ITUEvents

Machine Learning for Wireless LANs + Japan Challenge Introduction
ITU-ML5G-PS-031, ITU-ML5G-PS-032
7 August 2020

ITU

AI/ML in 5G

Challenge

Applying machine learning in communication networks

ai5gchallenge@itu.int

Register here

Join us on Slack

Sponsors

Organizer

ITU AI/ML in 5G Challenge

Global Round in Japan

ITU AI/ML in 5Gチャレンジ

- ITU-Tが企画する5GネットワークにAI/MLを活用して様々な問題解決を競う国際的なコンペティション
  - 今年が第1回で今後も実施予定
- 世界各国で10 のGlobal Roundを開催
  - 中国2組織，スペイン2組織，ブラジル，アメリカ，日本，インド，アイルランド，トルコ
  - 各国のGlobal Roundトップ3チームが，ITU-TのFinal Conference に推薦される
- 日本開催分を，RISING研究会（超知性ネットワーキングに関する分野横断型研究会）で運営
- TTC，5GMF，KDDI，NEC の後援・支援

（総務省のご支援を検討いただいています）

主催

スポンサー

5GMF

The Fifth Generation Mobile Communications Promotion Forum

第５世代モバイル推進フォーラム（5GMF）は、第５世代移動通信システム（5G）の早期実現を図るため、関連する研究開発及び標準化に係る調査研究・関係機関との連絡調整・情報の収集・普及啓発活動等を通じて、電気通信利用の健全な発展に寄与することを目的としています。本サイトでは5GMFの活動・トピックス・各フォーラムでの成果等をご紹介しつつ、5G関連ニュースやオピニオン等もお届けします。

＞第5世代移動通信システム「5G」とは？　＞White Paper & Report

「5Gチャレンジ・日本ラウンド」のご紹介

ITU-Tが企画する国際的なコンペティションである「5Gチャレンジ」が開催されております。5GネットワークにAI / ML（Artificial Intelligence / Machine Learning：人工知能 / 機械学習）を活用して様々な問題解決を競うもので、その予選コンペティションとなる「日本ラウンド」についてご紹介いたします。

2020.08.07

https://5gmf.jp

Top Overview Participation Theme 1 Theme 2 Theme 3 Rules Organizers

ITU
AI/ML in 5G Challenge
Global Round in Japan

Organizers

ITU

RISING Cross-Field Research Association of Super-Intelligent Networking

TTC Telecommunication Technology Committee

KDDI Research

5GMF The Fifth Generation Mobile Communications Promotion Forum

NEC

Theme 1 from KDDI
Analysis on Route Information Failure in IP Core Networks by NFV-Based Test Environment

Theme 2 from NEC
Network State Estimation by Analyzing Raw Video Data

Theme 3 from RISING (Not for Final Conference of ITU)
WiFi Location Estimation

https://www.ieice.org/~rising/AI-5G/

TTC Telecommunication Technology Committee 一般社団法人 情報通信技術委員会　English

https://www.ttc.or.jp/maedablog/20200803

TTCについて　入会案内　活動内容　標準・刊行物　トピックス　セミナー

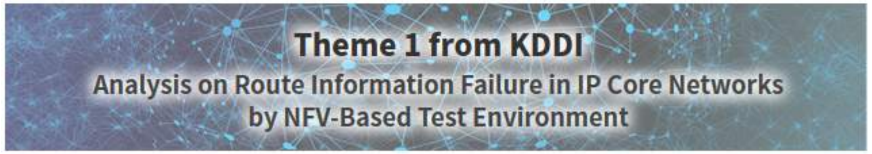
Home ＞マエダブログ ＞AI/MLを活用する5Gチャレンジ・日本ラウンドのウェビナー

2020/08/03 マエダブログ

AI/MLを活用する5Gチャレンジ・日本ラウンドのウェビナー

Global Round in Japan（日本開催分）

■ テーマ1（KDDI）
- 5Gに向けたIPコア網の
  障害・誤作動特定



■ テーマ2（NEC）
- RAWビデオデータによる
  ネットワーク状態推定

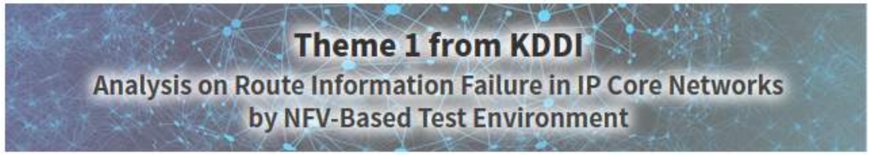
■ テーマ3（RISING）
- 無線関係のテーマ（このあと山本先生よりご紹介）

Global Round in Japan（日本開催分）

■ テーマ1（KDDI）

● 5Gに向けたIPコア網の
障害・誤作動特定

ITUのFinal conference 推薦対象



■ テーマ2（NEC）

● RAWビデオデータによる
ネットワーク状態推定

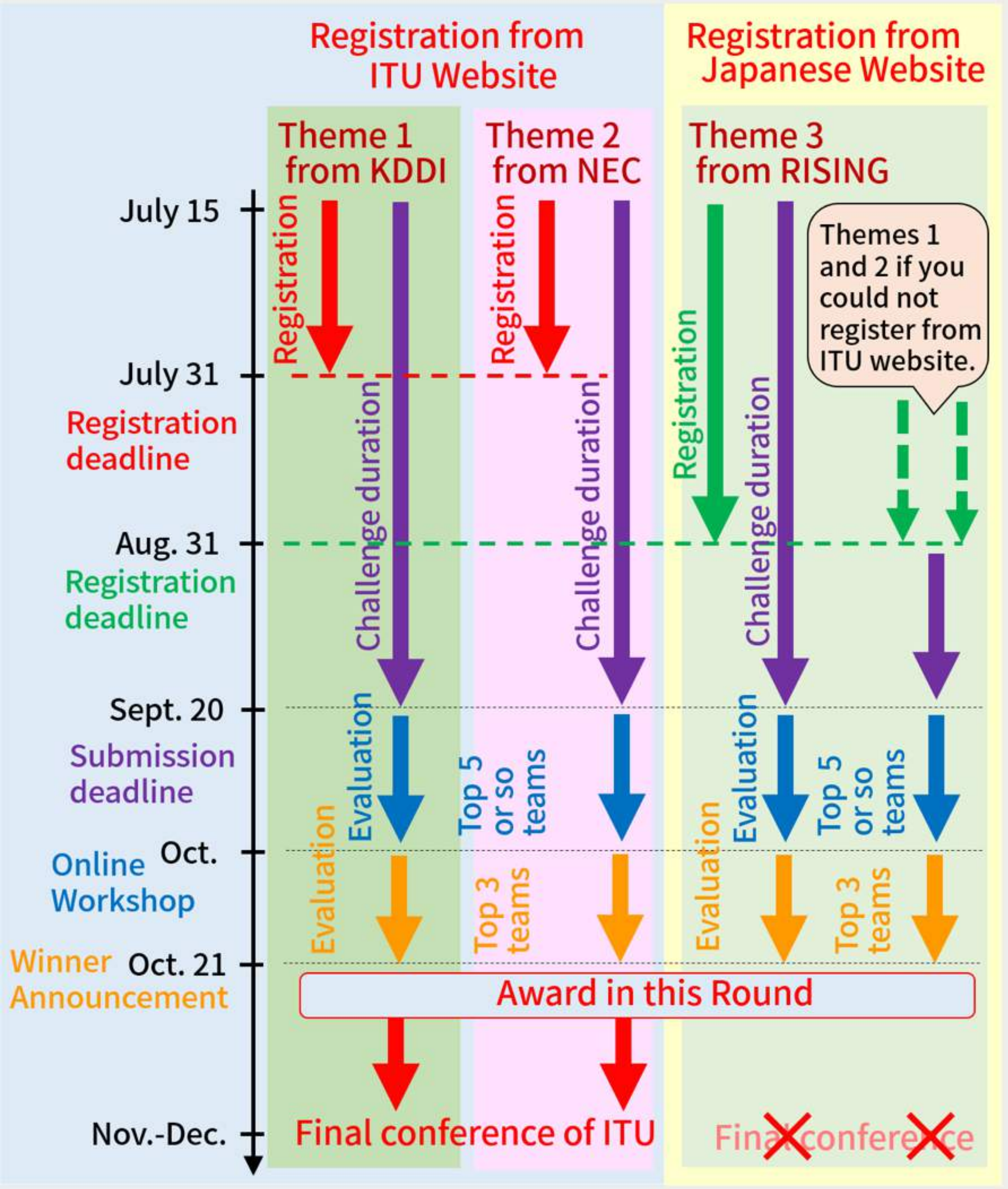
■ テーマ3（RISING）

● 無線関係のテーマ（このあと山本先生よりご紹介）

ITUのFinal conference 推薦対象ではない
（国内向け）

タイムスケジュール

- 日本開催分（各国で異なります）
  - 7月15日から開始（予定）
    - データセットの提供開始
  - テーマ1，2でFinal Conferenceを目指す場合は，
    ~~7月31日まで~~ 8月21日（延長）までにITUのHPからメインの参加登録
  - Final conferenceを目指さない人は，8月1日～8月31日までに日本開催HPから参加登録
  - 9月20日までに結果をメールで提出
  - 10月上旬に上位チームを発表
  - 10月に上位チーム対象のワークショップ
    （オンライン）を開催
  - 10月21日に各テーマの上位3チームをITUへ推薦
  - 11月～12月にITUのFinal Conference



Three Problem Sets:

- Theme 1 (KDDI)
- Theme 2 (NEC)
- Theme3 (RISING)

Submission Deadline: 2020/9/20

参加登録

- ITU AI/ML in 5G 全体へのRegistration
  - 8月21日締切
  - どのGlobal Roundにも参加可能
  - 1チーム1～4名
  - 2つのカテゴリ：Students, Professional
  - ITU AI/ML in 5G で検索すれば見つかります
  - Final conferenceへの推薦対象
  - 日本開催分はテーマ1とテーマ2が対象
    - テーマ3だけに取り組む場合は，この登録は不要
- Japan RoundへのRegistration
  - 8月21日以降は，ITUへの登録ができないため，
    こちらのみの登録になります．
  - テーマ1～3まで参加可能ですが，Final conferenceへの推薦はありません
  - 登録〆切：8月31日

Organizers

Akihiro Nakao（Chair）
Univ.of Tokyo

Takeo Fujii
Univ. of Electro-Comm.

Yoichi Maeda
TTC

Tomohiro Otani
KDDI Research, Inc.

Hideyuki Shimonishi
NEC Corp.

Takuji Tachibana
Univ. of Fukui

Kazuya Tsukamoto
Kyushu Inst. of Tech.

Committee Members

Koichi Adachi
Univ. of Electro-Comm.

Daisuke Anzai
Nagoya Inst. of Tech.

Yusuke Hirota
NICT

Masahiro Sasabe
NAIST

Ryoichi Shinkuma
Kyoto Univ.

Yusuke Shinohara
NEC

Suguru Kameda
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Okayama Univ.

Daisuke Umehara
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Tokushima Univ.

Yoshiaki Narusue
Univ. of Tokyo

Daiki Nobayashi
Kyushu Inst. of Tech.

Koji Yamamoto
Kyoto Univ.

Shinji Yamashita
Fujitsu Lab.

RISING

Cross-Field Research Association of Super-Intelligent Networking

2019/11/26-27

246 participants

111 Posters

We have organized a cross-field (across 19 technical committees of IEICE) symposium to apply AI/ML to networking

Today’s Webinar Agenda

Part 1: Invited Expert Talks

Advanced Traffic Classification Through In-Network Machine Learning, Prof. Akihiro Nakao (U of Tokyo),
Machine Learning for Wireless LANs, Associate Prof. Koji Yamamoto (Kyoto University),

Part 2: Problem Sets in the Global Challenge

ITU-ML5G-PS-031: Network State Estimation by Analyzing Raw Video Data. (Tomohiro Otani, KDDI Research, Inc)
ITU-ML5G-PS-032: Analysis on route information failure in IP core networks by NFV-based test environment. Takanori Iwai(NEC Corporation)

https://itu.zoom.us/webinar/register/9815956026267/WN_Pdc0-r05TmujTGX0gatprw

[Invited Expert Talk]
Advanced Traffic Classification Through In-Network Machine Learning

2020/7/29

Aki Nakao
The University of Tokyo

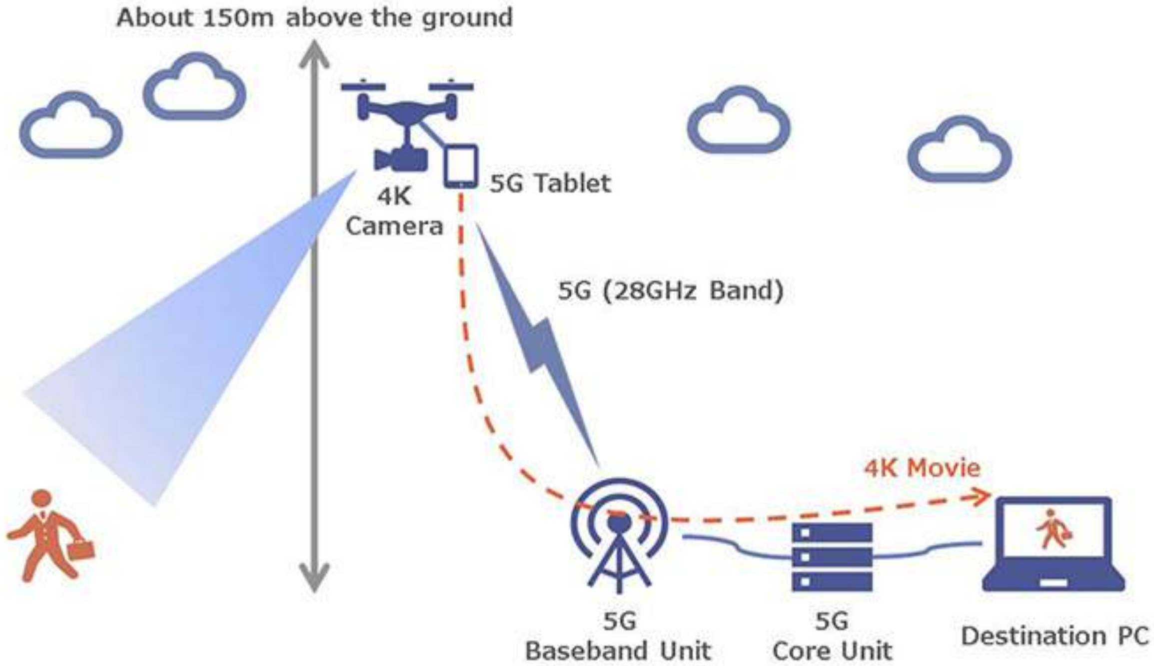
Professor
Vice Dean of Interfaculty Initiative in Information Studies
Advisor to the President of The University of Tokyo

Akihiro Nakao

- Advisor to the President of the University of Tokyo
- Vice Dean, Interfaculty Initiative in Information Studies
- Professor, the University of Tokyo

- Chairman of 5GMF Network Committee
- Chairman of Local5G Committee, Broadband Association
- Various Roles in Ministry of Internal Affairs and Communication (MIC), Japanese Government
- Executive CTO of FLARE NETWORKS

KDDI and The University of Tokyo Demonstrate Japan's First Real Time 4K Video Transmission using 5G Drone



Nakao Research Laboratory of The University of Tokyo together with KDDI has completed the field trial of a live 4K video transmission from a drone via 5G technology.

