona, and P. Napoletano, "Benchmark analysis of representative deep neural network architectures," *IEEE Access*, vol. 6, pp. 64 270–64 277, 2018

How to Deal with This?

Machine Learning Models

Machine Learning Runtimes

Machine Learning Hardware



Source: S. Bianco, R. Cadene, L. Celona, and P. Napoletano, “Benchmark analysis of representative deep neural network architectures,” *IEEE Access*, vol. 6, pp. 64 270–64 277, 2018

Machine Learning Runtimes

	TensorFlow	TensorFlow Lite
Topology	**Variable**	**Fixed**
Weights	**Variable**	**Fixed**
Binary Size	**Unimportant**	**High Priority**
Distributed Compute	**Needed**	**Not Needed**
Developer Background	**ML Researcher**	**Application Developer**

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Machine Learning Runtimes

Architecture

Trained TensorFlow Model

↓

TensorFlow Lite **Converter**

↓

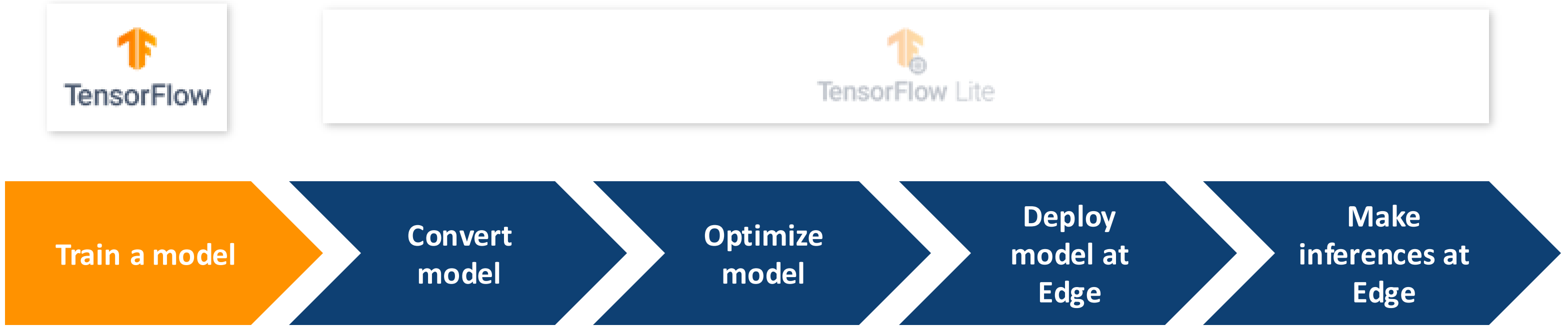
TensorFlow Lite **Model File** *(.tflite)*

