LightTune: Lightweight Online Fine-tuning for 6G

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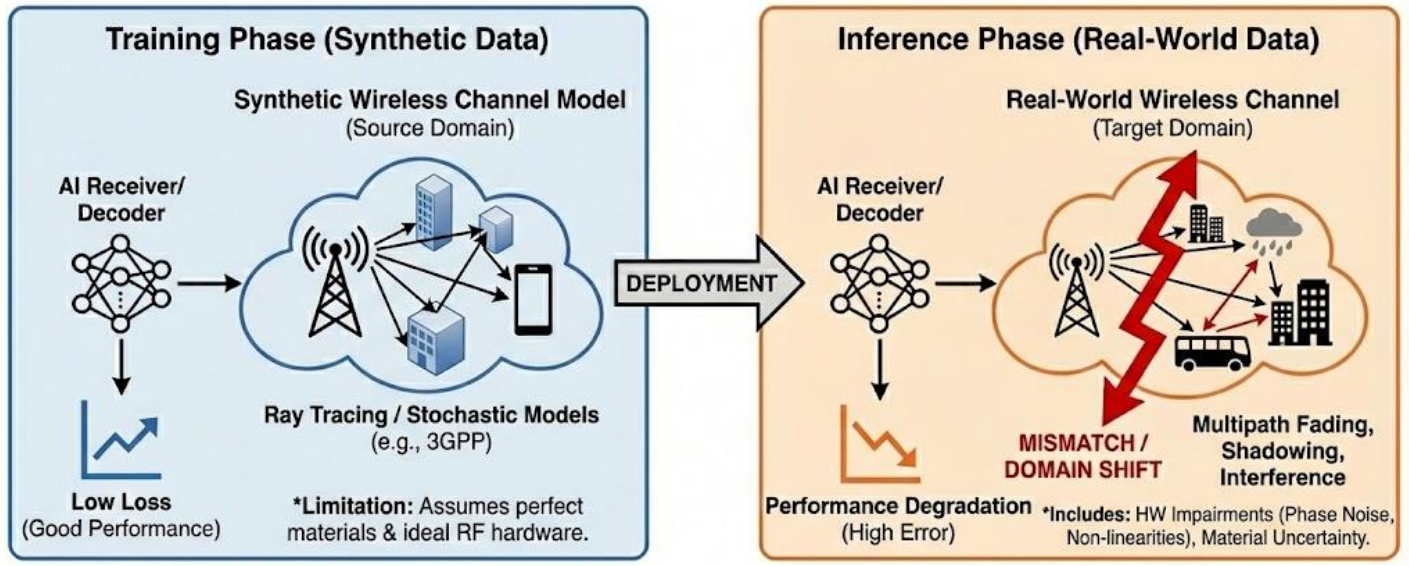
Outline

1. Motivation & Related Works
2. Proposed Online Fine-tuning Algorithm: LightTune
3. Applications of LightTune in 5G/6G
4. Takeaways

Motivation: Training-Test Mismatch

- ML training done with synthetic data and/or limited real data
- At inference, their performance may degrade due to the training-test mismatch
  - Synthetic data does not capture the real-world complexity
  - Even if real-data is used in training, the mismatch can still happen



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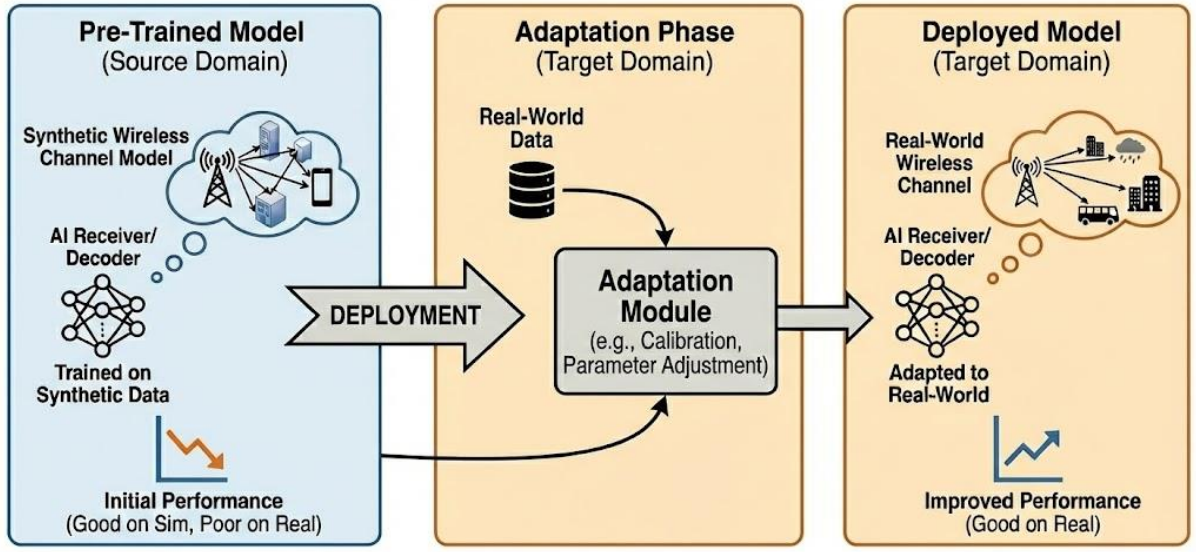
Motivation: Training-Test Mismatch

- ML models need to adapt after being deployed
- For mobiles, this needs to be done with minimal storage and computations



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Background and Related Works

- How can on-device ML models adapt with minimal overhead?