The experiment was carried out in an effort to realize consumer services that can benefit hugely from drones, such as public safety and surveillance, agriculture monitoring and disaster response.

The experiment area was set up in the university's Kashiwa campus using Samsung Electronics' 5G equipment such as a base station and a tablet. A video stream shot from the air using a 4K camera mounted on a drone was transmitted to the ground using the 28GHz frequency band designated for 5G mobile communication in the near future.

Text: Akihiro Nakao (Professor)
Proofreading: David Buist (Project Senior Specialist)

THE UNIVERSITY OF TOKYO

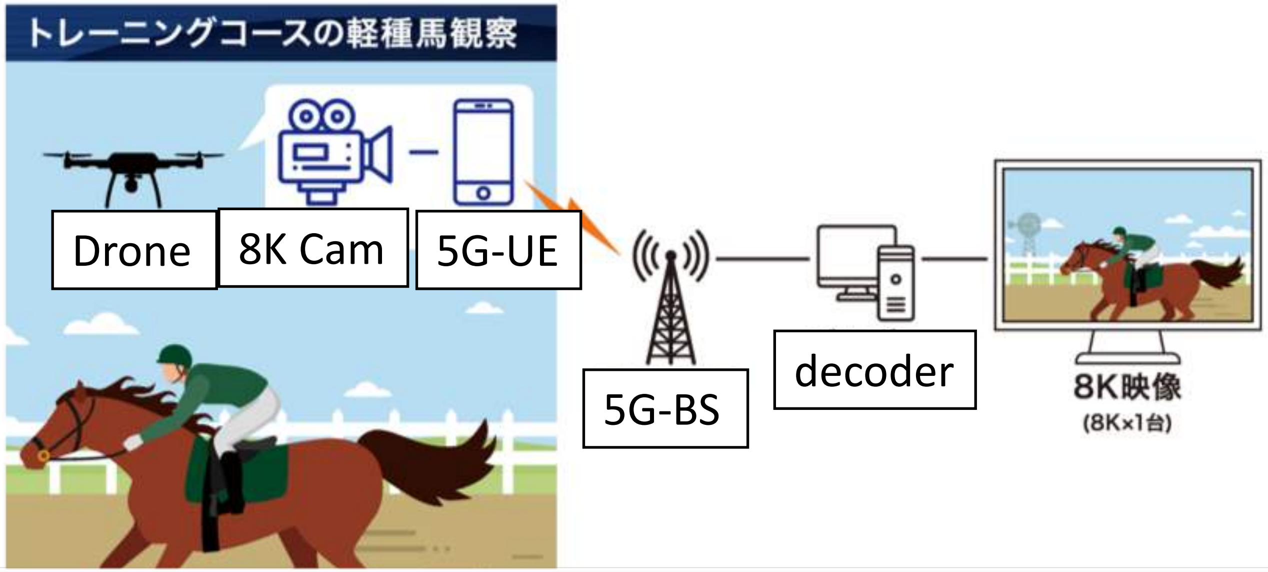

WAVE ONE
START
START

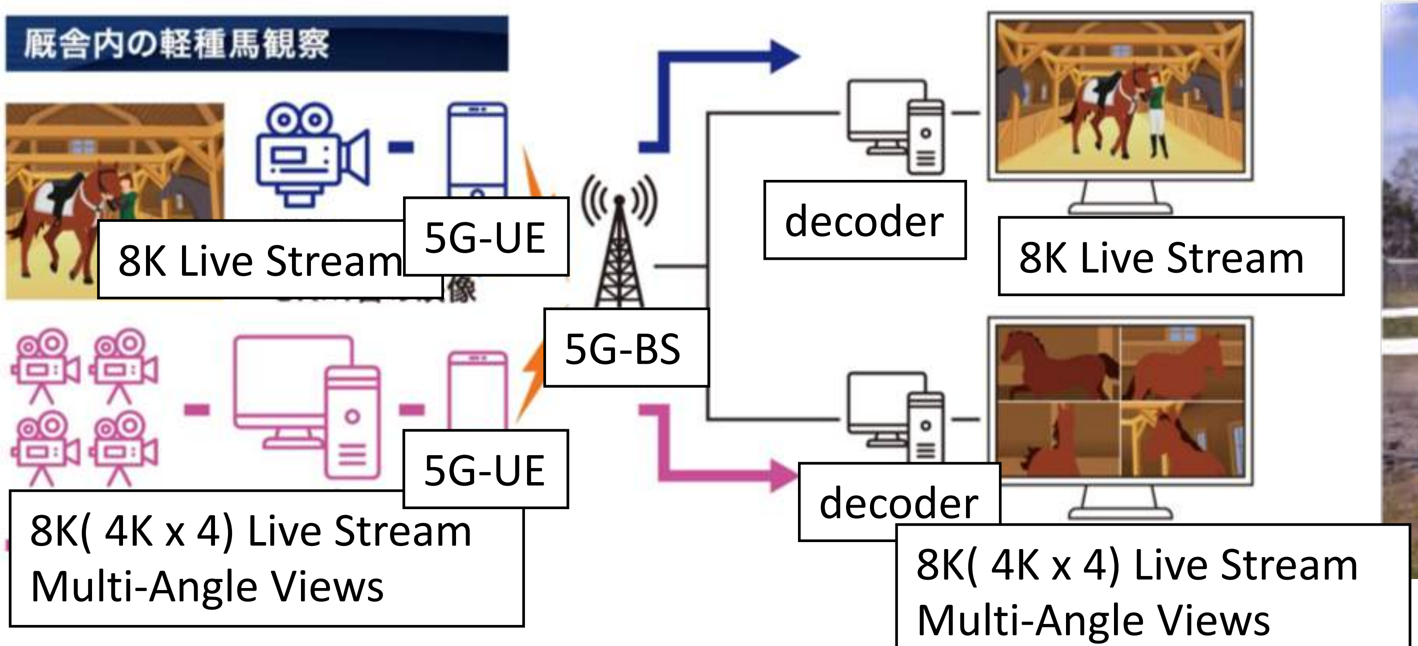
8K Live Streaming with 5G for Remotely Monitoring Race-Horses

～World-First 5G Drone 8K Live Streaming～

2019/11 Released

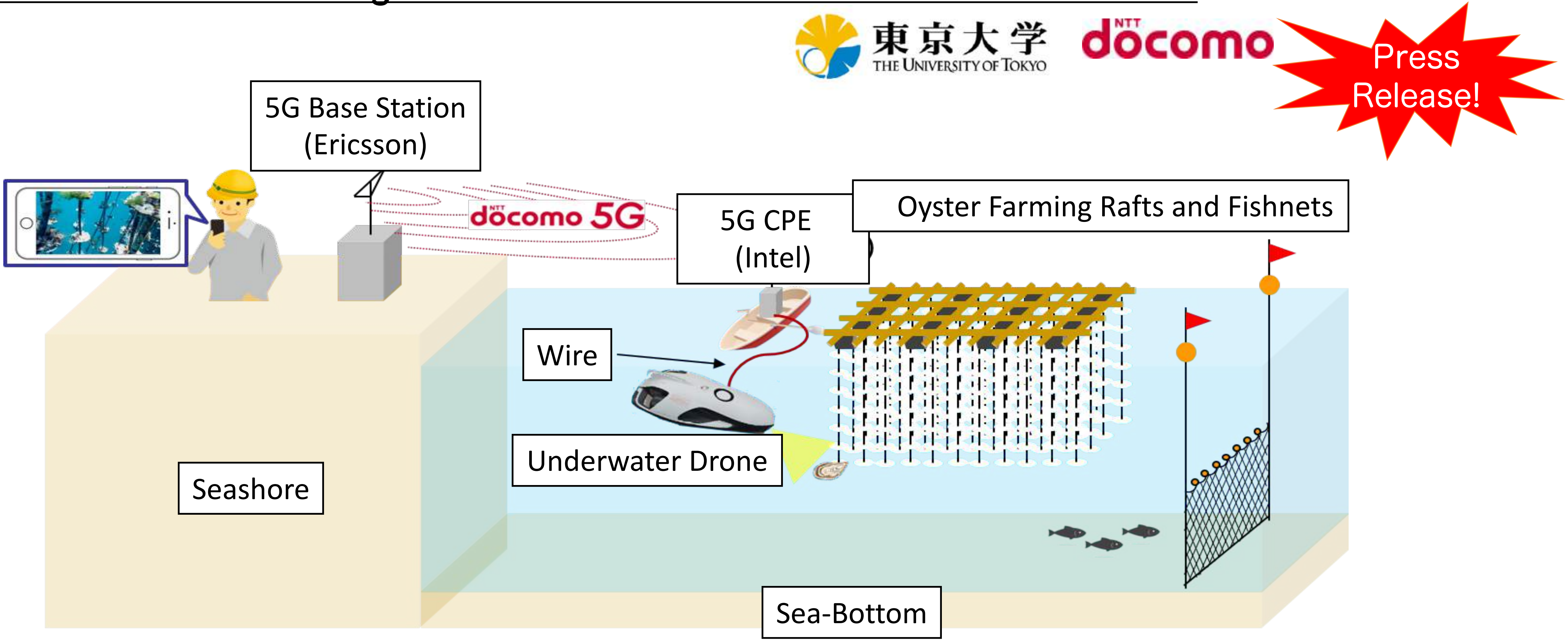
Press Release!





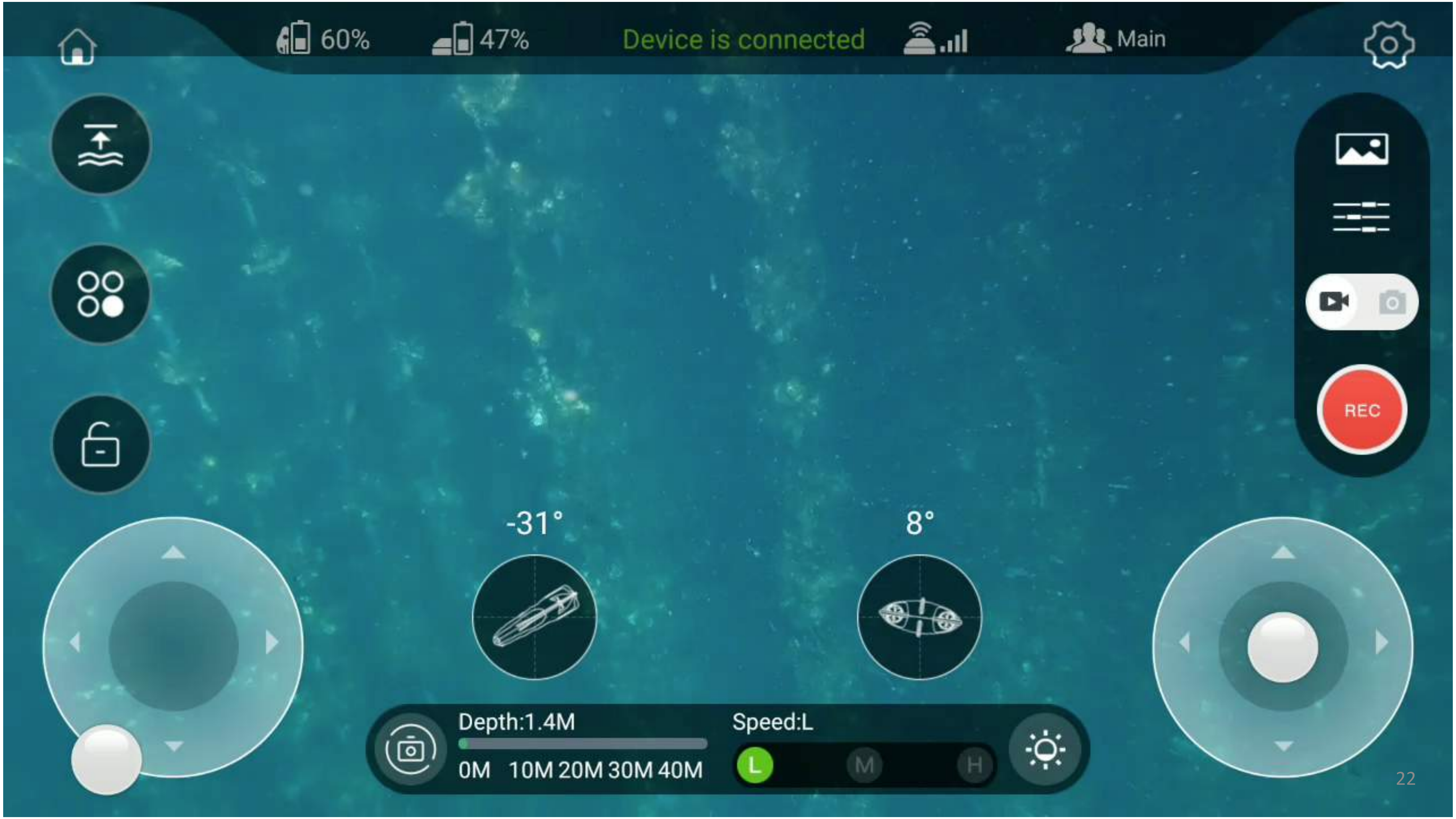
2019/11 Released

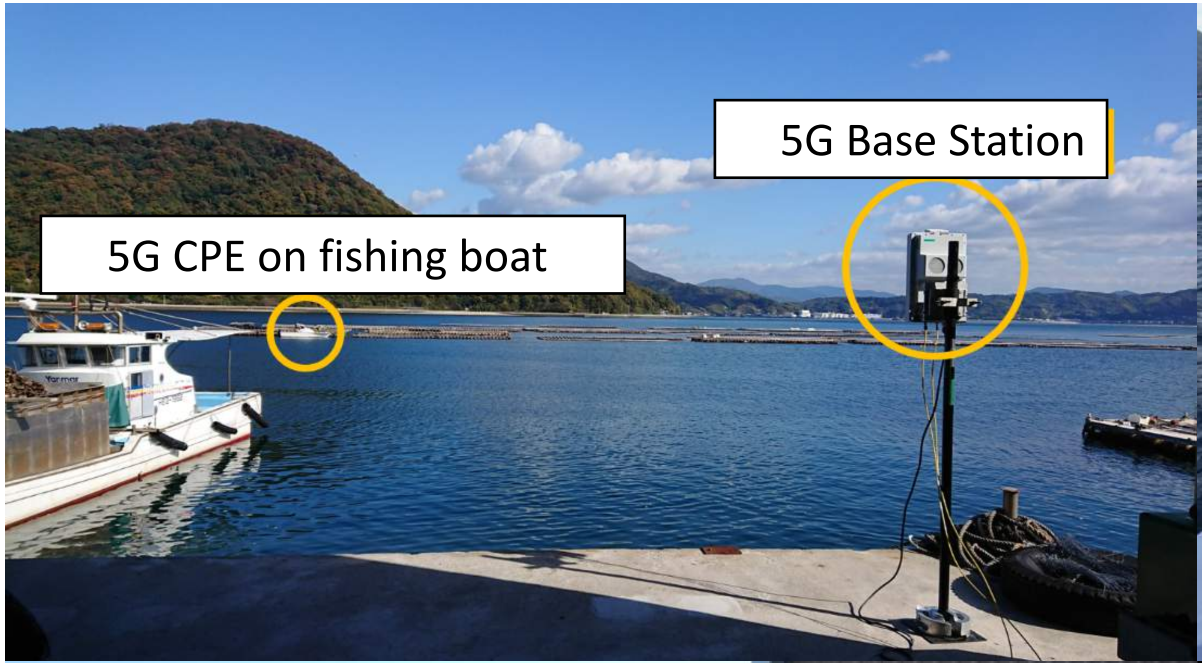
5G Live Videso Streaming and Realtime Control of Under-Water Drone