iOS

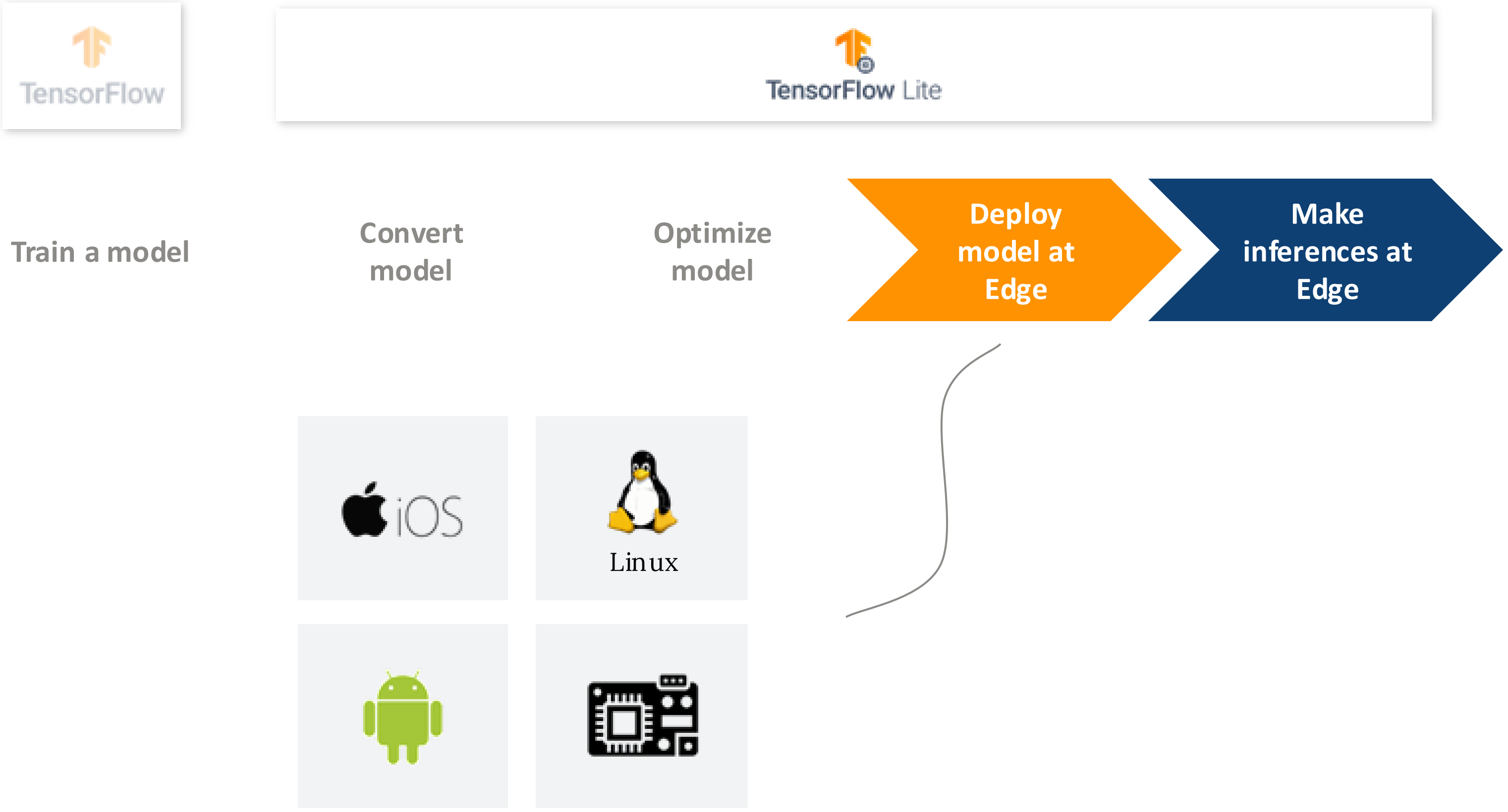
Machine Learning Runtimes

?

Machine Learning Runtimes



Machine Learning Runtimes



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Machine Learning Runtimes

TensorFlow

TensorFlow Lite

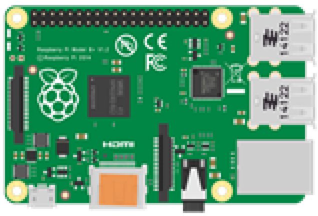
Train a model

Convert model

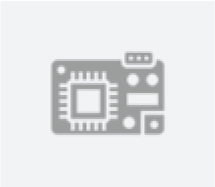
Optimize model

Deploy model at Edge

Make inferences at Edge



Linux



Raspberry Pi

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Machine Learning Runtimes

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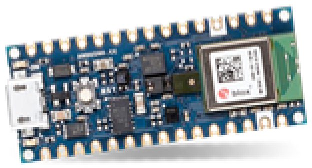
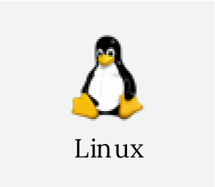
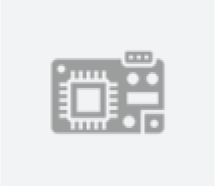


Microcontroller





Exercise Part 1 – A ’tiny’ TinyML activity

Notebook 1: TinyML Training

- Train a small CNN on MNIST.
- Quantize to INT8 → see size & accuracy differences.
- Export TFLite model & accuracy.
- ***Activity**:* Run cells, observe FP32 vs INT8 trade-offs.

https://shorturl.at/kQfav

Exercise Part 1 – A ’tiny’ TinyML activity

Wha the TinyML notebook does

Loads dataset

- Uses **MNIST** (28 × 28 grayscale digits).
- Normalizes pixel values (0–1).

Defines a small CNN

- Conv → Pool → Conv → Pool → Flatten → Dense → Dense.
- Very lightweight architecture (dozens of KB parameters).
- Designed to be feasible on an MCU-class device.

Trains the model

- Runs for a few epochs on MNIST.
- Achieves reasonable accuracy (e.g., ~0.92 FP32 baseline).

Converts to TensorFlow Lite (TFLite) INT8

- Uses **post-training quantization** with representative samples.
- Forces model to use INT8 for both inputs and outputs.
- Saves to models/mnist_cnn_int8.tflite.

Evaluates INT8 accuracy

- Runs inference with the quantized model.
- Prints INT8 accuracy on test set (e.g., ~0.88).

What it doesn’t do

- Doesn’t run on real MCU hardware (no flashing).
- Doesn’t include pruning or distillation (just quantization).
- Only trains on MNIST (simple dataset, just for demonstration).

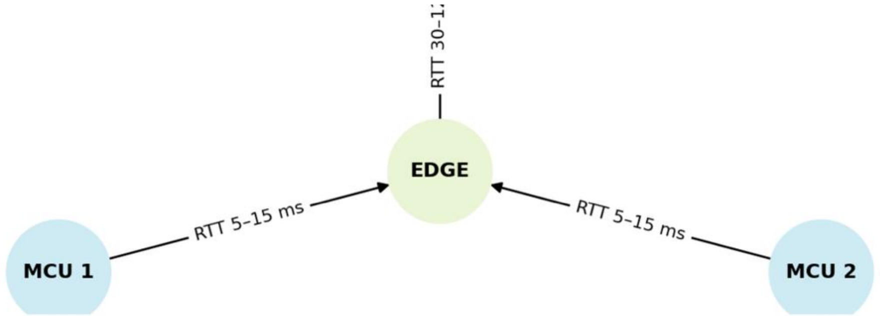
Exercise Part 2 – Distributed AI Inference Simulator

- Motivation: Real distributed AI systems have heterogeneous devices.
- Simulated devices: End-Devices (ex. MCU) , Edge, Cloud.
- Requests: Computer Vision tasks + Language Model tasks.
- Metrics: latency, accuracy, energy, deadline.