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- Prior works in ML-based Wireless
  1) Online Calibration/Adaptation
     - ML models are not updated
     - Then, ML predictions are successively calibrated based on the real-world observations

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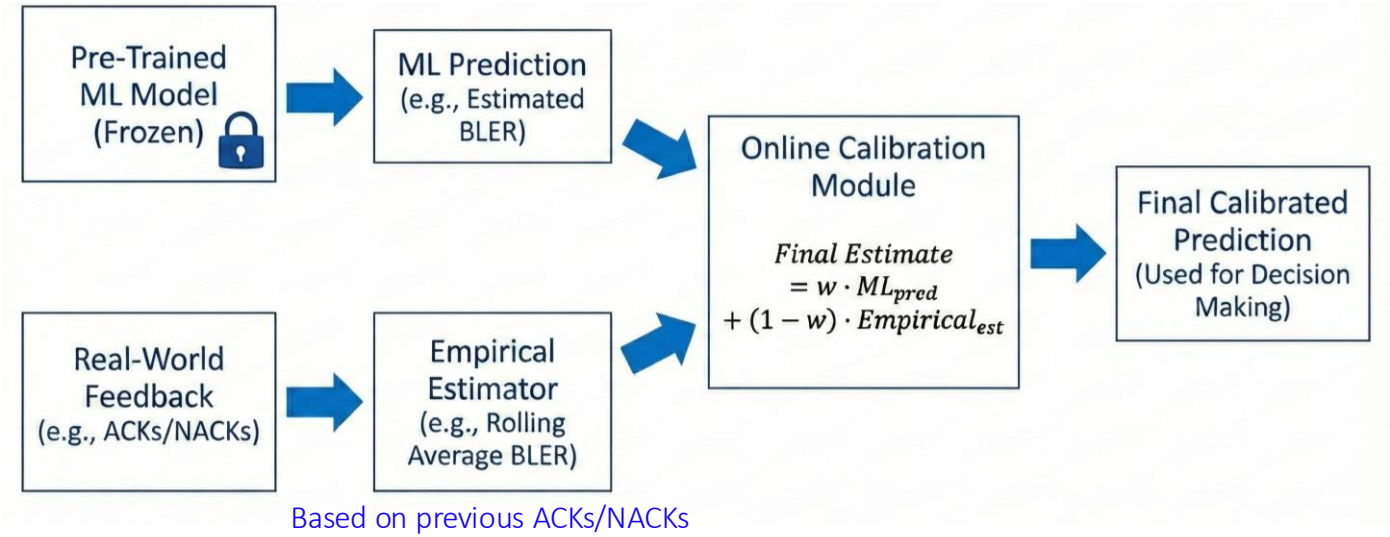
     - Example: Block Error Rate (BLER) Prediction



[A. Baknina et al., "Adaptive CQI and RI Estimation for 5G NR: A Shallow Reinforcement Learning Approach," in IEEE GLOBECOM, 2020]
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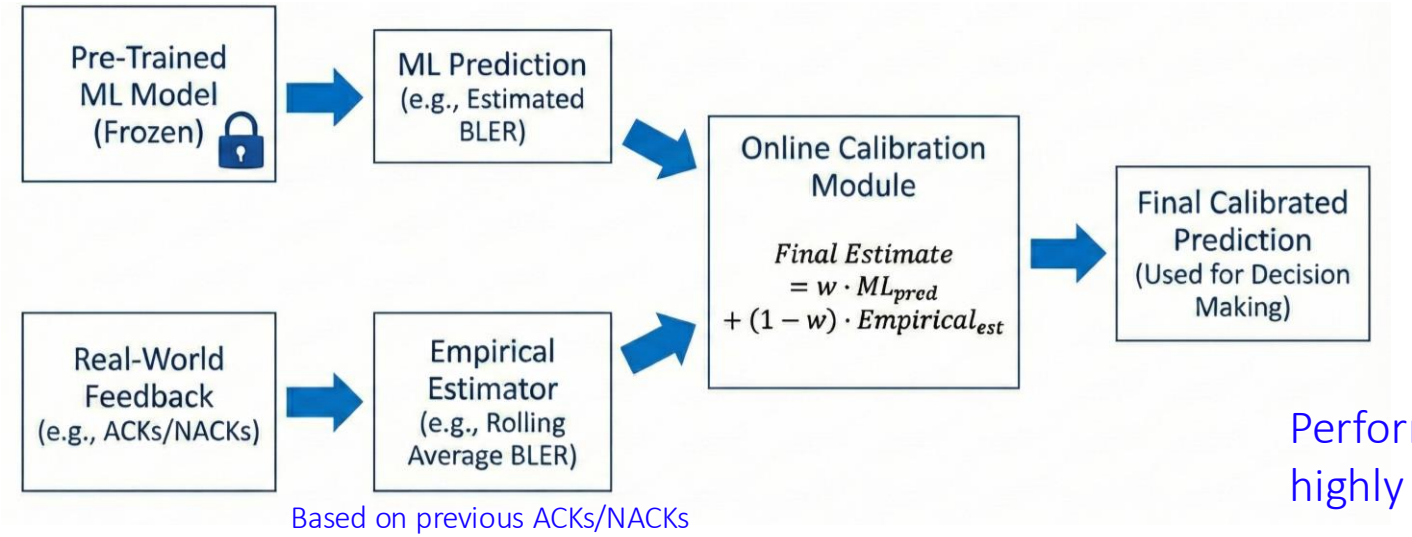

Performance still degrades in highly dynamic environments !

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- How can on-device ML models adapt with minimal overhead?
- Prior works in ML-based Wireless
  - 2) Online Learning (e.g., Reinforcement Learning, Continual Learning)
    - Requires frequent model updates, online gradient computations, backpropagation, replay buffer, …
    - Mobiles (esp. in wireless modem) may not be able to support this

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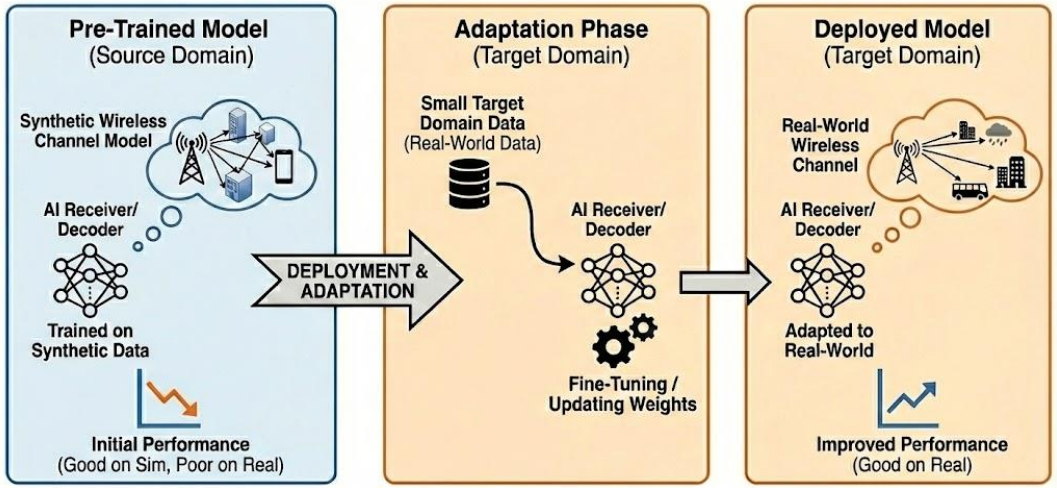
  - 3) Online Fine-tuning (Simpler)
    - Mobiles may not be able to support this as well