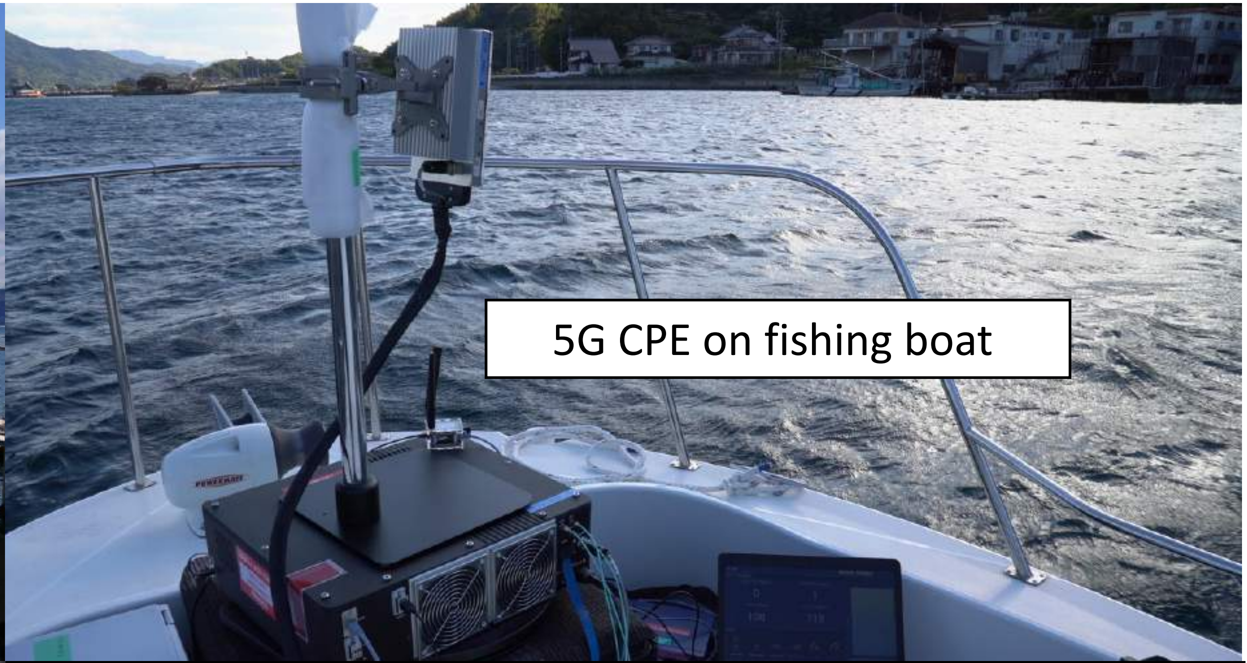


- Remote realtime monitoring Oyster Farming Rafts and Fishnets through water-drone
- 5G base station at the seashore and 5G CPE on the fishing boat
- URLLC for controlling under water drone
- eMBB for live video streaming
- 28GHz millimeter wave band over 100-150m distance between the boat and the seashore

5G Live Videso Streaming and Realitime Control of Under-Water Drone




5G Base Station
5G CPE on fishing boat

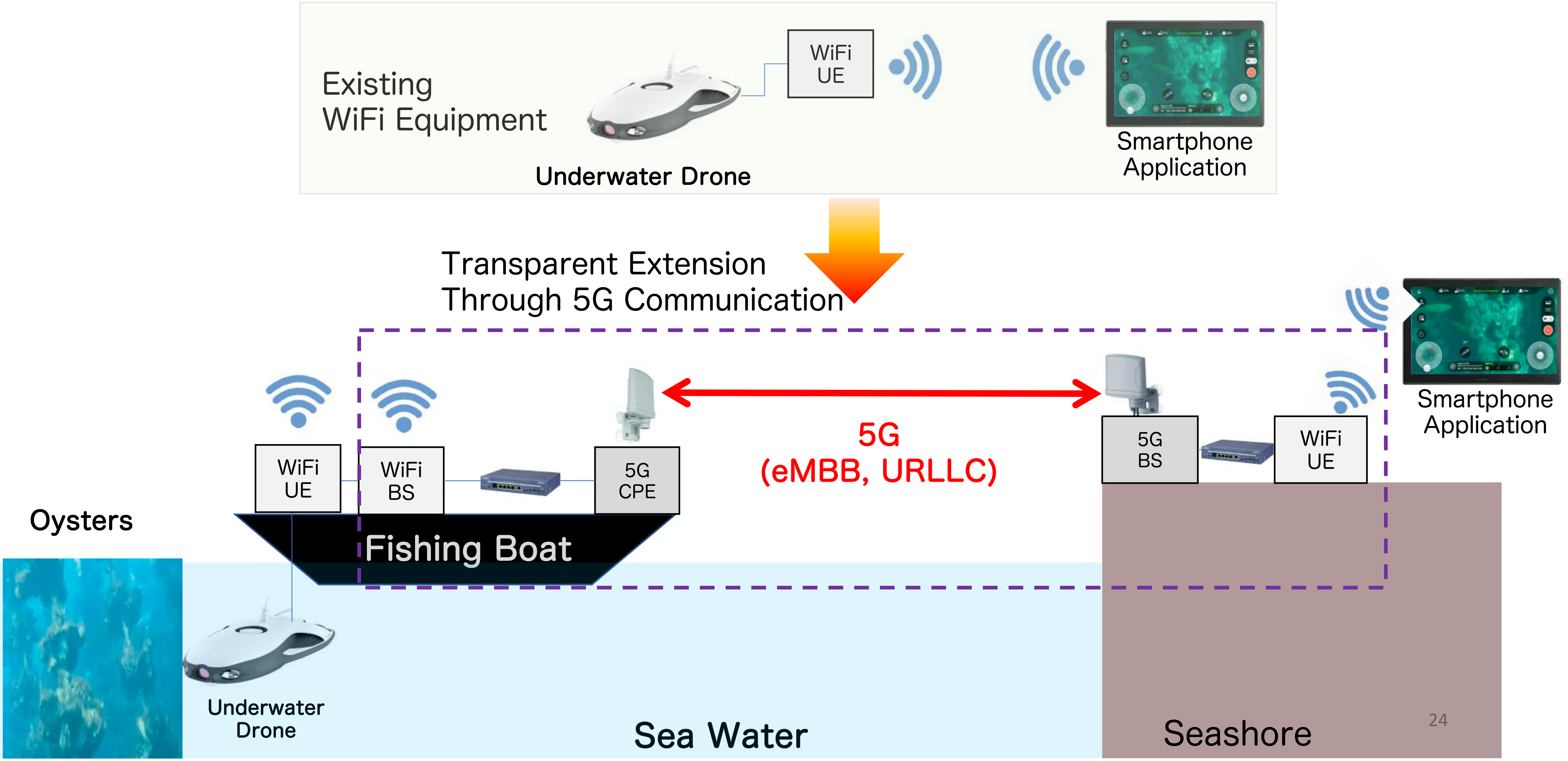

5G CPE on fishing boat


5G Base Station


66%
51%
Device is connected
Main
REC
34°
20°
Depth:4.3M
Speed:L
0M 10M 20M 30M 40M
L
M
H

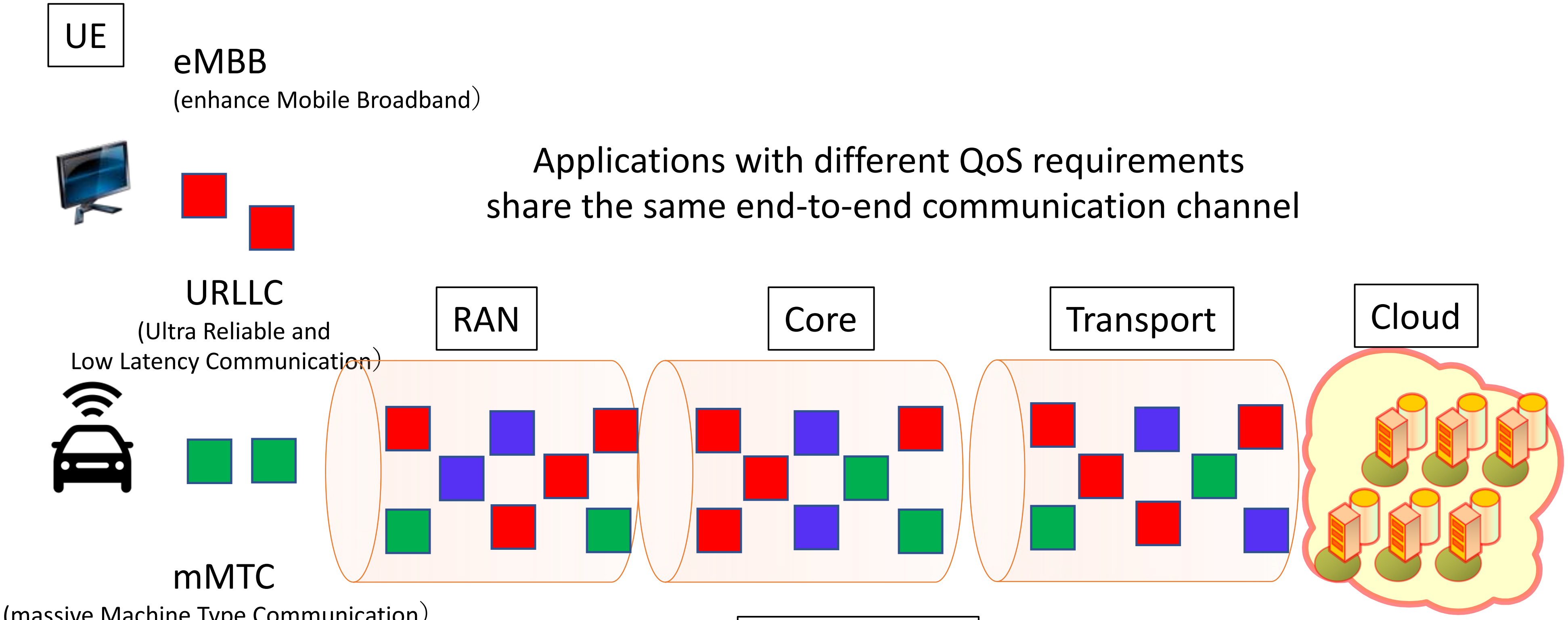
東京大学 THE UNIVERSITY OF TOKYO

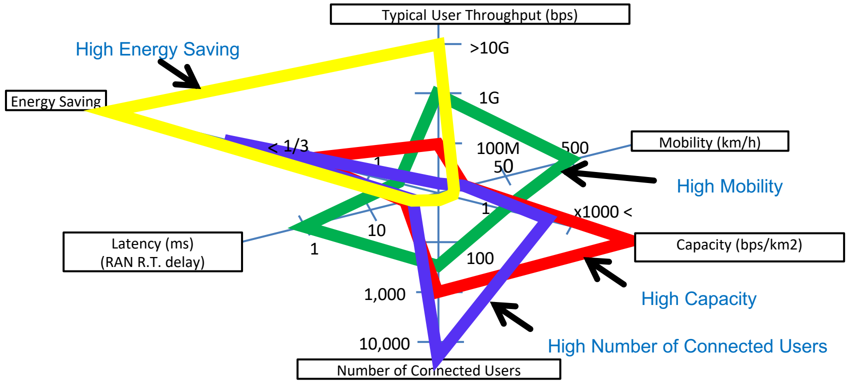
5G Transparent Extension of Control Range of WiFi equipment (underwater drone)



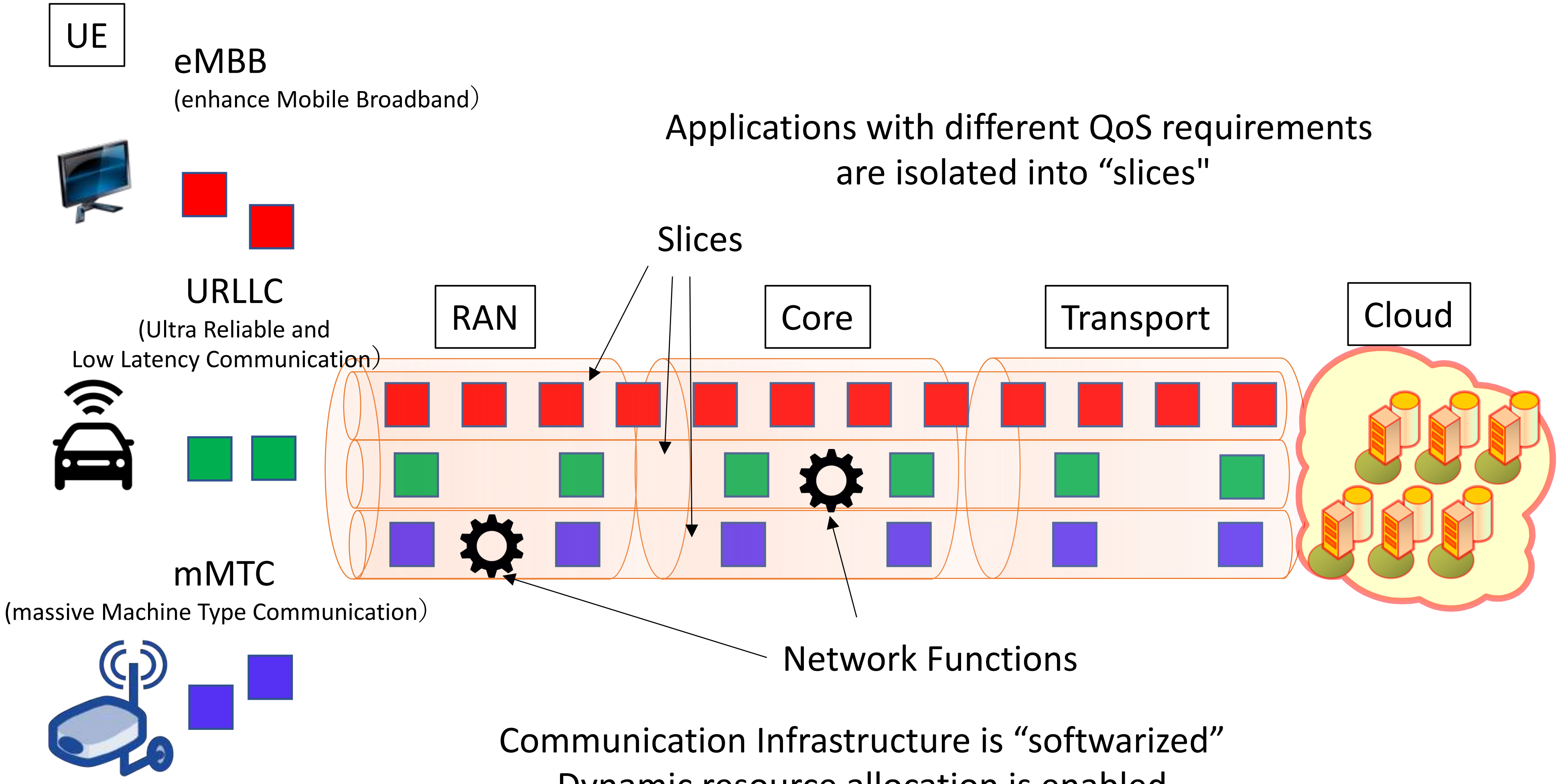
Without Network Slicing on Per-App Basis