Simulator Overview (i)

Simulator Walkthrough

- Configure devices & network.
- Configure and generate workloads.
- Evaluate baseline AI inference allocation policies:
    - Always Local
    - Always Cloud
    - Confidence Threshold
    - Latency-Aware
    - Hybrid
- *Activity:* Run policies, interpret plots (Accuracy vs Deadline, Energy vs Accuracy).



	id	type	route	correct	latency_ms	energy_mJ	confidence	deadline_ms	deadline_met
0	0	cv	MCU/tinycnn	☑	7	0.14	0.7297	54	☑
1	1	cv	MCU/tinycnn	☑	7	0.14	0.9093	99	☑
2	2	lm	MCU/slm	☐	12,020	240.4	0.8353	2,529	☐
3	3	cv	MCU/tinycnn	☑	7	0.14	0.8243	63	☑
4	4	cv	MCU/tinycnn	☑	7	0.14	0.8915	99	☑
5	5	cv	MCU/tinycnn	☑	7	0.14	0.7231	55	☑

Simulator Overview (ii)

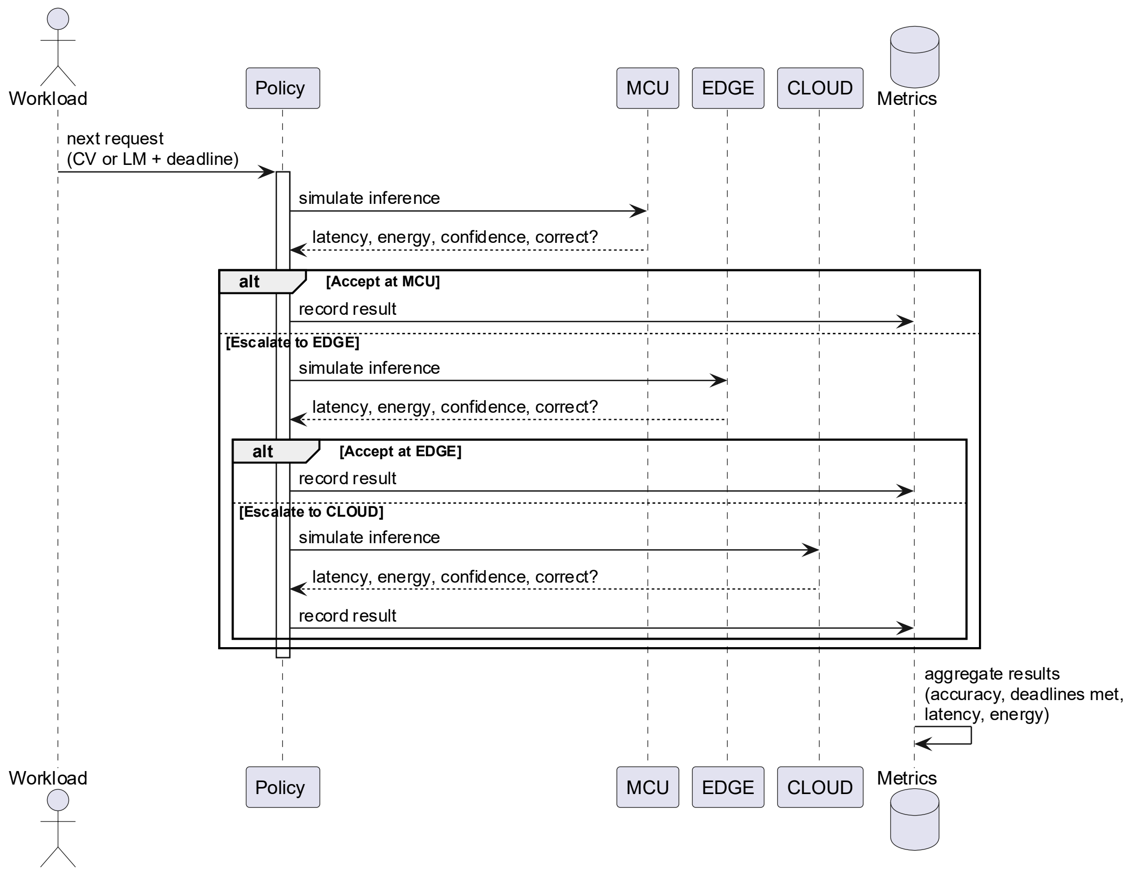
Workload generation
- Mix of *Computer Vision* (easy/hard) and *Language Mo*dels (short/long) requests
- Each has a **deadline_ms** constraint