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Our work: LightTune

- A lightweight online fine-tuning algorithm suitable for on-device learning
  - e.g., mobile phones (esp. wireless modem), edge devices, …
- Suitable when the ground-truth of the predicted metric becomes available after a delay
  - e.g., Throughput prediction, Block error rate (BLER) prediction, …
- As an application, we use LightTune for link adaptation in 5G/6G
  - Up to 9.5% average throughput improvement compared to baselines

Our work: LightTune

1) Backpropagation-free
   - ✓ Fine-tuning using forward passes only

2) Threshold-based
   - ✓ Only fine-tunes when needed, not continuously

3) Buffer-less
   - ✓ Sample-by-sample fine-tuning

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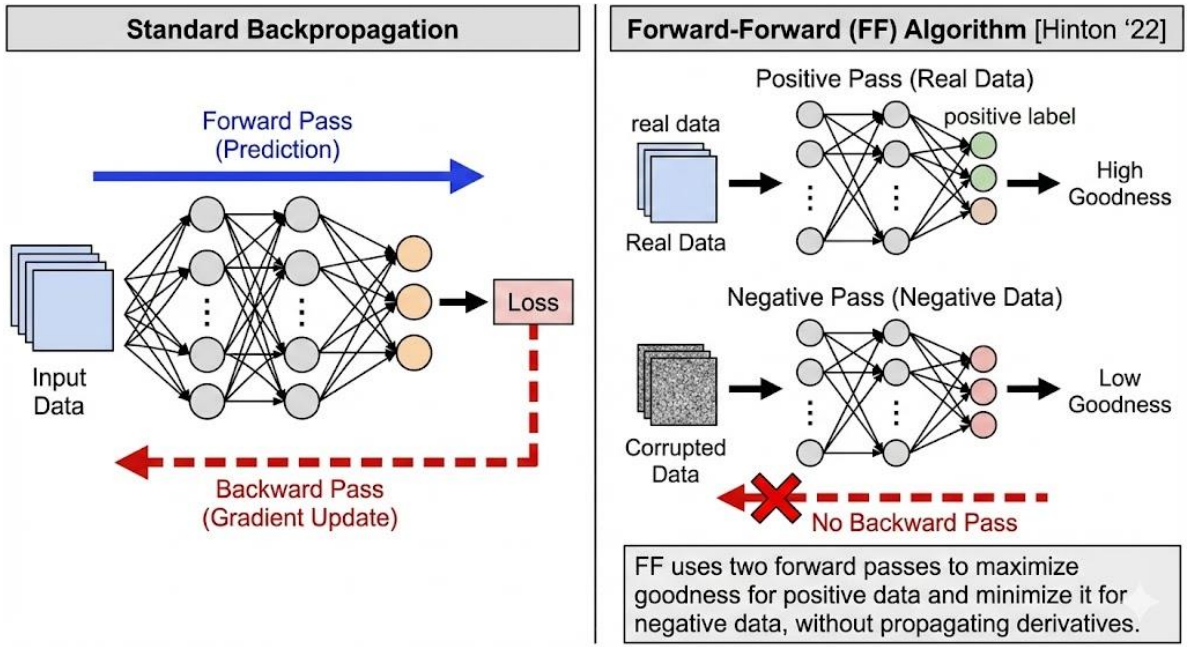
LightTune: Detailed Algorithm

1) Backpropagation-free by leveraging the forward-forward (FF) algorithm



Used mainly in computer vision

G. Hinton, "The Forward-Forward Algorithm: Some Preliminary Investigations," arXiv preprint arXiv:2212.13345, 2022.

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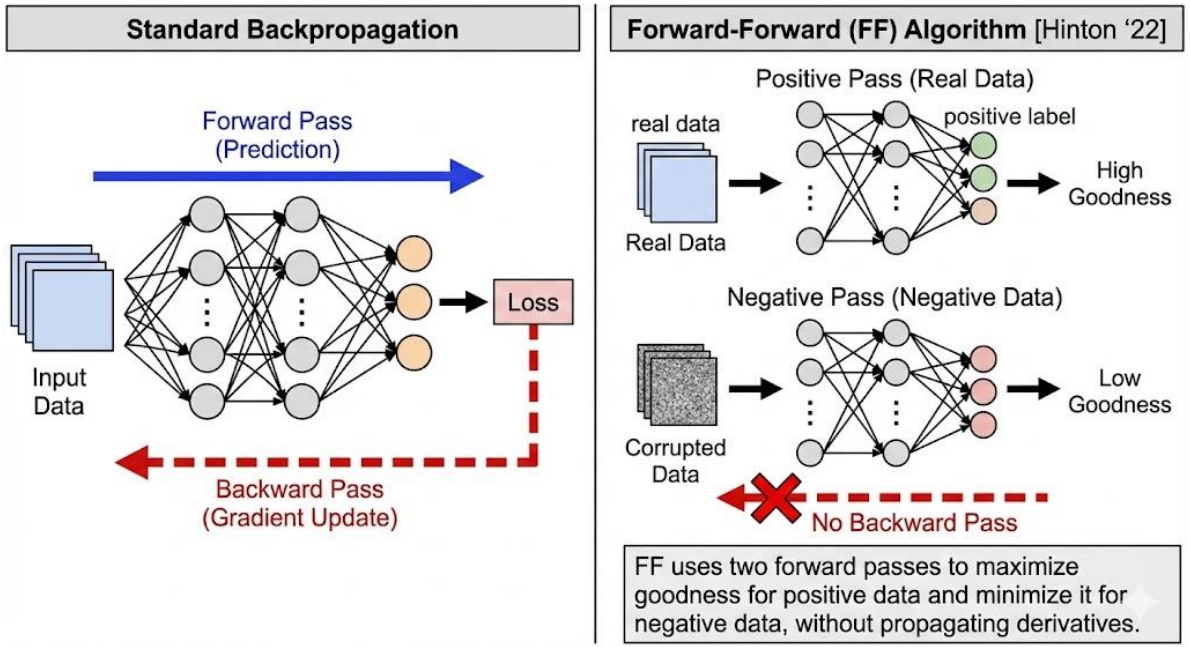

- ✓ Memory-efficient
  - In FF, RAM scales with the size largest layer
  - In backpropagation, RAM scales with depth of the network and layer sizes
- ✓ Simplicity
  - No computational graph nor Autodiff engines are needed