Applications with different QoS requirements
share the same end-to-end communication channel





With Network Slicing on Per-App Basis

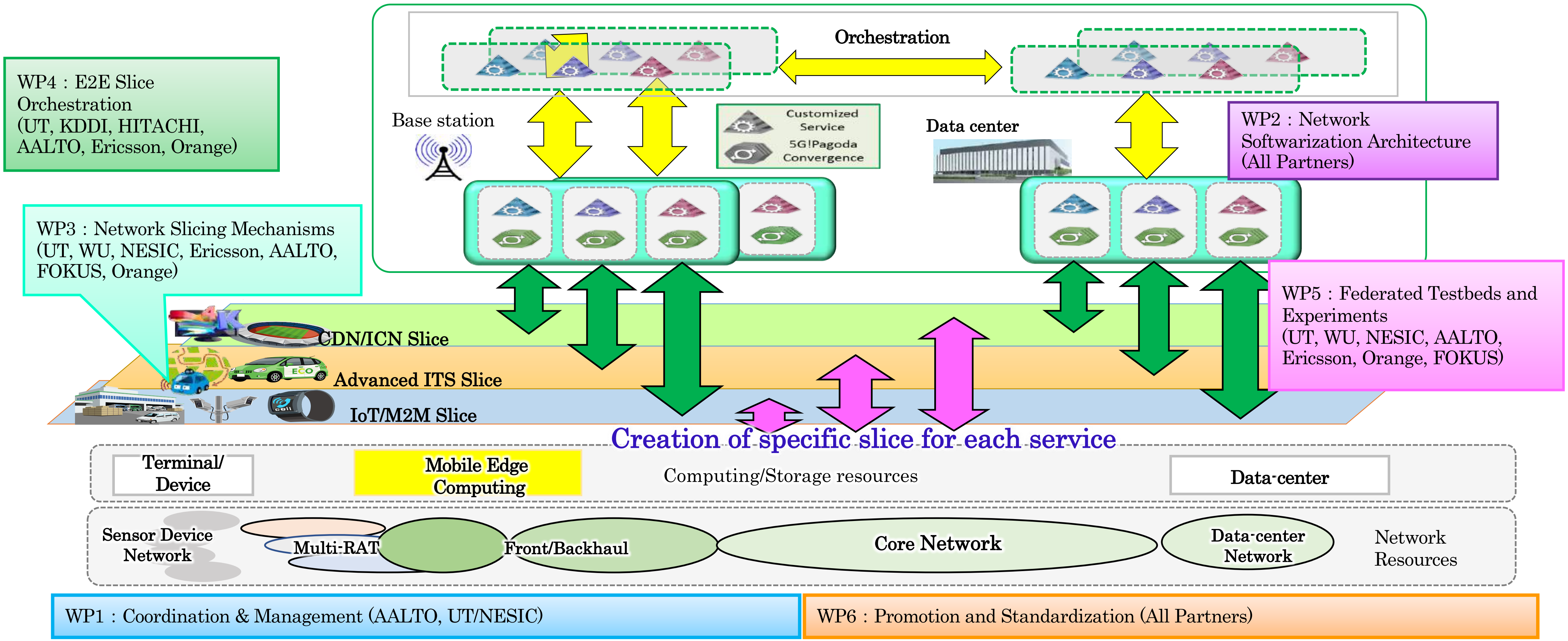


Applications with different QoS requirements
are isolated into “slices"

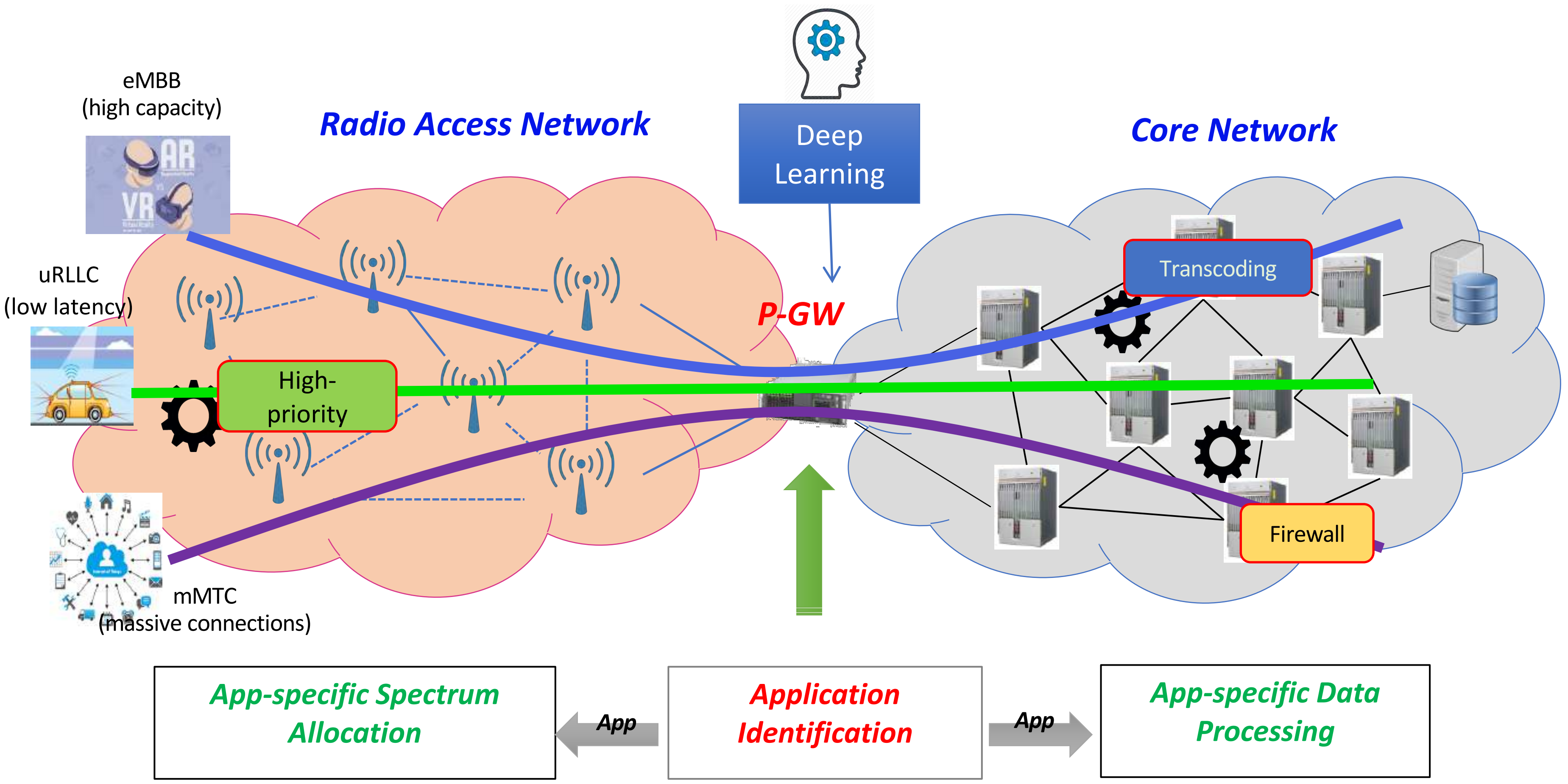
Communication Infrastructure is “softwarized”
Dynamic resource allocation is enabled
Network functions can be executed

5G! Pagoda's View on Future Mobile Infrastructure

5G/IoT Service Centric Network Slicing Control and Operations over Multi-Domains and Multi-Technologies

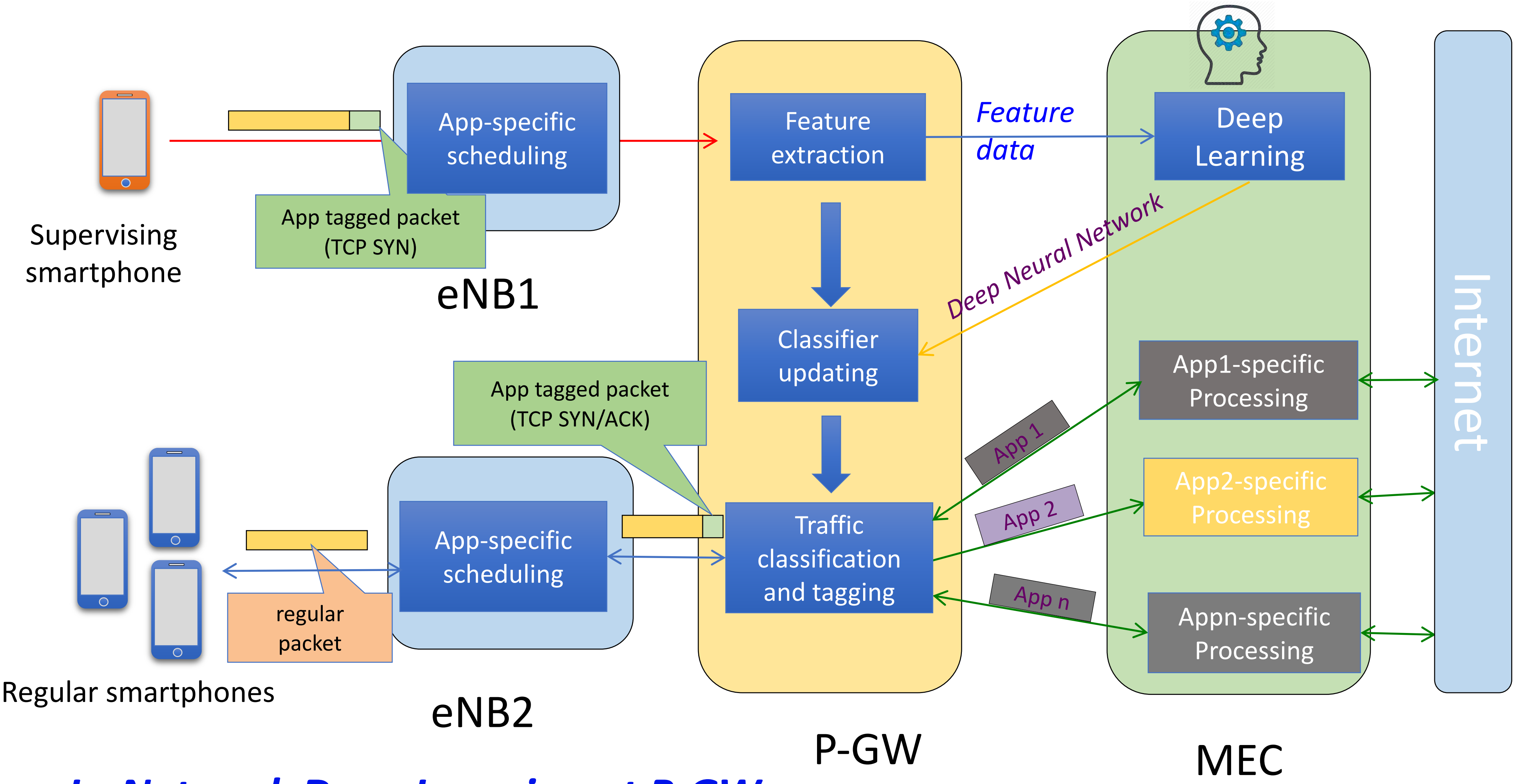


Per-Application Network Slicing for Mobile Networks



- P-GW is the best point to perform application identification since all the traffic go through it
- P-GW can convey its identified app-info to both RAN and CN.