Policy routing
- Decides where to run each AI inference request: **MCU → EDGE → CLOUD**
- Models: TinyCNN / INT8 / FP32 / SLM / LLM

Simulated inference
- **Latency** = compute time + network RTT
- **Energy** ∝ latency × device energy factor
- **Confidence** sampled from accuracy/quality
- **Correctness** drawn probabilistically

Decision semantics
- **Confidence Threshold**: accept if confidence ≥ thr
- **Deadline Margin**: only use device if latency ≤ margin × deadline

Evaluation
- Record: latency_ms, deadline_met, energy_mJ, correct
- Aggregate to compare policies (plots: Accuracy vs Deadline, Energy vs Accuracy)



Example

Say a CV request comes in:

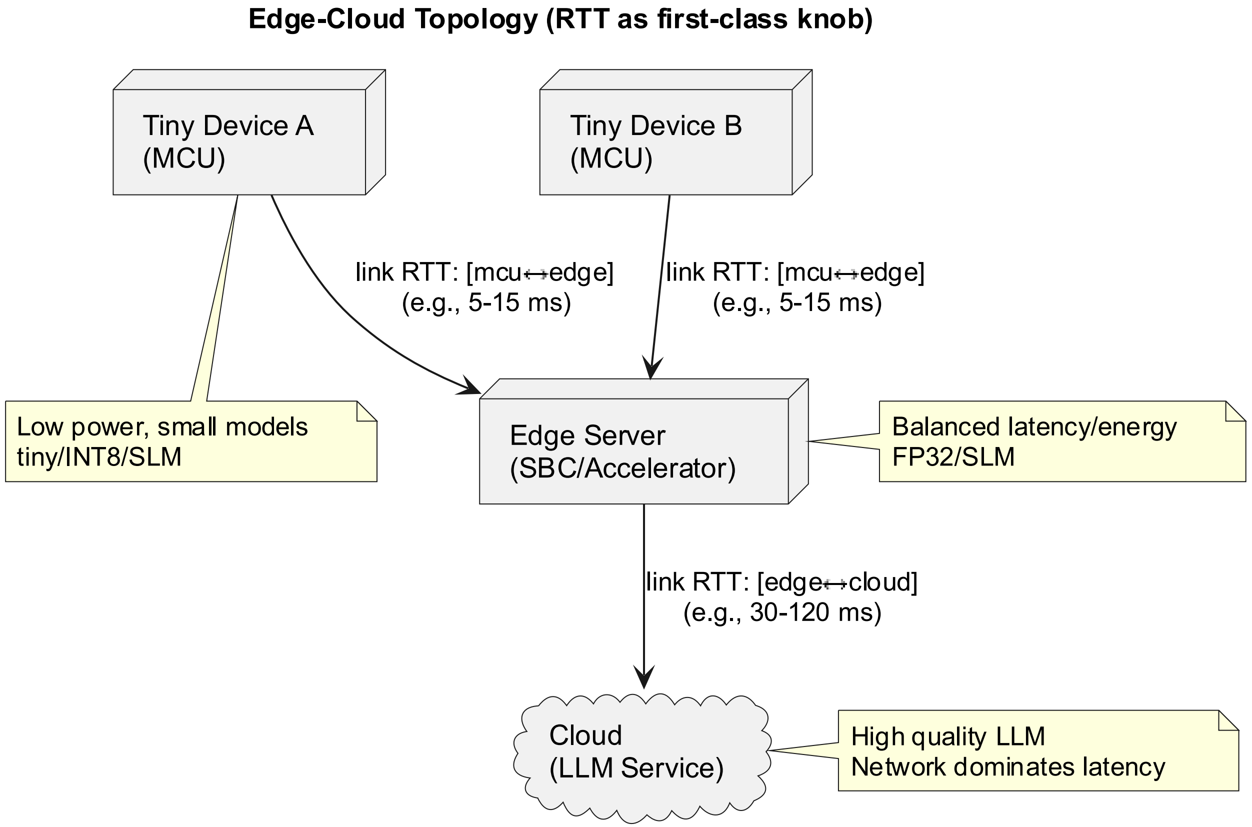
- Difficulty = **hard**, deadline = **80 ms**
- Policy = **Confidence Threshold (0.78)**
- First try MCU/int8: accuracy ~0.8, confidence ~0.7. Since 0.7 < 0.78, **reject**
- Try EDGE/fp32: accuracy ~0.86, confidence ~0.82 → accept
- Simulated latency = 35 ms (with RTT). Deadline met (≤80)
- Random draw → correct = True
- Energy computed ~1.2 mJ

Result row =

{route:"EDGE/fp32", correct:True, latency_ms:35, deadline_met:True, energy_mJ:1.2}.