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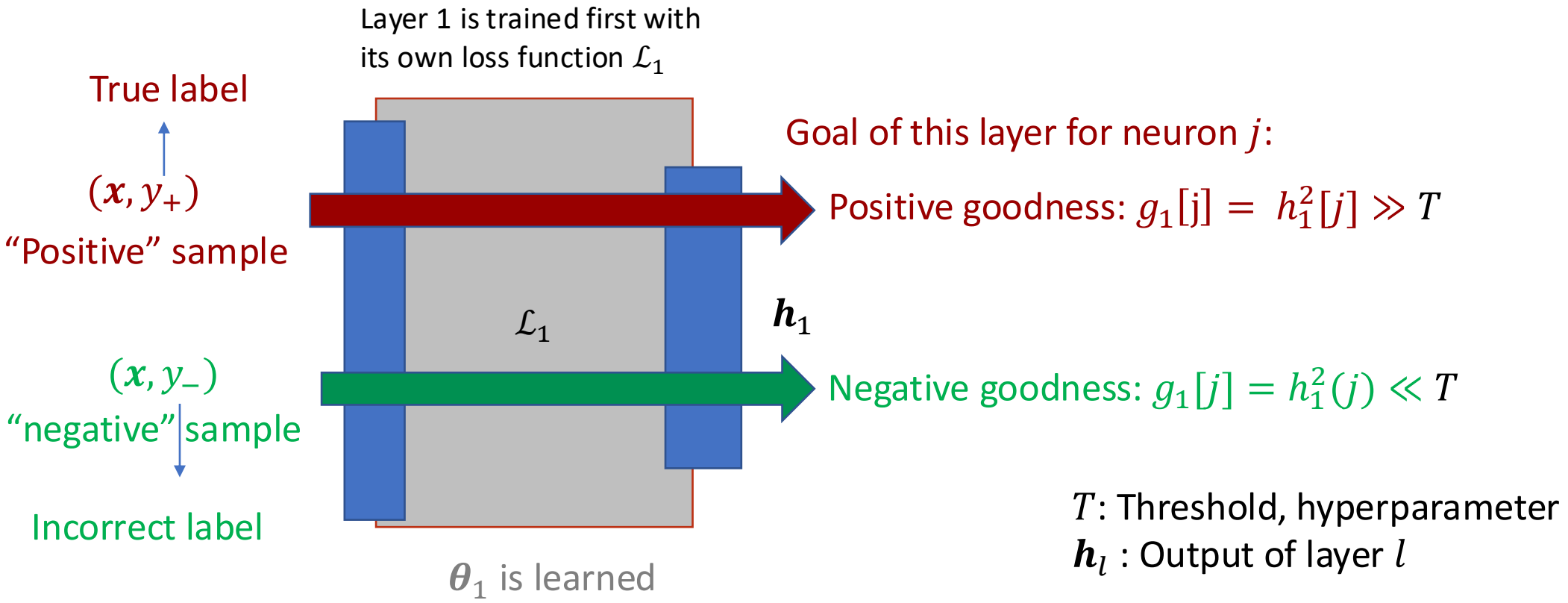

T: Threshold, hyperparameter

$\boldsymbol{h}_l$: Output of layer l

✓ Training is sequential, layer by layer

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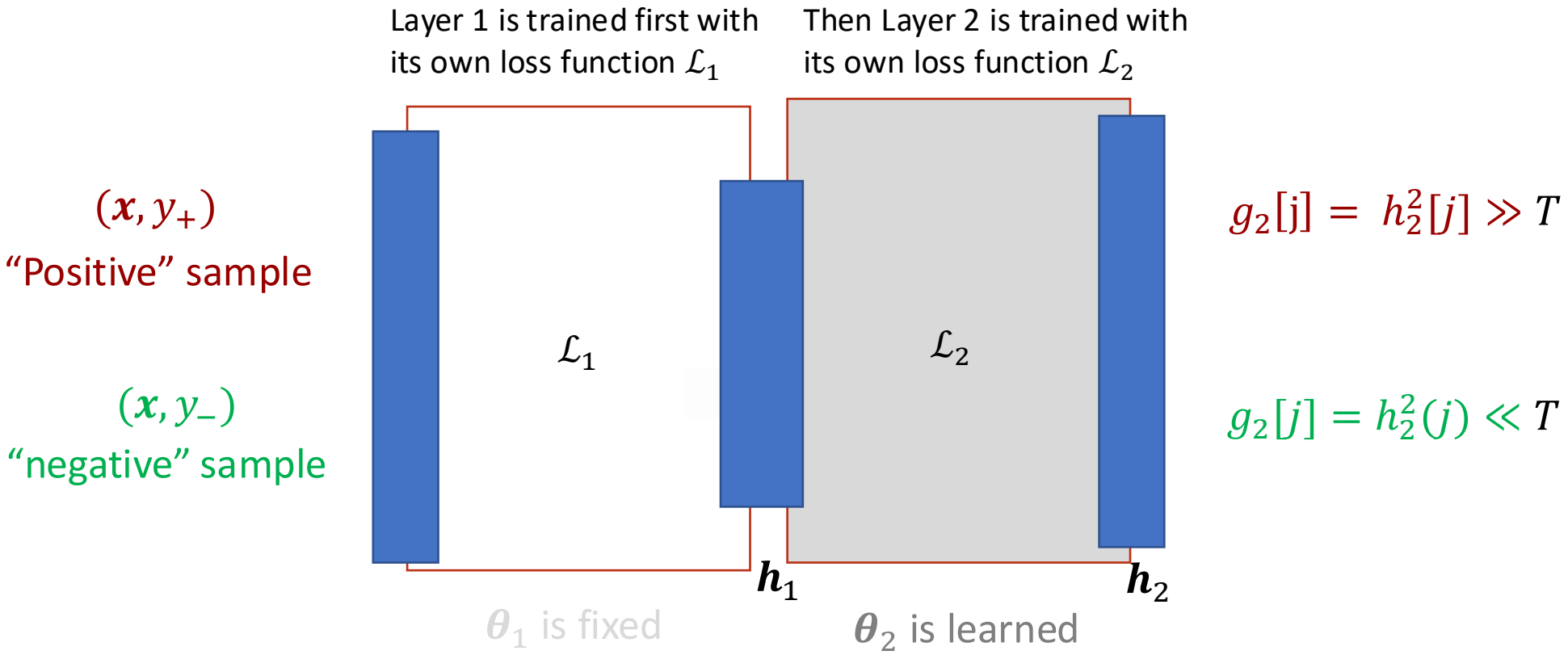