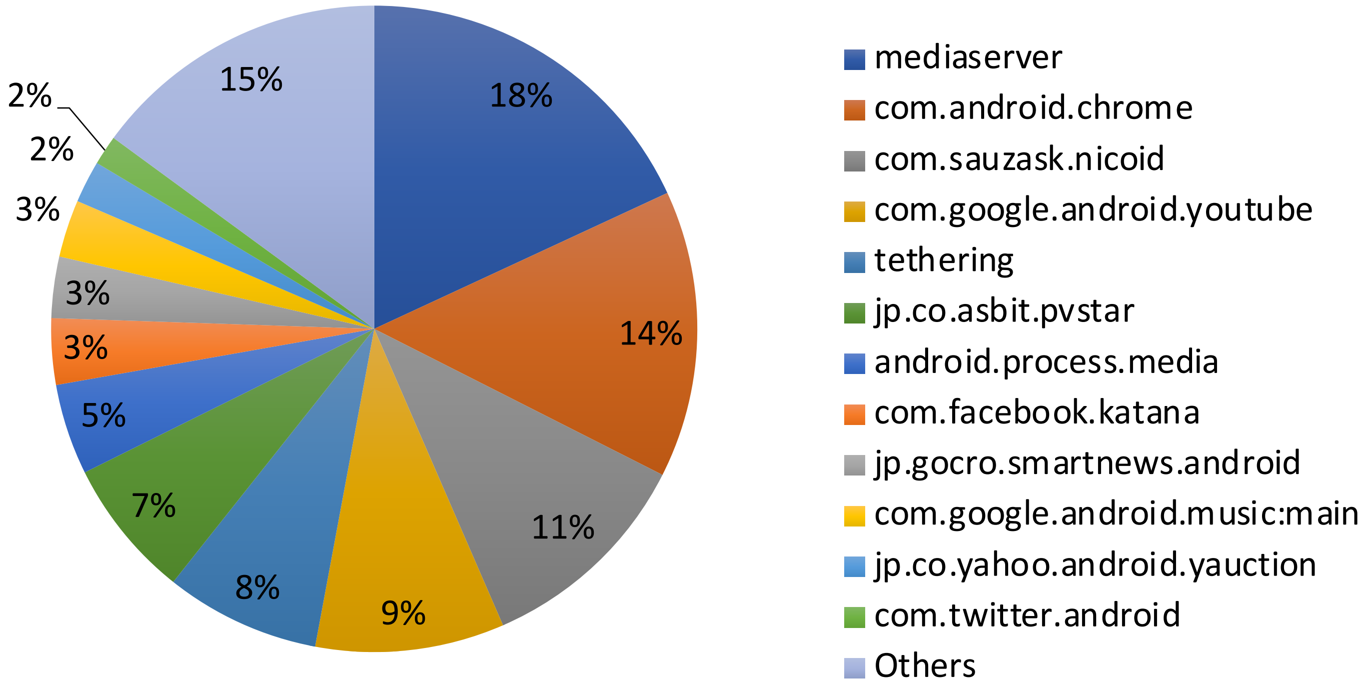
(Deep) Machine Learning-based App-Slicing Architecture



In-Network Deep Learning at P-GW:

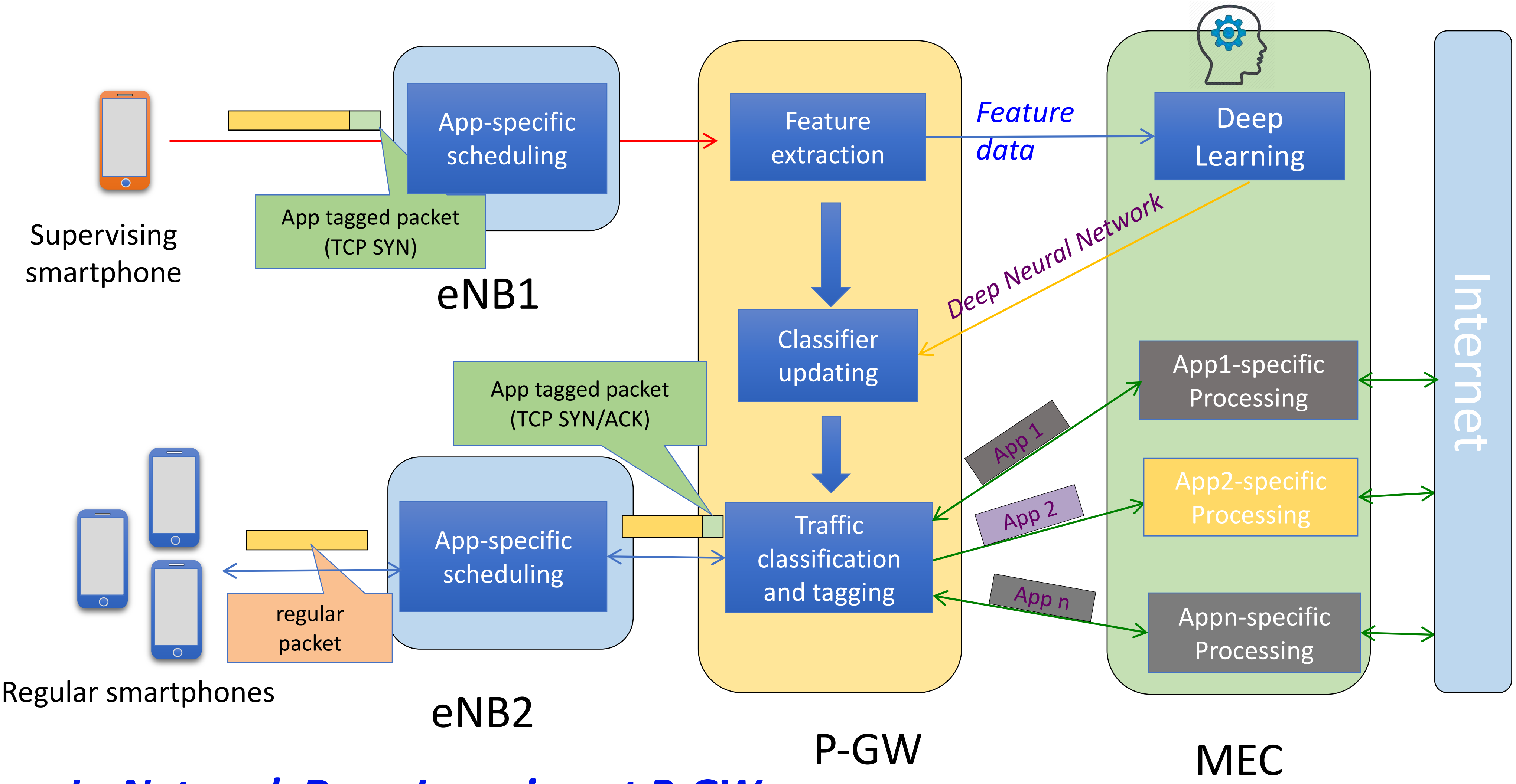
- UL: classifies traffic to different app-specific MEC for processing
- DL: tags acknowledgement packets (e.g., zero-payload SYN/ACK) from different application with app-info and sends to eNB for app-specific RB scheduling

Breakdown of Real MVNO Traffic



- Observations
  - Video Streaming (43%)
    - mediaserver, com.sauzask.nicoid, com.google.android.youtube, android.process.media
  - Web browsing (14%)
    - com.android.chrome
  - Tethering (7.8%)
  - Social networks (4.8%)
    - com.facebook.katana, com.twitter.android

(Deep) Machine Learning-based App-Slicing Architecture



In-Network Deep Learning at P-GW:

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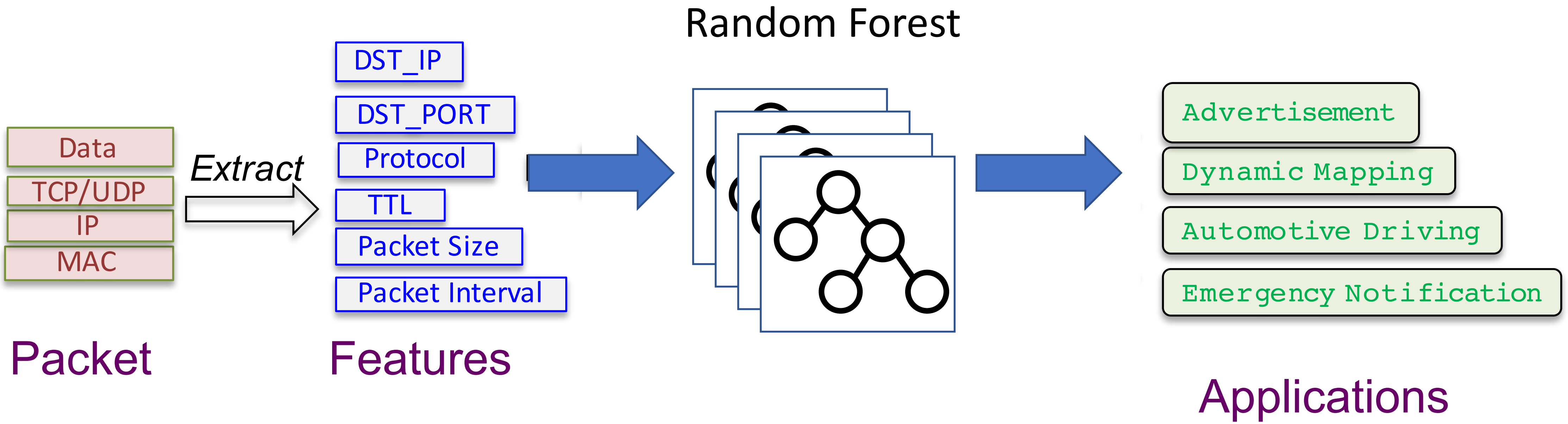
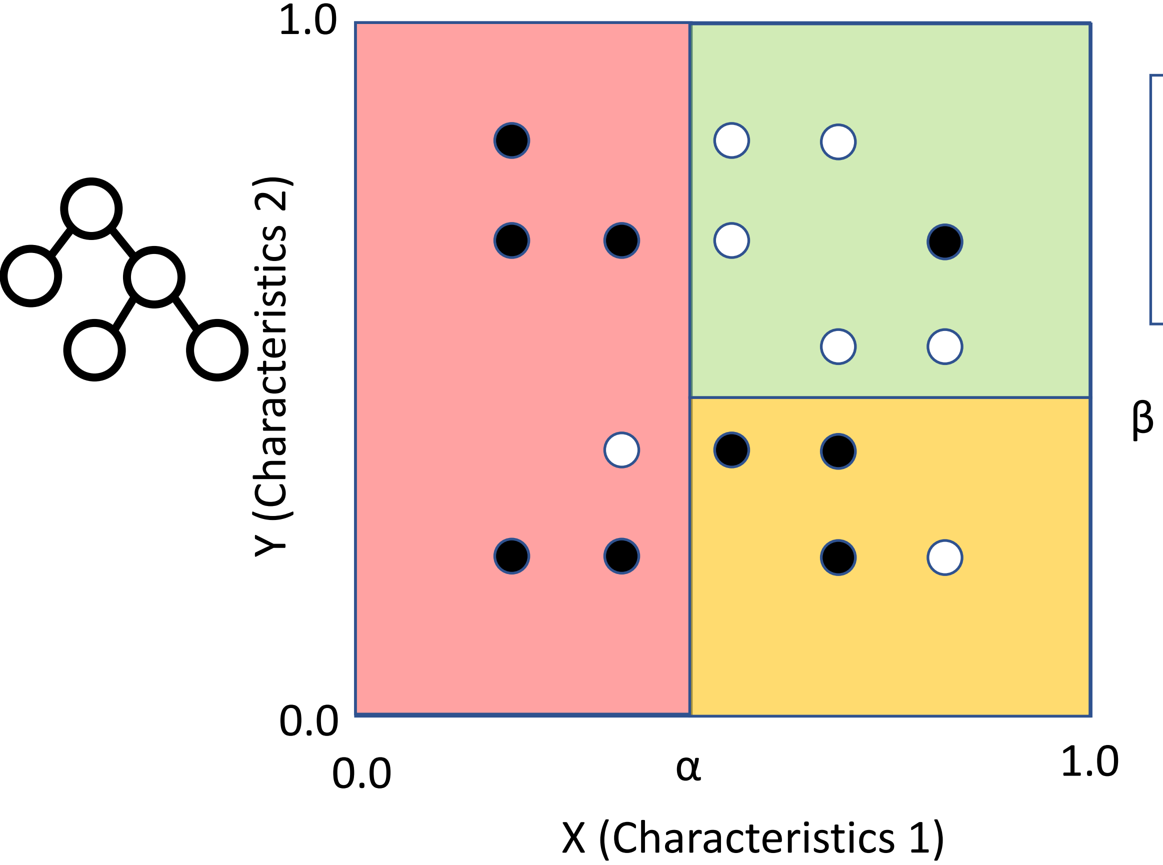
Random Forest