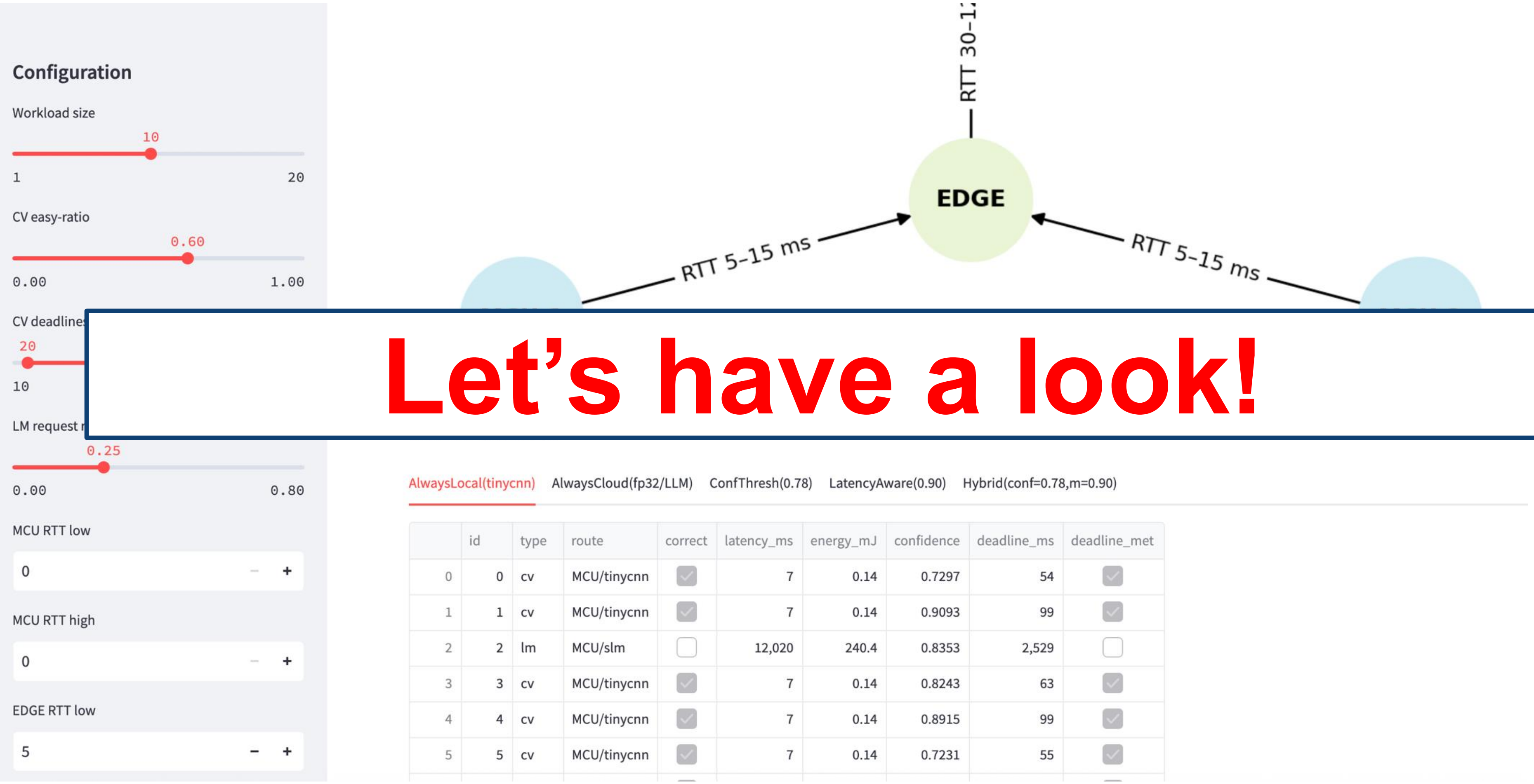
Aggregate across 100+ such requests → plots of Accuracy vs Deadline, Energy vs Accuracy, etc.

Exercise Part 2



Multiple MCUs are shown for realism (different request sources).
Requests are processed independently in series (no queues).

Exercise Part 2



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Let’s have a look!

Distributed Edge AI Simulator

Motivation: Real edge systems have heterogeneous devices.

Simulated devices: End Devices (ex. MCU), Edge, Cloud

Let’s walk through the code!

Requests: Computer Vision tasks + Language Model tasks.

Metrics: latency, accuracy, energy, deadline.

Generate_workload() – how tasks are created.

```
# Energy model constant
ENERGY_K = 0.02

#Emulated device profiles (latency ms, energy factor)
DEFAULT_DEVICES = {
    "MCU":   {"latency": {"fp32": 80, "int8": 25, "tinycnn": 7, "slm": 12000}, "energy_factor": 1.0, "net_rtt": (0, 0)},
    "EDGE":  {"latency": {"fp32": 22, "int8": 10, "tinycnn": 4, "slm": 4000},  "energy_factor": 1.4, "net_rtt": (5, 15)},
    "CLOUD": {"latency": {"fp32": 12, "int8": 12, "tinycnn": 12, "slm": 1500}, "energy_factor": 1.9, "net_rtt": (30, 120)},
}

# Baseline accuracy matrix for "vision-like" tasks
# Accuracy model (per difficulty). Rough, but shows trade-offs.
# You can adjust for your audience: larger gaps → clearer trade-offs.
ACC_MATRIX = {
    "easy": {"fp32": 0.92, "int8": 0.88, "tinycnn": 0.80, "slm": 0.0},
    "hard": {"fp32": 0.86, "int8": 0.80, "tinycnn": 0.70, "slm": 0.0},
}

# For language model (SLM/LLM) requests we model "quality" as accuracy-like metric
LM_QUALITY = {
    "short": {"slm": 0.70, "llm_cloud": 0.90},
    "long":  {"slm": 0.60, "llm_cloud": 0.92},
}
```