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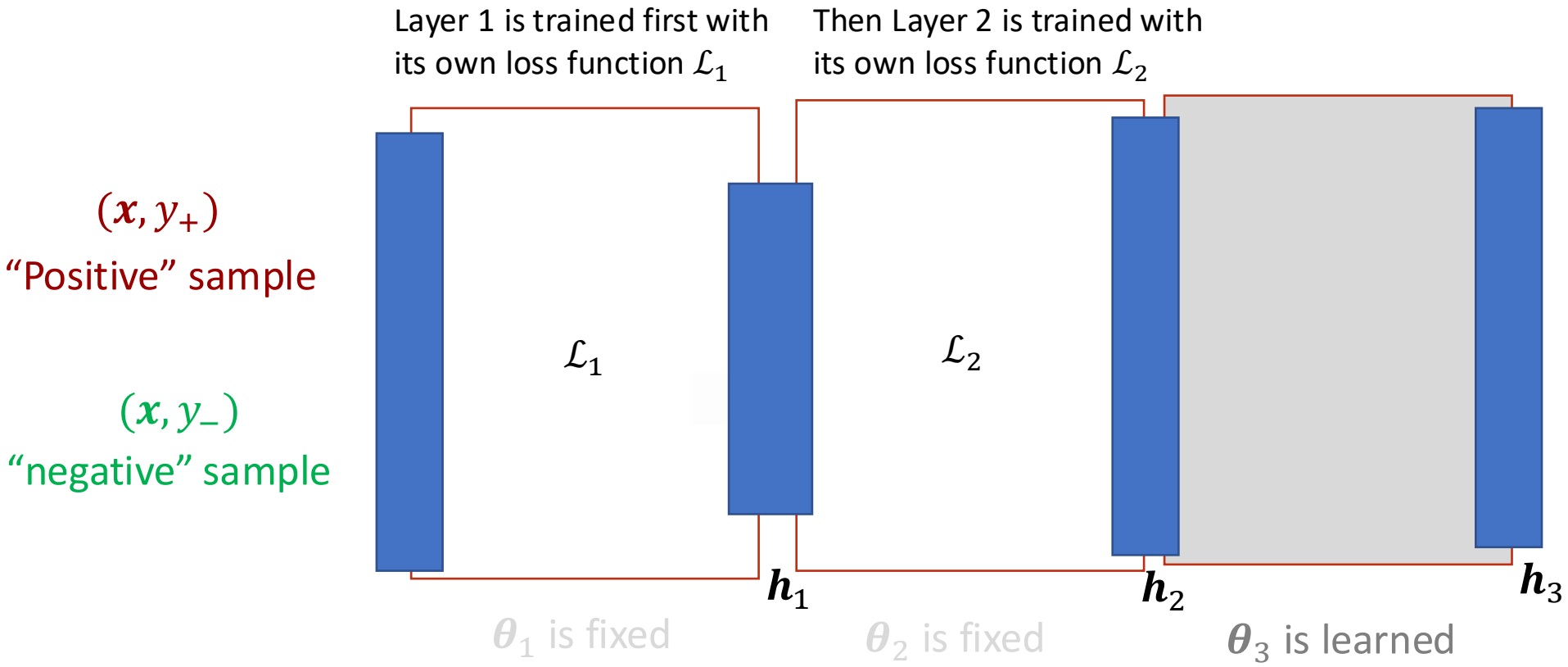

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LightTune: Proposed Loss Function

1) Backpropagation-free by leveraging the forward-forward (FF) algorithm
   - Softplus loss typically used in the FF algorithm

$$\mathcal{L}_{\text{Softplus},l} = \frac{1}{|\mathcal{S}_+|}\sum_{i\in\mathcal{S}_+}\frac{1}{M_l}\sum_{j=1}^{M_l}\ln\left(1+e^{-\left(g_{+,l}^{(i)}[j]-T\right)}\right) + \frac{1}{|\mathcal{S}_-|}\sum_{i\in\mathcal{S}_-}\frac{1}{M_l}\sum_{j=1}^{M_l}\ln\left(1+e^{\left(g_{-,l}^{(i)}[j]-T\right)}\right).$$

>>

<<

$g_{+,l}[j]$: positive goodness of neuron j in layer l
$g_{-,l}[j]$: negative goodness of neuron j in layer l
$\mathcal{S}_+$: set of positive samples
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<<

Needs exponentiations & divisions to compute derivatives !!

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- To avoid the exponentiations and divisions, we propose an on-device friendly loss

$g_{+,l}[j]$: positive goodness of neuron j in layer l
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$\mathcal{S}_+$: set of positive samples
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$$\mathcal{L}_{\text{Prop},l} = \frac{1}{|\mathcal{S}_+|}\sum_{i\in\mathcal{S}_+}\frac{1}{M_l}\sum_{j=1}^{M_l}\left((g_{+,l}^{(i)}[j]-T)^2 - 4(g_{+,l}^{(i)}[j]-T)\right) + \frac{1}{|\mathcal{S}_-|}\sum_{i\in\mathcal{S}_-}\frac{1}{M_l}\sum_{j=1}^{M_l}\left((g_{-,l}^{(i)}[j]-T)^2 + 4(g_{-,l}^{(i)}[j]-T)\right).$$

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LightTune: Lightweight Gradient Computations

1) Backpropagation-free by leveraging the forward-forward (FF) algorithm
   - Closed-form gradients for each layer
   - Just lightweight computations to fine-tune

$$\nabla_{\boldsymbol{W}_l} \mathcal{L}_{\text{Prop},l} = [(2(\boldsymbol{g}_{+,l} - T) - 4) \odot 2\boldsymbol{h}_{+,l} \odot \mathbf{1}(\boldsymbol{x}_{+,l} > 0)]\, \boldsymbol{x}_{+,l}^\top + [(2(\boldsymbol{g}_{-,l} - T) + 4) \odot 2\boldsymbol{h}_{-,l} \odot \mathbf{1}(\boldsymbol{x}_{-,l} > 0)]\, \boldsymbol{x}_{-,l}^\top,$$
$$\nabla_{\boldsymbol{b}_l} \mathcal{L}_{\text{Prop},l} = (2(\boldsymbol{g}_{+,l} - T) - 4) \odot 2\boldsymbol{h}_{+,l} \odot \mathbf{1}(\boldsymbol{x}_{+,l} > 0) + (2(\boldsymbol{g}_{-,l} - T) + 4) \odot 2\boldsymbol{h}_{-,l} \odot \mathbf{1}(\boldsymbol{x}_{-,l} > 0).$$