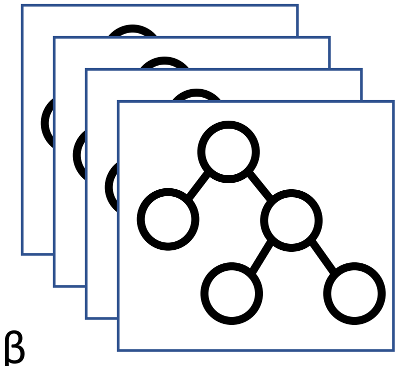
Decision Tree



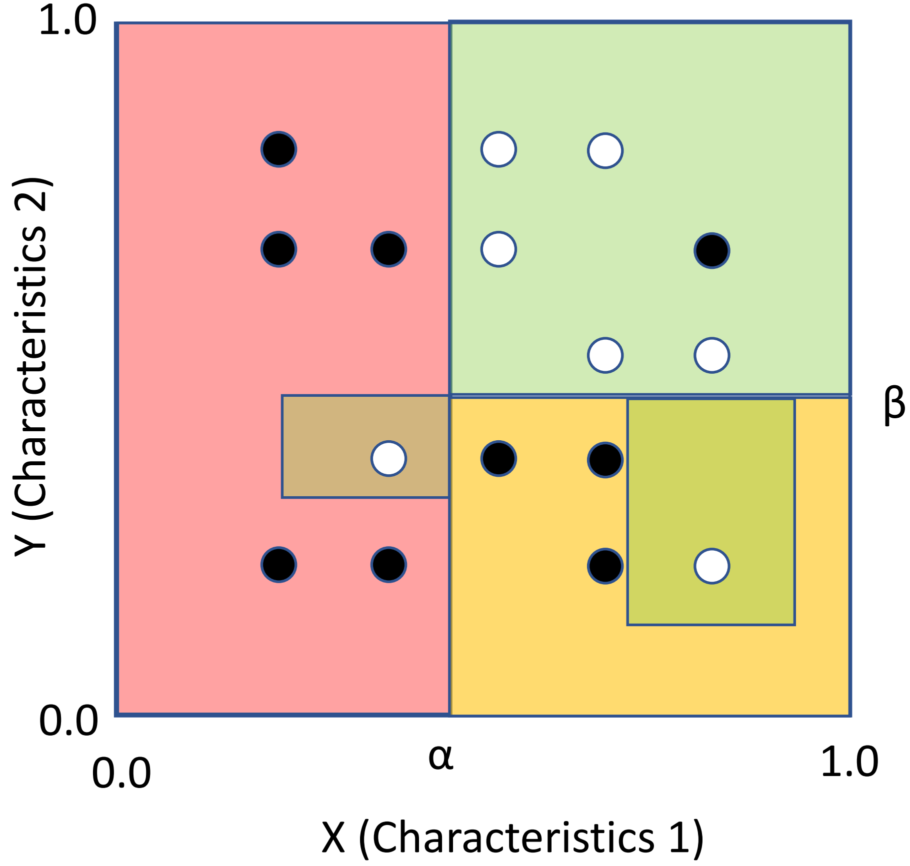
White Dots: X > α and Y > β

Classification Accuracy ~ 80%

Ensemble



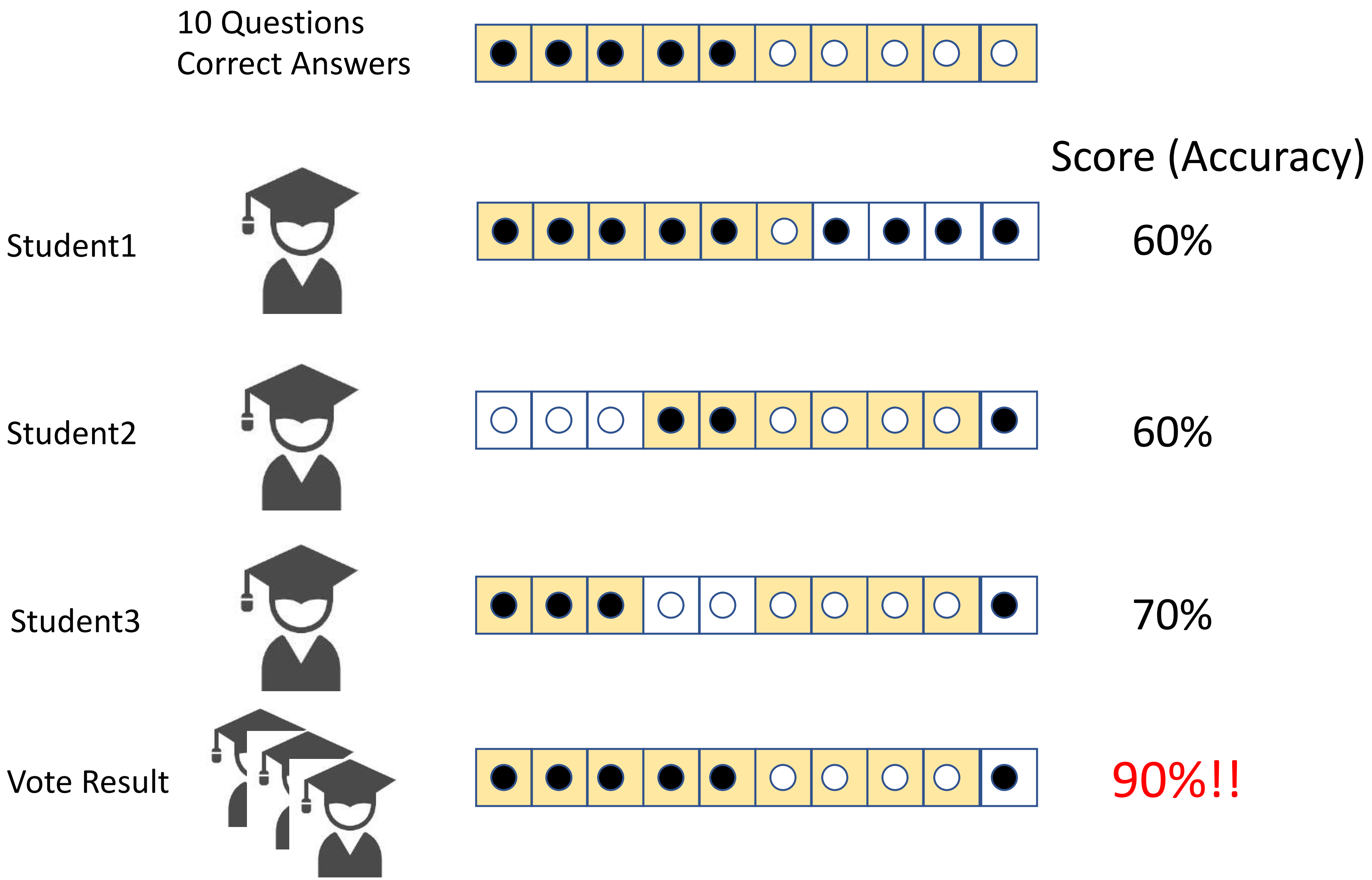
Random Forest



Classification Accuracy ~ 94%

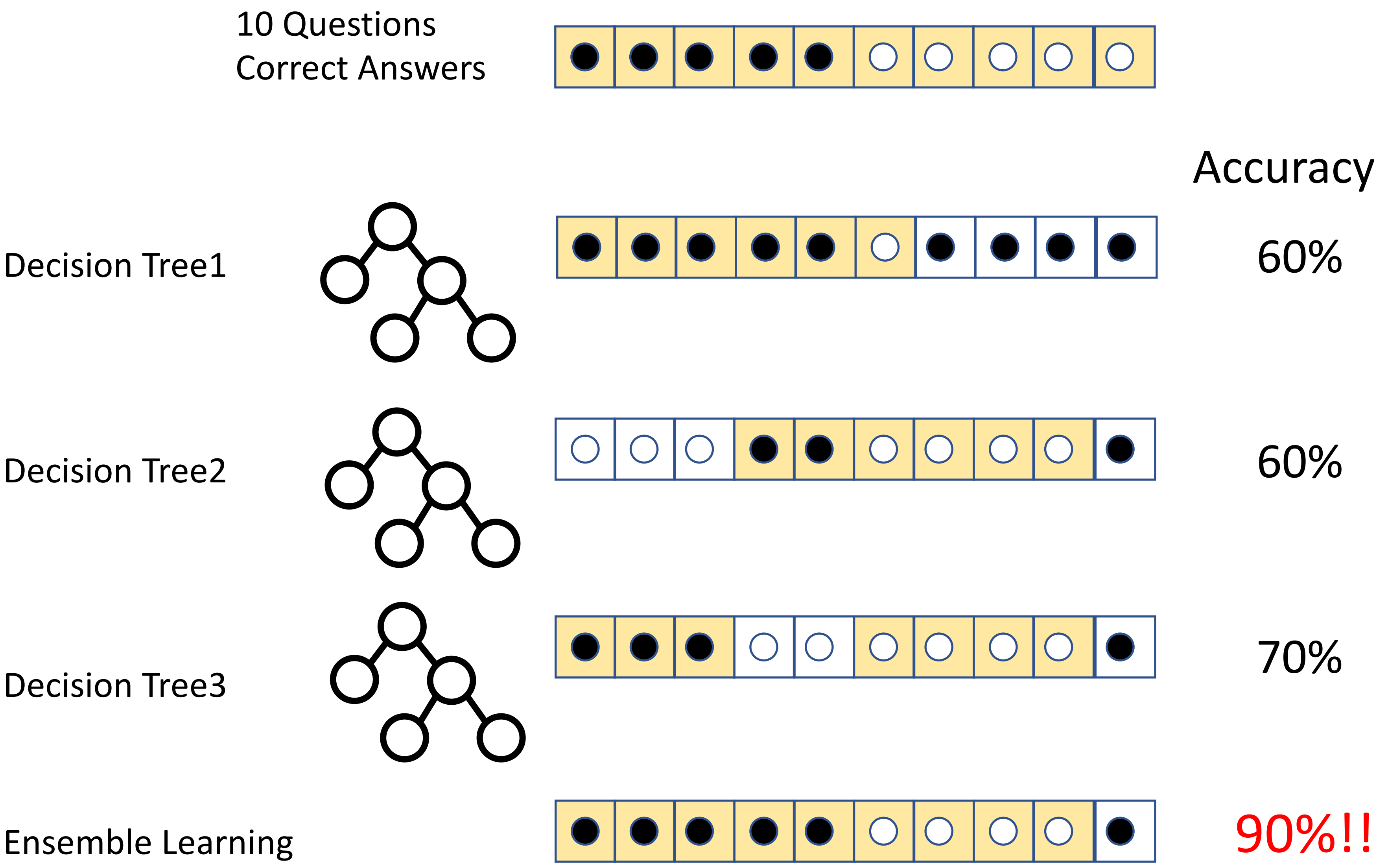
Ensemble Learning

Vote among Weak Studnets

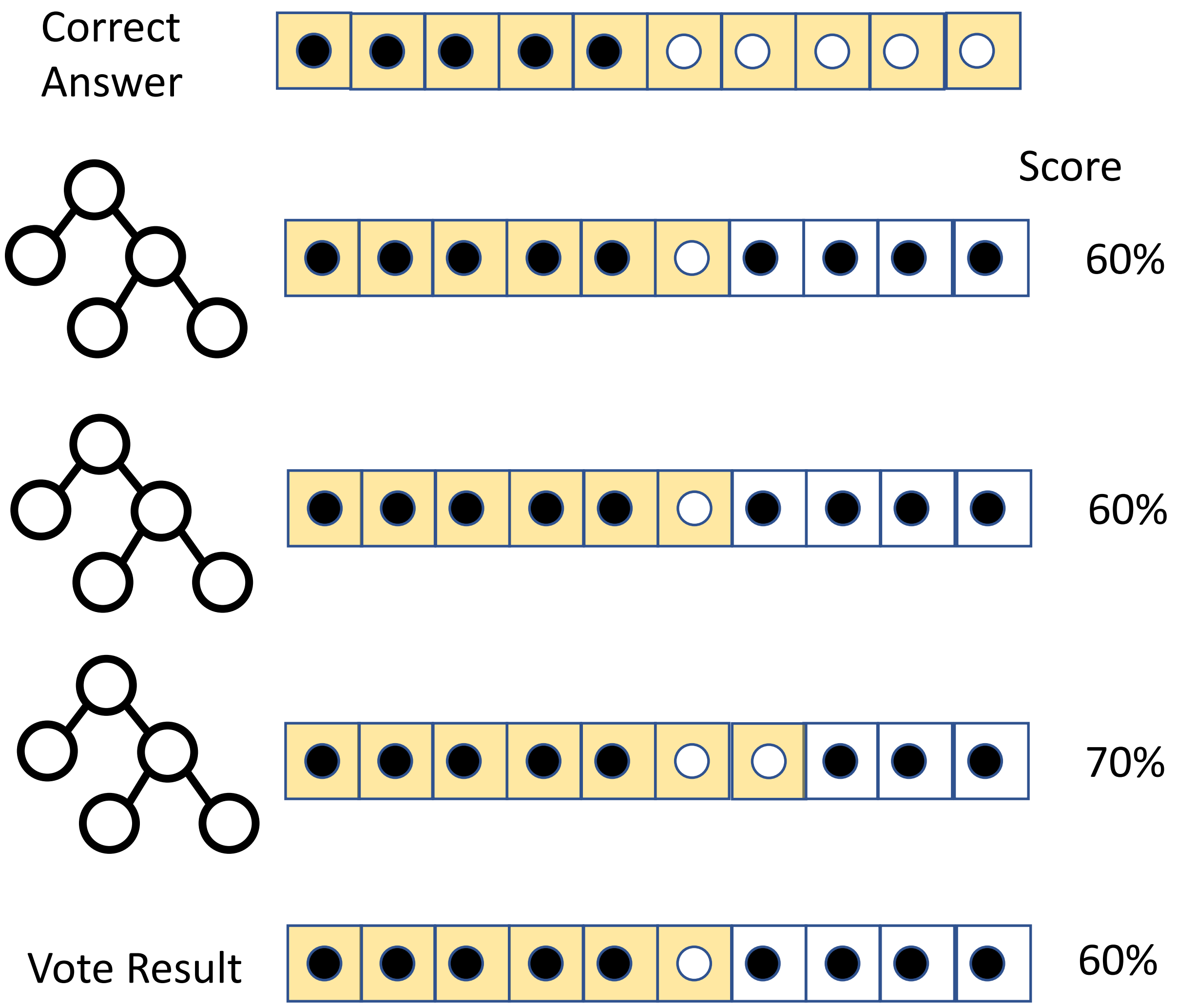


Ensemble Learning

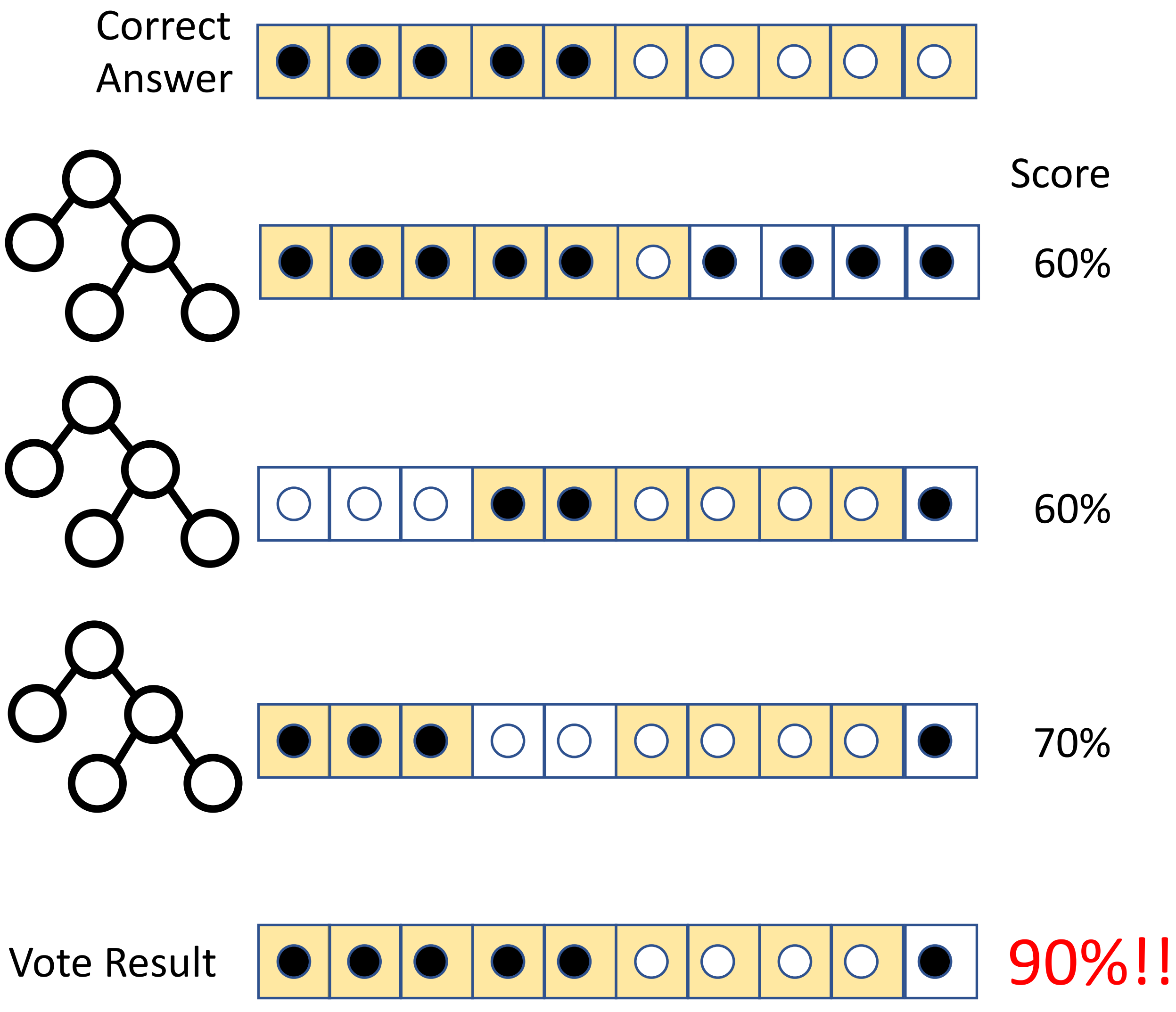
Vote among Weak Classifier (Deterministic Tree)