Generate_workload() – how tasks are created.

```
#Generate workload (10 requests by default)
def generate_workload(n=10, easy_ratio=0.6, deadline_range=(20,120), lm_ratio=0.2):
    rows = []
    for i in range(n):
        if random.random() < lm_ratio:
            length = "long" if random.random() < 0.4 else "short"
            deadline = random.randint(deadline_range[0]+2000, deadline_range[1]+13000)
            rows.append({"id": i, "type":"lm", "length": length, "difficulty": None, "deadline_ms": deadline})
        else:
            difficulty = "easy" if random.random() < easy_ratio else "hard"
            deadline = random.randint(*deadline_range)
            rows.append({"id": i, "type":"cv", "length": None, "difficulty": difficulty, "deadline_ms": deadline})
    print(pd.DataFrame(rows))
    return pd.DataFrame(rows)
```

infer() / lm_infer() – how devices behave

```python
def infer(device_name: str, model_name: str, difficulty: str, devices: dict) -> tuple:
    dev = devices[device_name]
    base_lat = dev["latency"].get(model_name, 999)
    rtt = rnd_net_rtt(dev["net_rtt"])
    latency = base_lat + rtt
    # Energy model (arbitrary but consistent):
    # energy (mJ) = energy_factor * latency_ms * k
    energy = dev["energy_factor"] * latency * ENERGY_K
    # Simulate confidence loosely from accuracy
    acc = ACC_MATRIX.get(difficulty, {}).get(model_name, 0.75)
    conf = float(np.clip(np.random.normal(loc=0.65 + 0.3*acc, scale=0.1), 0.01, 0.999))
    correct = (random.random() < acc)
    return correct, float(latency), float(energy), conf
```

infer() / lm_infer() – how devices behave

```python
def lm_infer(route: str, length: str, devices: dict) -> tuple:
    """
    route: 'MCU/slm', 'EDGE/slm', or 'CLOUD/llm_cloud'
    length: 'short' or 'long'
    Returns (correct, latency_ms, energy_mJ, confidence, quality)
    """
    if route.startswith("CLOUD"):
        base = devices["CLOUD"]["latency"].get("slm", 1500)
        rtt = rnd_net_rtt(devices["CLOUD"]["net_rtt"])
        latency = base + rtt + (10 if length=="long" else 5)
        energy = devices["CLOUD"]["energy_factor"] * latency * ENERGY_K
        quality = LM_QUALITY[length]["llm_cloud"]
    else:
        tier = "EDGE" if route.startswith("EDGE") else "MCU"
        base = devices[tier]["latency"].get("slm", 12000)
        rtt = rnd_net_rtt(devices[tier]["net_rtt"])
        latency = base + rtt + (20 if length=="long" else 8)
        energy = devices[tier]["energy_factor"] * latency * ENERGY_K
        quality = LM_QUALITY[length]["slm"]
    correct = (random.random() < quality)
    conf = float(np.clip(np.random.normal(loc=0.6 + 0.3*quality, scale=0.1), 0.01, 0.999))
    return correct, float(latency), float(energy), conf, quality
```

Policies (always_local, conf_threshold, etc.) – design ideas

```python
def pol_conf_threshold(req, devices, thr=0.78):
    if req["type"]=="lm":
        c1, l1, e1, conf1, _q1 = lm_infer("MCU/slm", req["length"], devices)
        if conf1 >= thr:
            return "MCU/slm", c1, l1, e1, conf1
        c2, l2, e2, conf2, _q2 = lm_infer("EDGE/slm", req["length"], devices)
        if conf2 >= thr:
            return "EDGE/slm", c2, l2, e2, conf2
        c3, l3, e3, conf3, _q3 = lm_infer("CLOUD/llm_cloud", req["length"], devices)
        return "CLOUD/llm_cloud", c3, l3, e3, conf3
    else:
        c1, l1, e1, conf1 = infer("MCU", "int8", req["difficulty"], devices)
        if conf1 >= thr:
            return "MCU/int8", c1, l1, e1, conf1
        c2, l2, e2, conf2 = infer("EDGE", "fp32", req["difficulty"], devices)
        if conf2 >= thr:
            return "EDGE/fp32", c2, l2, e2, conf2
        c3, l3, e3, conf3 = infer("CLOUD", "fp32", req["difficulty"], devices)
        return "CLOUD/fp32", c3, l3, e3, conf3
```

evaluate_policy() – how we test them

```python
def evaluate_policy(workload_df: pd.DataFrame, policy_fn, devices: dict) -> pd.DataFrame:
    out = []
    for _, req in workload_df.iterrows():
        route, correct, latency, energy, conf = policy_fn(req, devices)
        out.append({
            "id": int(req["id"]), "type": req["type"], "route": route, "correct": bool(correct),
            "latency_ms": float(latency), "energy_mJ": float(energy), "confidence": float(conf),
            "deadline_ms": int(req["deadline_ms"]), "deadline_met": float(latency) <= float(req["deadline_ms"])
        })
    print(pd.DataFrame(out))
    return pd.DataFrame(out)
```