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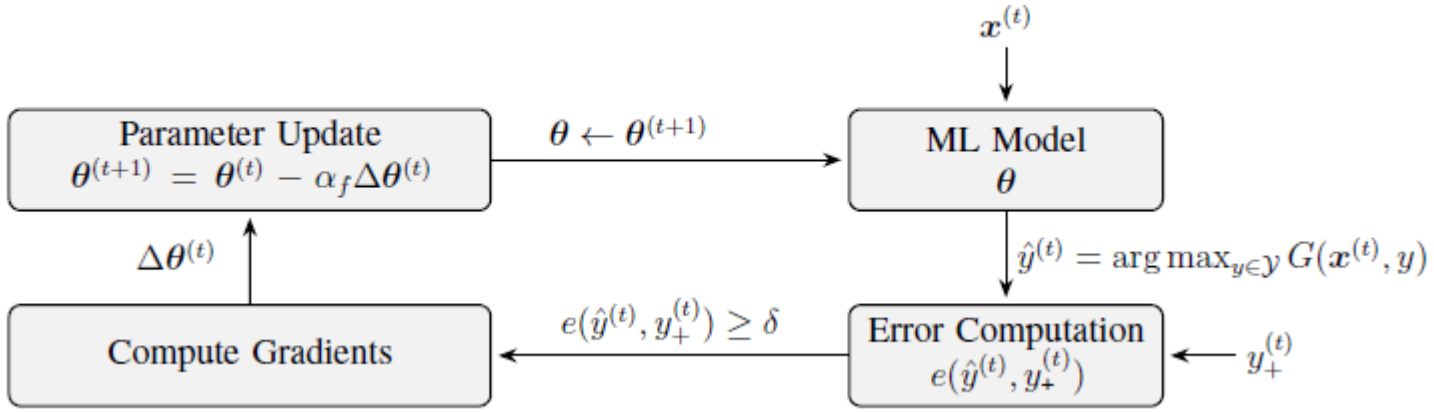
LightTune: Detailed Algorithm

2) Threshold-based

- Fine-tuning is only performed when needed
  - ✓ When error prediction error reaches a pre-defined threshold δ

3) Buffer-less

- Updates are performed on a sample-by-sample basis (i.e., no buffer)



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LightTune: Convergence

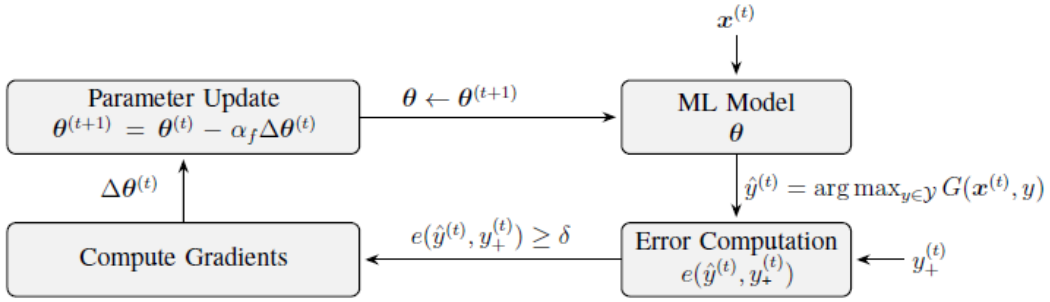
Theorem: Assuming

(1) boundedness of the data and the model,

(2) non-degeneracy,

(3) stationarity,

(4) uniform negative sampling, LightTune ensures that for ReLU MLPs, we have



$$\lim_{t \to \infty} \Pr\left(\left|\hat{y}^{(t)} - y_+^{(t)}\right| \geq \delta\right) = 0$$

Prediction error

Pre-defined threshold

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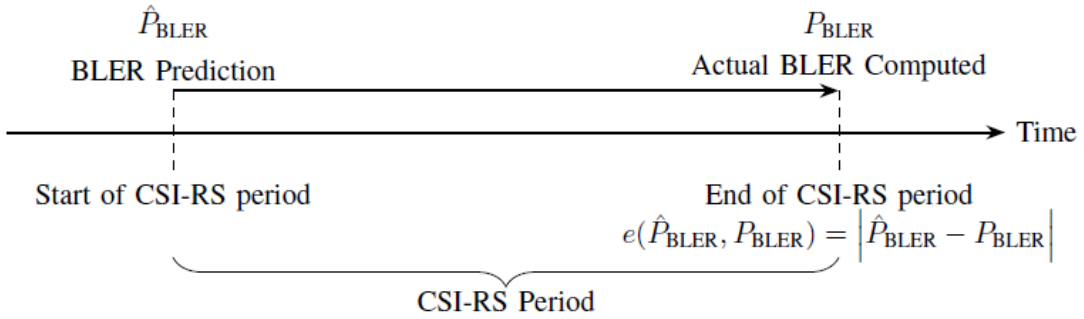
Applications of LightTune: Block Error Rate (BLER) Prediction

- BLER prediction has many application in 5G/6G including link adaptation, PMI selection, …
- Ground-truth can be computed after a delay (i.e., end of the CSI-RS period)



$$P_{\text{BLER}} = \frac{n_{\text{NACK}}}{n_{\text{NACK}} + n_{\text{ACK}}}$$

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Applications of LightTune: Block Error Rate (BLER) Prediction

- To simulate the training-test mismatch, we choose mismatched training and test conditions.