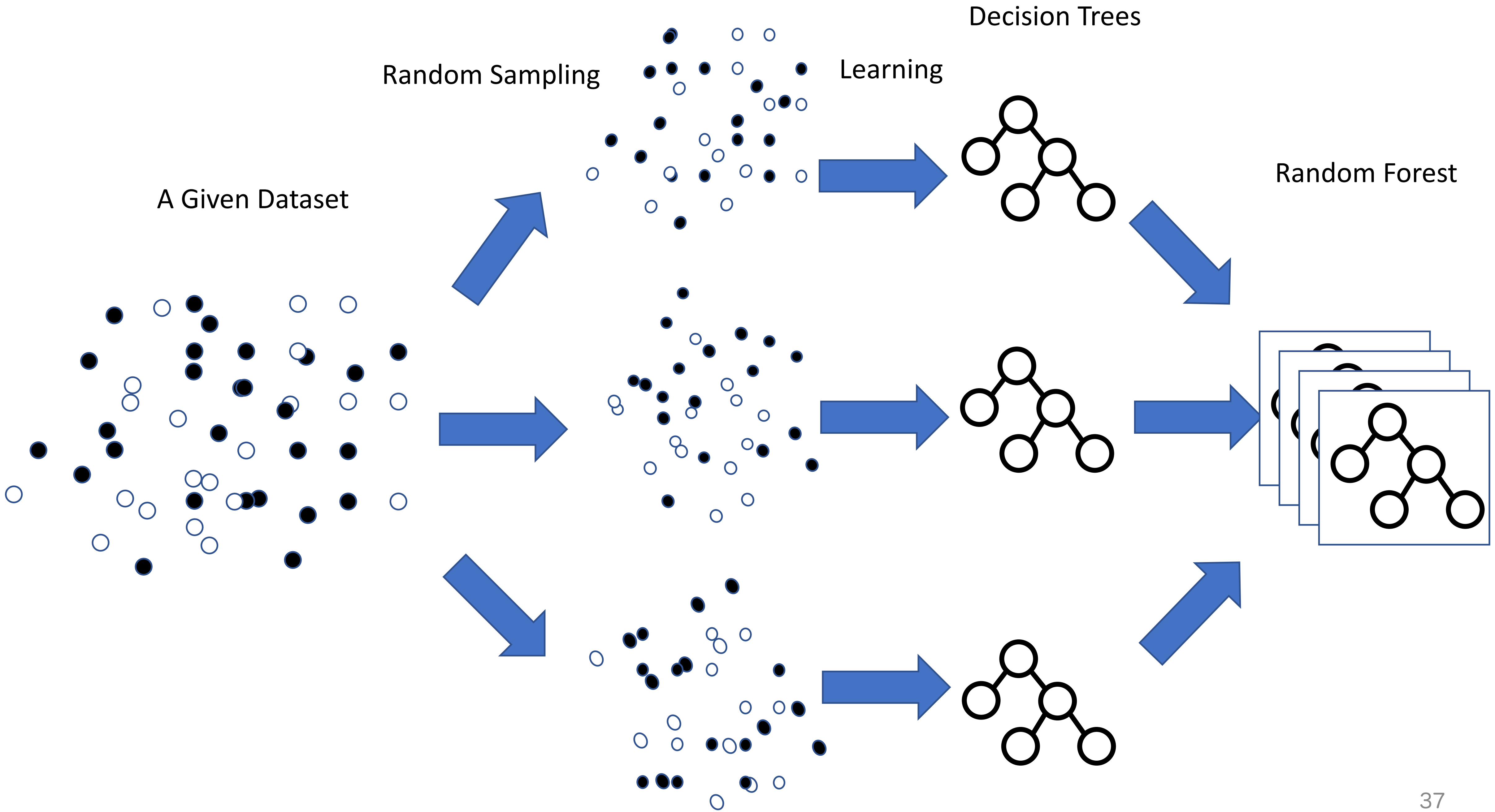
Bad Choice of Weak Classifiers



Good Choice of Weak Classifiers



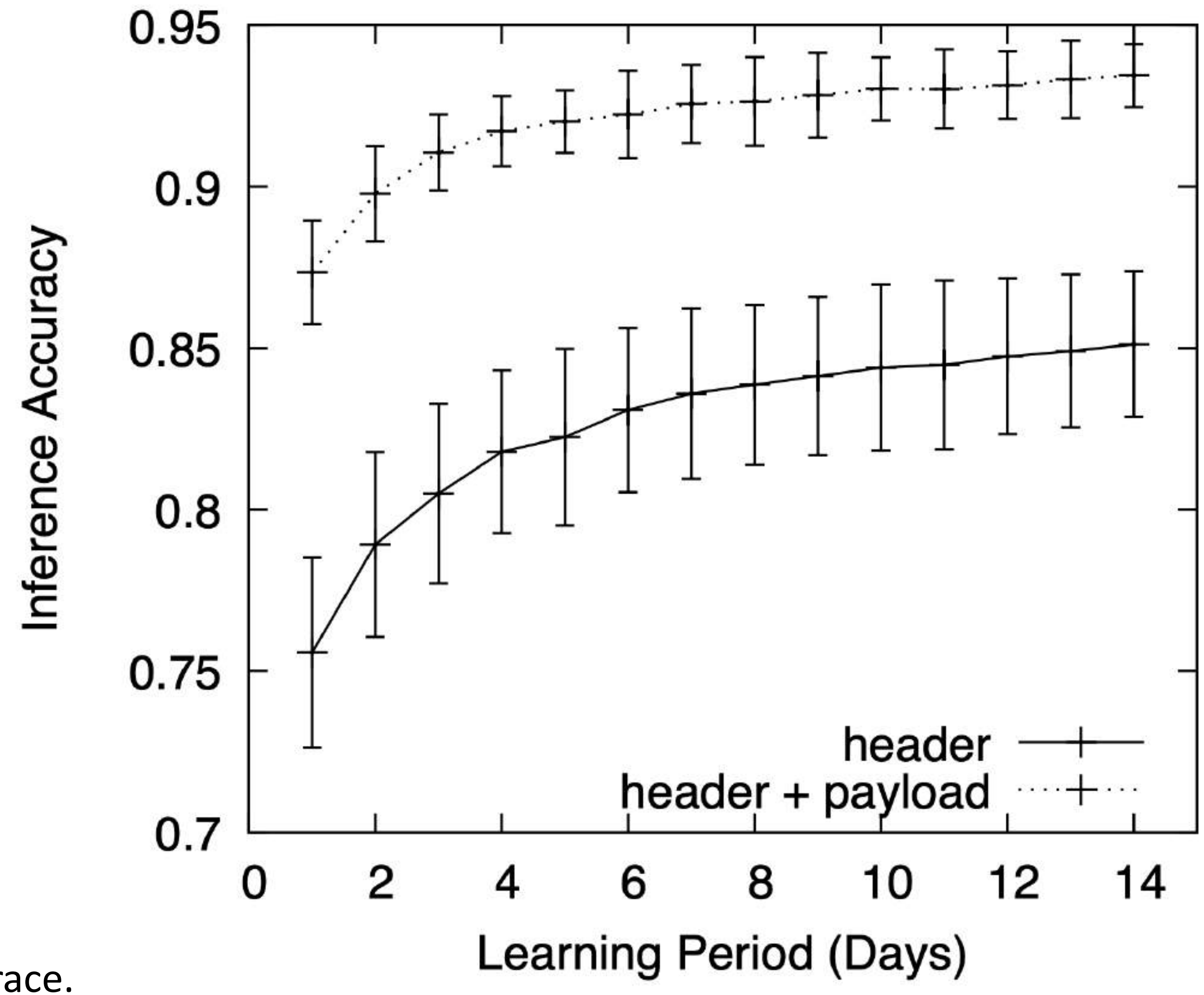
Uncorrelated Weak Classifiers Produces Better Classification


Decision Trees
Random Sampling
Learning
A Given Dataset
Random Forest

20 Features of Traffic Flows

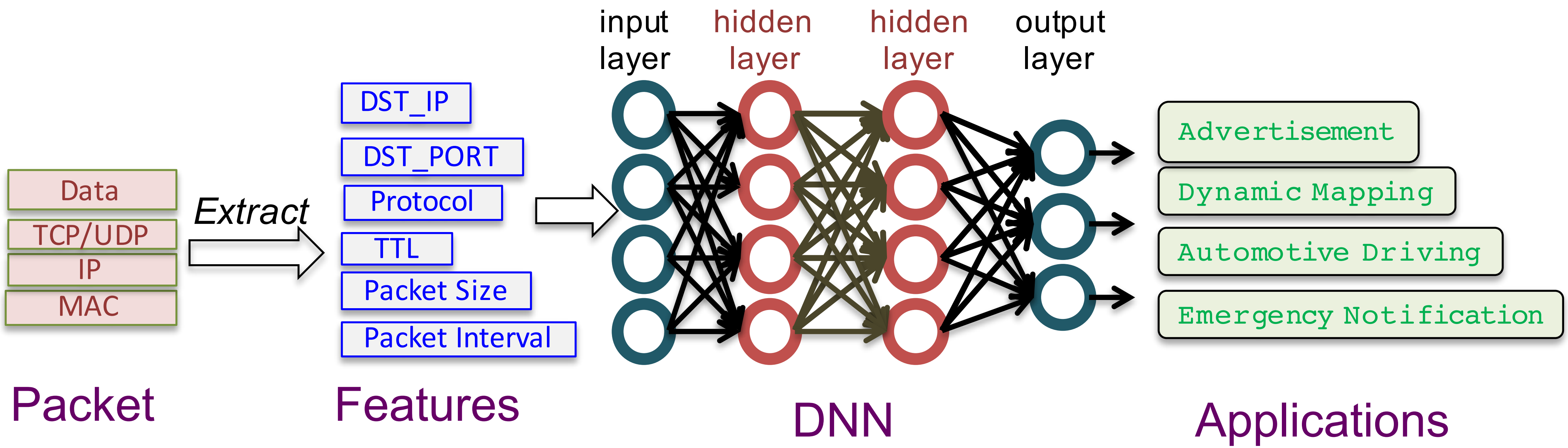
Application Classification Accuracy

Destination IP Address
Destination Port Number
Source Port Number
average of the src→dst packet lengths
variance of the src→dst packet lengths
maximum of the src→dst packet lengths
average of the src←dst packet lengths
variance of the src←dst packet lengths
maximum of the src←dst packet lengths
average of the src→dst packet arrival
variance of the src→dst packet arrival
average of the src←dst packet arrival
variance of the src←dst packet arrival
source window-size in SYN packet
destination window-size in SYN packet
ratio of the ACK-PSH flags in the all TCP
dst→src packet count/ src←dst packet



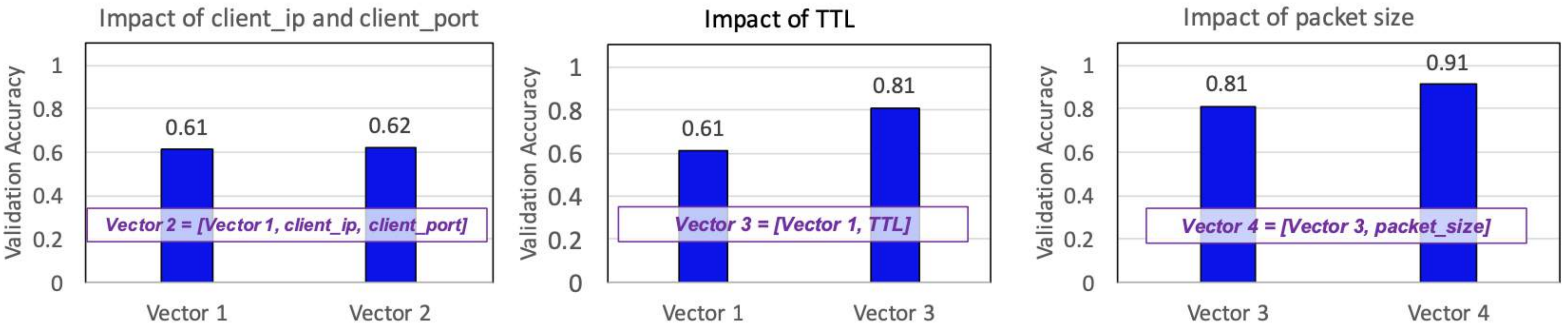
Yellow cells: feature designed based on the trace.
white cells: designed based on existing research.

Deep Learning



- Step 1: The system extracts feature vectors from packets and feed the vectorized features into the input layer of DNN (deep neural network)
- Step 2: Training model DNN is defined with an input layer, multiple fully connected hidden layers, and an output layer. Each hidden layer is a feed-forward neural network.
- Step 3: Output layer is built with softmax regression mode and its output is a probability vector over applications. The packet is identified as the application with highest probability.

Selection of Feature Vectors



(a) (b) (c)

Vector 1 = <server_ip, server_port, proto>

(a) Feature <client_ip, client_port> has almost no impact on the identification accuracy.

(b) Feature TTL has a great impact on the identification accuracy because TTL is a metric of distance from the application server to the P-GW. The distance is application-specific.

(c) Feature packet_size is also a useful feature because client and server need to exchange information during connection establishment. The size of exchange information is application-specific.