Exercise Part 2 – Group Work Setup

- Form groups of 3–5 participants.
  - But feel free to work alone :)
- Each group extends the simulator with one or more new ideas / features.
- Work in the code, document what you tried + results.

- You don’t need to “finish” → just experiment.
- Focus on **what changes in the trade-offs**.
- Capture a quick result (plot or table).
- Prepare a 2 / 3 minute summary

Challenge Cards

- Option 1: Enrich LM modeling (e.g., task length scaling).
- Option 2: More realistic energy models (battery, DVFS).
- Option 3: Add new accelerators (GPU, TPU) → new latencies.
- Option 4: Vary traffic (bursty, arrival rates).
- Option 5: New topologies (multi-edge, hierarchical).
- Option 6: Smarter policies (queue-aware, RL-inspired).
- Option 7: Modify Quality
- Option 8: Always edge
- **Option 9: Your choice!!**

Group Work

Suggested flow for the 50-min group session

Explore the Code (5–10 min)

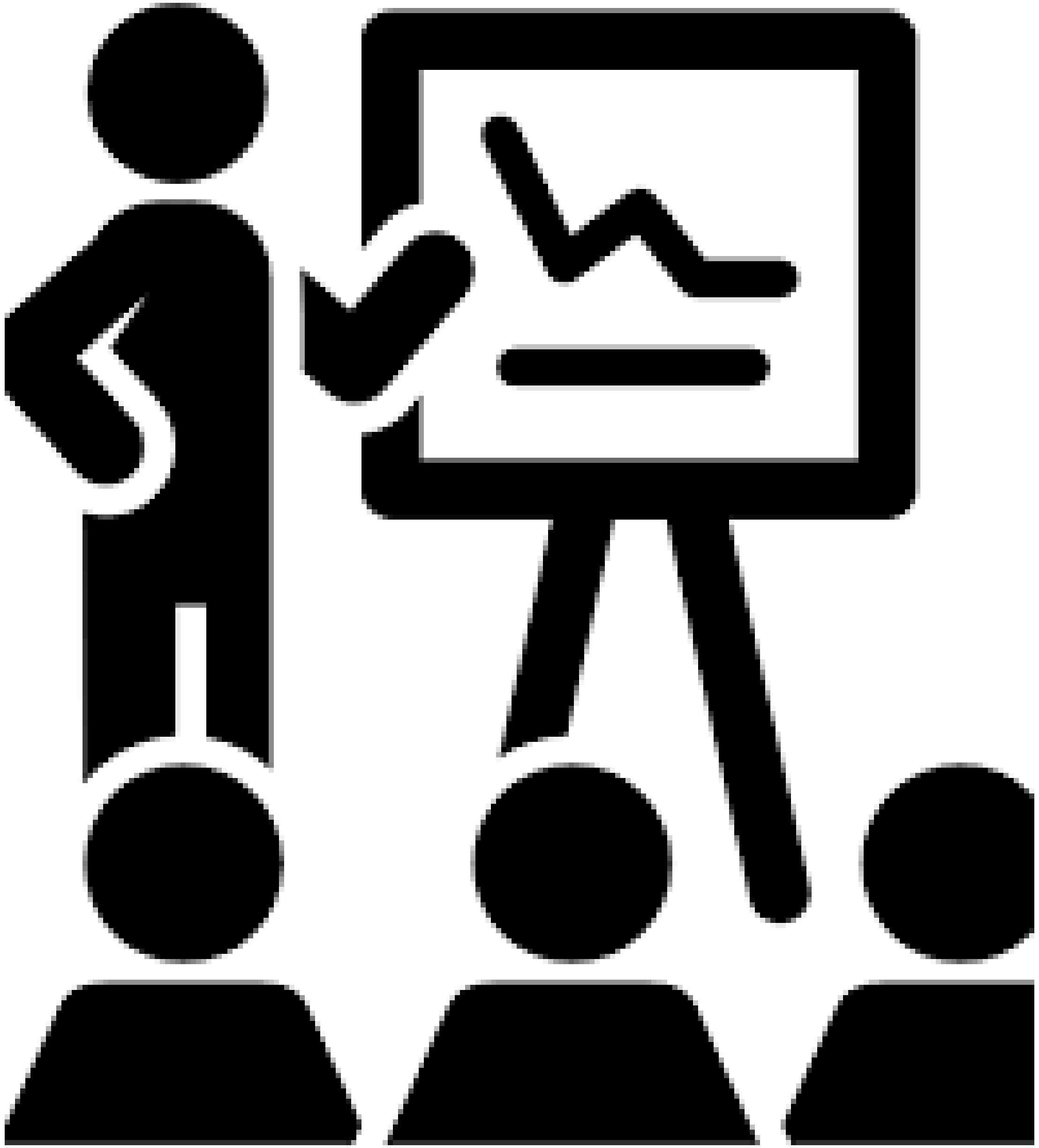
1. Skim through simulate.py and notebook cells
2. Make sure everyone in the group understands the baseline