Parameter	Training	Test
Channels	TDL-A30	TDL-A30, TDL-B50, TDL-C200
SNR	Low (0–12 dB)	Low/Medium/High (0–40 dB)
Delay Profile	Low Delay	Low/High Delay
Doppler Frequency	Low (10 Hz)	Low/Medium (10–50 Hz)

Parameter	Value
Neural Network Size	`[13, 32, 32]`
Activation Function	ReLU
Offline Learning Rate α	0.03
Online Learning Rate α_f	0.03
Fine-tuning Threshold δ	0.3
Optimizer	Adam ($\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$)
Threshold T	9
Epochs	22,000
Training Samples	83,200
BLER Quantization Step	$\lambda = 0.1$

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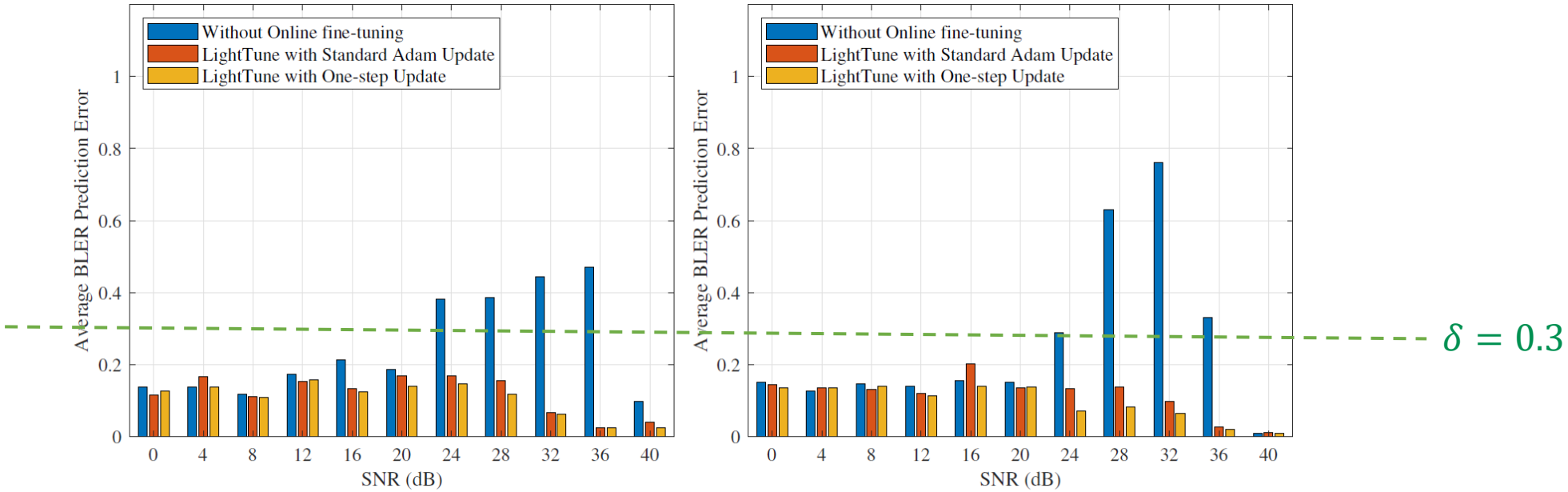
Applications of LightTune: Block Error Rate (BLER) Prediction

- Online fine-tuning is a must!



(a) TDL-A30 (Doppler freq. = 10 Hz) (b) TDL-B50 (Doppler freq. = 30 Hz)

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Applications of LightTune: Link Adaptation in 5G/6G

- Conventional table-based link adaption algorithms [e.g., Peralta‘22] are slow to converge
  - Initially, they may select CQIs with high BLER

E. Peralta et al., “Outer loop link adaptation enhancements for ultra reliable low latency communications in 5G,” in IEEE VTC, 2022.

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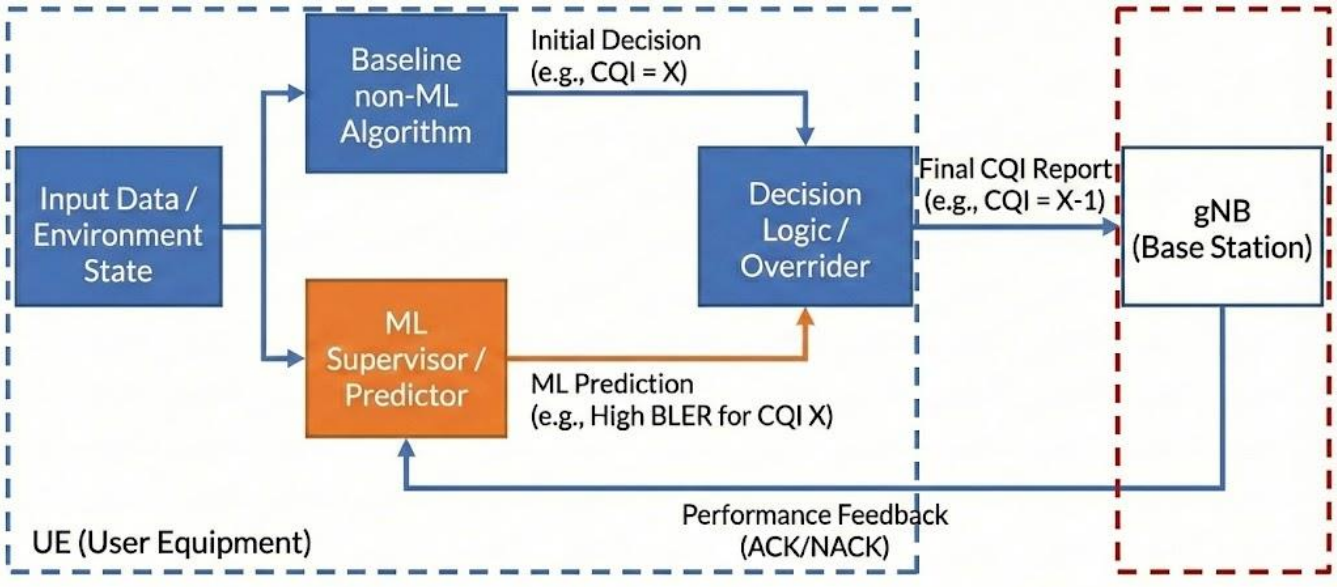
Applications of LightTune: Link Adaptation in 5G/6G

- Conventional table-based link adaption algorithms [e.g., Peralta‘22] are slow to converge
  - Initially, they may select CQIs with high BLER
- To mitigate this high BLER, we use our BLER prediction algorithm as a backoff mechanism.