Brainstorm Extensions (5–10 min)

1. Discuss which challenge card to pick (LM modeling, accelerators, energy, traffic…)
2. Agree on one idea to prototype

Implement & Test (25–30 min)

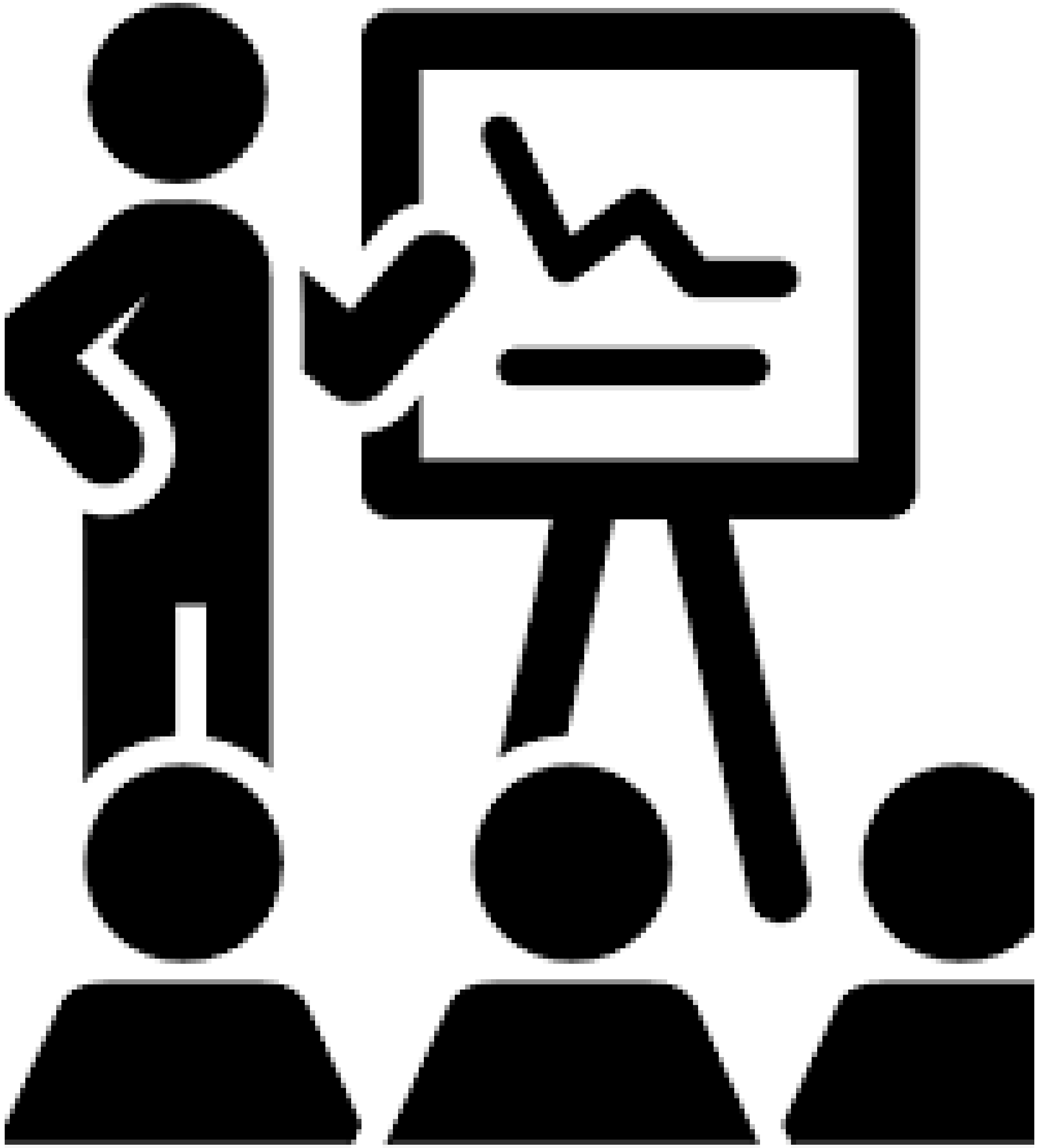
1. Modify the simulator or notebook
2. Run a few policies and collect quick results (table or plot)



Group Presentations

Each group:

- What extension did you try?
- What changed in results?
- One insight or question.



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