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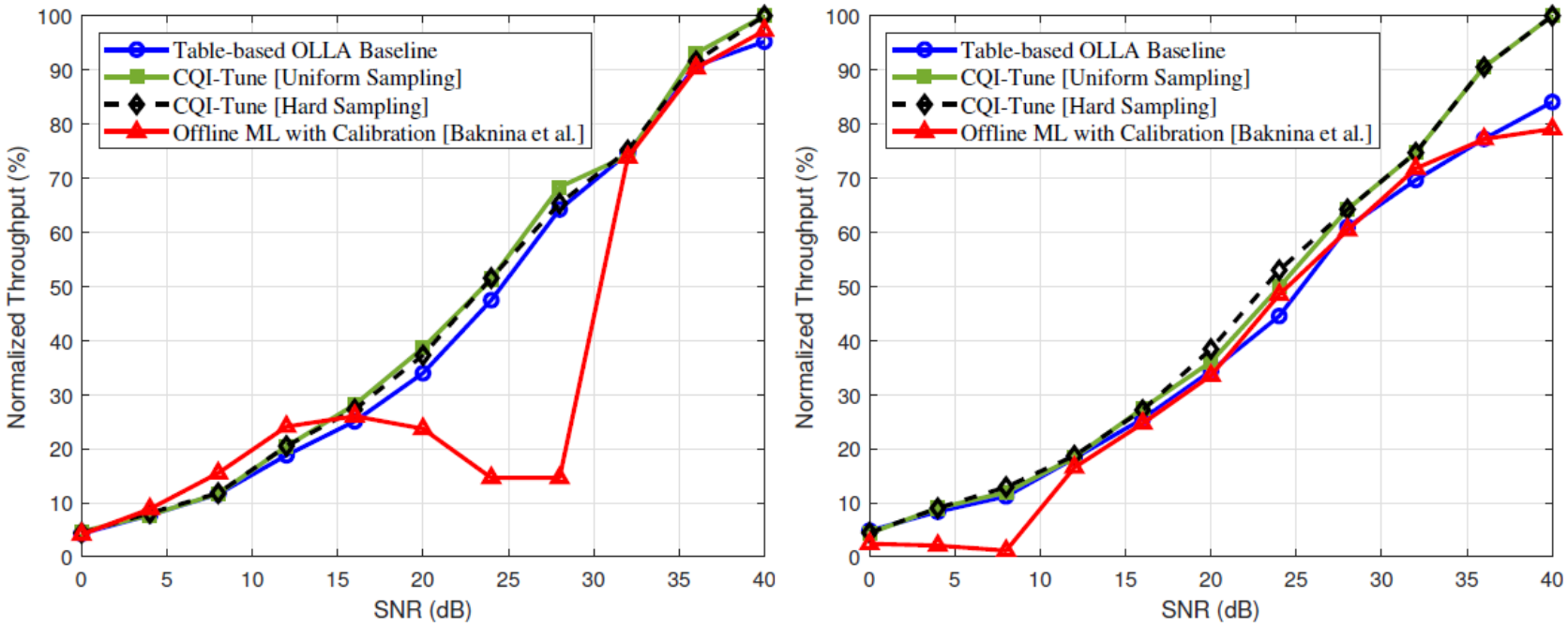
- Based on the BLER prediction algorithm, we propose a CQI selection algorithm.



(a) TDL-B50 (Dop. freq. = 30 Hz). (b) TDL-C200 (Dop. freq. = 50 Hz)

Up to 9.5% throughput improvement

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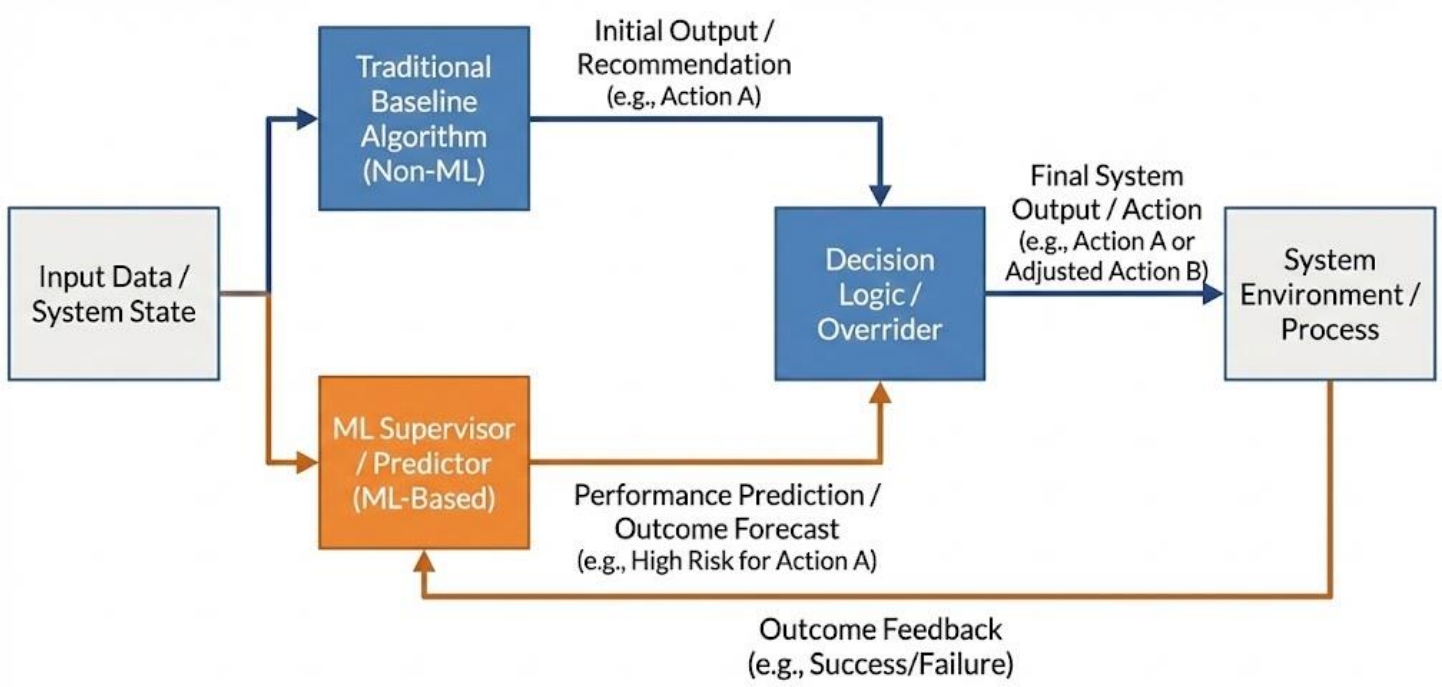
Takeaways & Future Work

1. Online fine-tuning is essential for ML-based wireless algorithms
2. We showed case for CQI selection, but LightTune can be applied to other problems
   - Rank Selection
   - PMI Selection
   - …..

Takeaways & Future Work

3. Instead of using ML entirely, ML can serve just as a guide for the baseline algorithm
   - Less complexity than using ML entirely
   - Starting from good initial solution (i.e., baseline solution)



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Thank you
Questions?