References

- Akihiro Nakao and Ping Du, “Toward In-Network Deep Machine Learning for Identifying Mobile Applications and Enabling Application Specific Network Slicing”, IEICE Transactions E101-B, No.7, pp.1536-1543, 2018.
- Ping Du, Akihiro Nakao, Zhaoxia Sun, Lei Zhong and Ryokichi Onishi, “Deep Learning-based C/U Plane Separation Architecture for Automotive Edge Computing”, The Fourth ACM/IEEE Symposium on Edge Computing (SEC), 2019.
- Ping Du and Akihiro Nakao, "Deep Learning-based Application Specific RAN Slicing for Mobile Networks”, IEEE International Conference on Cloud Networking (CloudNet), 2018.
- Takamitsu Iwai, Akihiro Nakao (University of Tokyo), Adaptive Mobile Application Identification Through In-Network Machine Learning, APNOMS 2016

ネットワーク層 AI による専門家不要 NW へ

Before

ネットワーク専門家が
分析から調整まで数日を要する

いざローカル5Gを
使おうとすると・・・

ネットワークの性能を
フルに発揮し十分な品質を
提供するためには

通信混雑や競合を
回避する運用

ネットワークの専門家が
分析から調整に数日を要する
運用が課題

After

専門家不要でリアルタイムに
分析から調整を実現

基地局

テレワーク

工場無線化

交通管制

柔軟で簡単・迅速な
ネットワーク運用

通信トラヒック
観測

ネットワーク層
AI

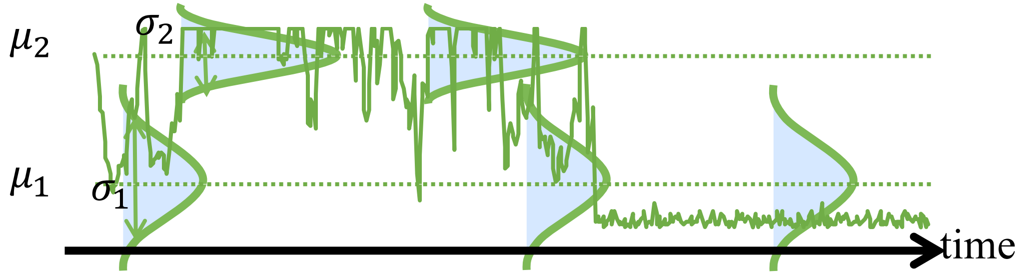
ネットワーク層 AI により
通信の分析・制御を自動化し

専門家不要で
リアルタイムに分析から
調整する運用を実現

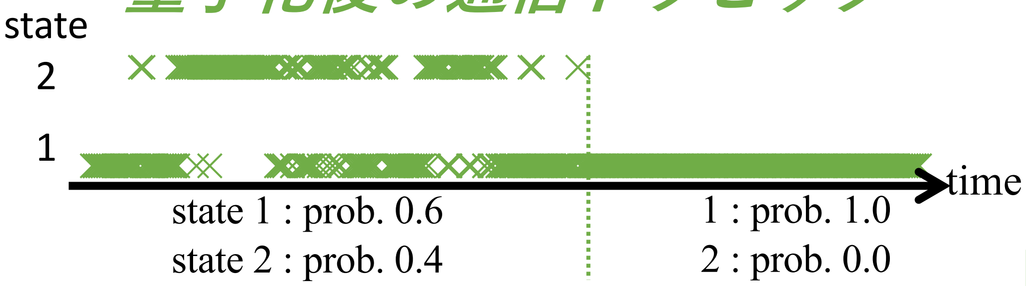
階層的な確率的状態遷移モデル

観測した通信トラヒックを量子化し、量子化後の通信トラヒックをクラスタリングすることによってコンテキストを推定する。

観測した通信トラヒック



量子化後の通信トラヒック



コンテキスト推定値

Learn

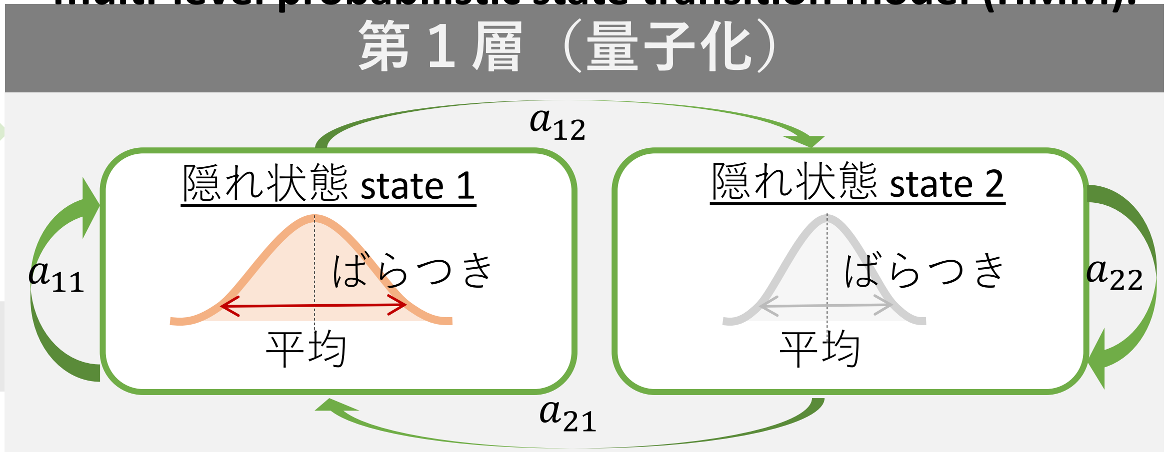
Estimate

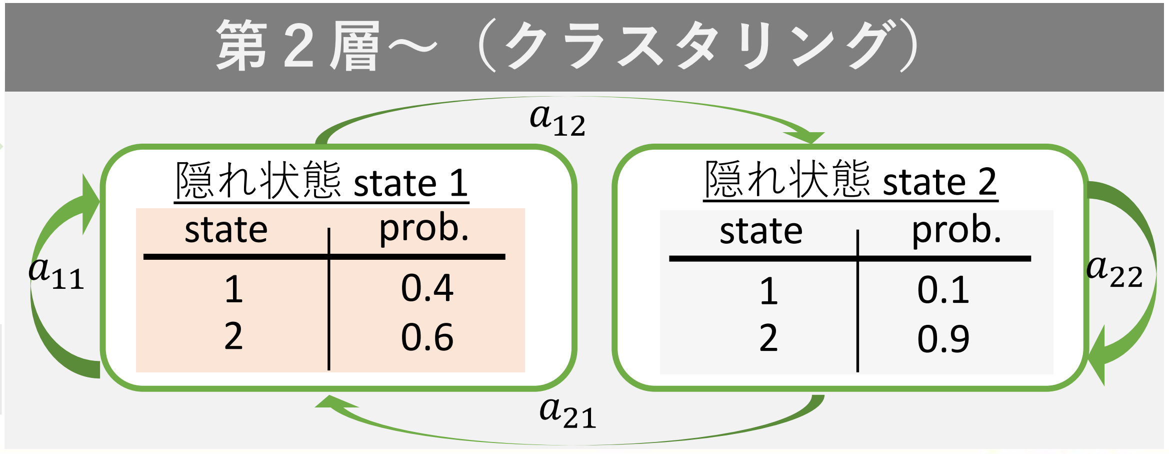
Learn

Estimate

階層的な確率的状態遷移モデル

multi-level probabilistic state transition model (HMM).





パラメータの自動更新

観測した通信トラヒックのパターンが未知のパターンかどうかを判定し、モデルにパターンを追加・更新する。

コンテキストマッチング

最新トラヒックから生成したモデルと更新前モデルをマッチングし、未学習コンテキストか否かを判定する。

$$\mathrm{CosSimilarity}(\theta_i^k, \theta_j^{\mathrm{old}}) = \frac{{\theta_i^k}^{\mathrm{T}} \theta_j^{\mathrm{old}}}{\|\theta_i^k\| \|\theta_j^{\mathrm{old}}\|}$$

Recent model　　Old model

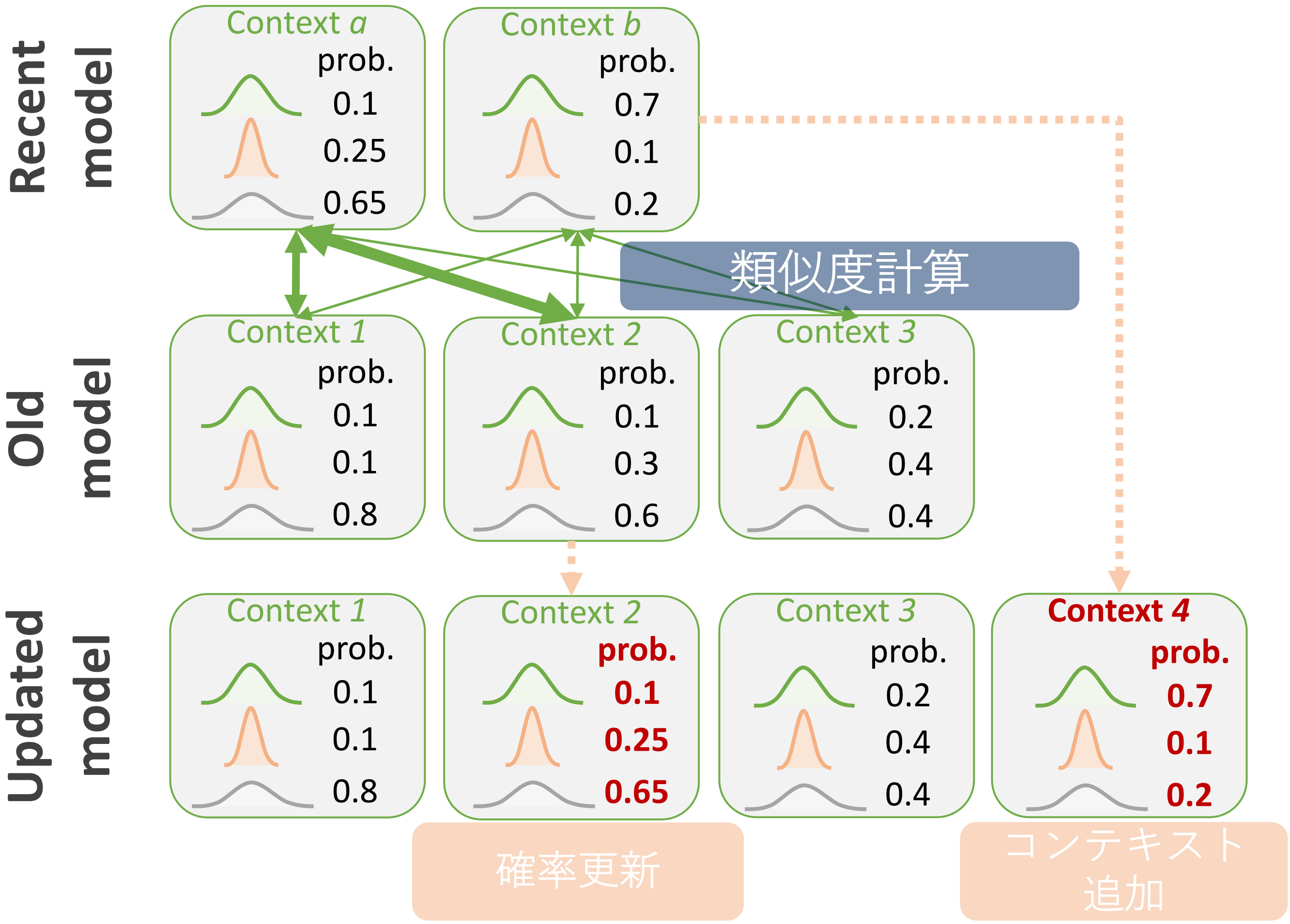
モデル更新

未知のパターンの場合

コンテキストのトラヒックパターンを新たにモデルに追加

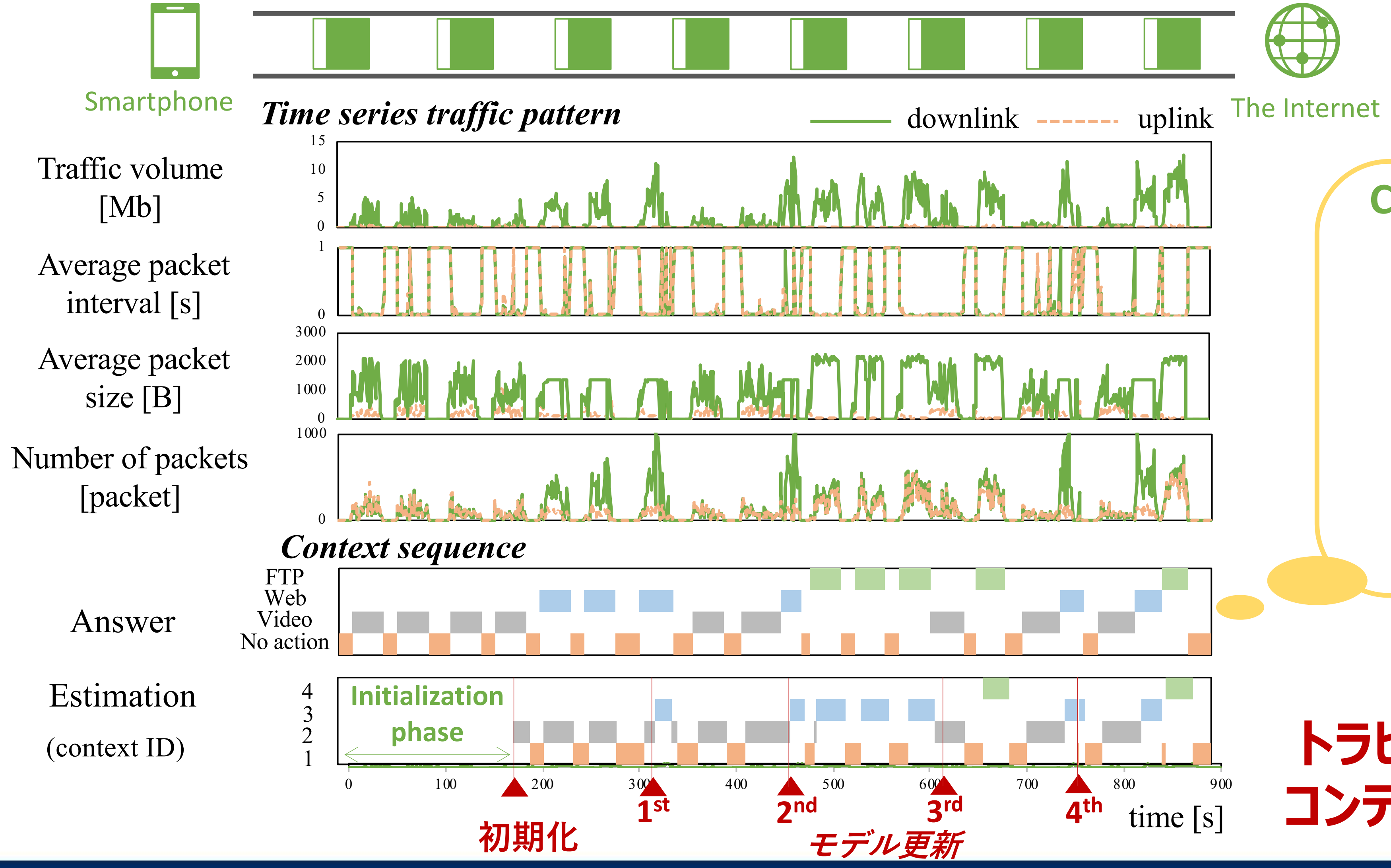
既出パターンの場合

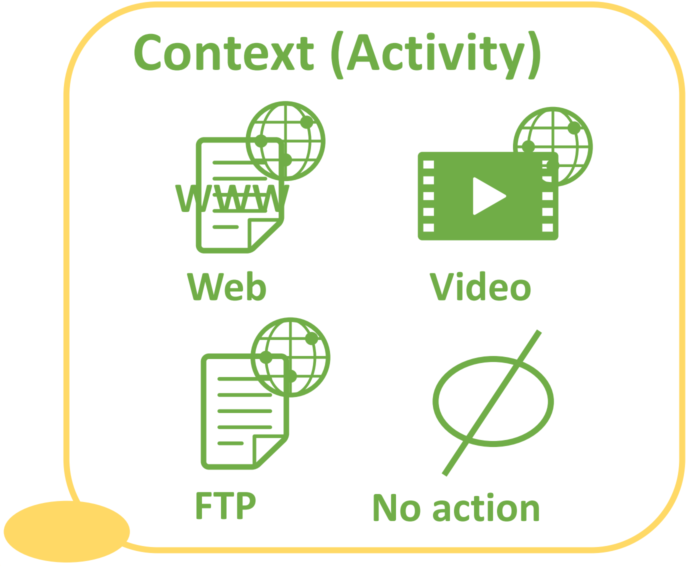
最新パターンに確率を更新



スマートフォンユーザのアクティビティ推定実験

事前学習なしでコンテキスト（アクティビティ）を推定できるか？



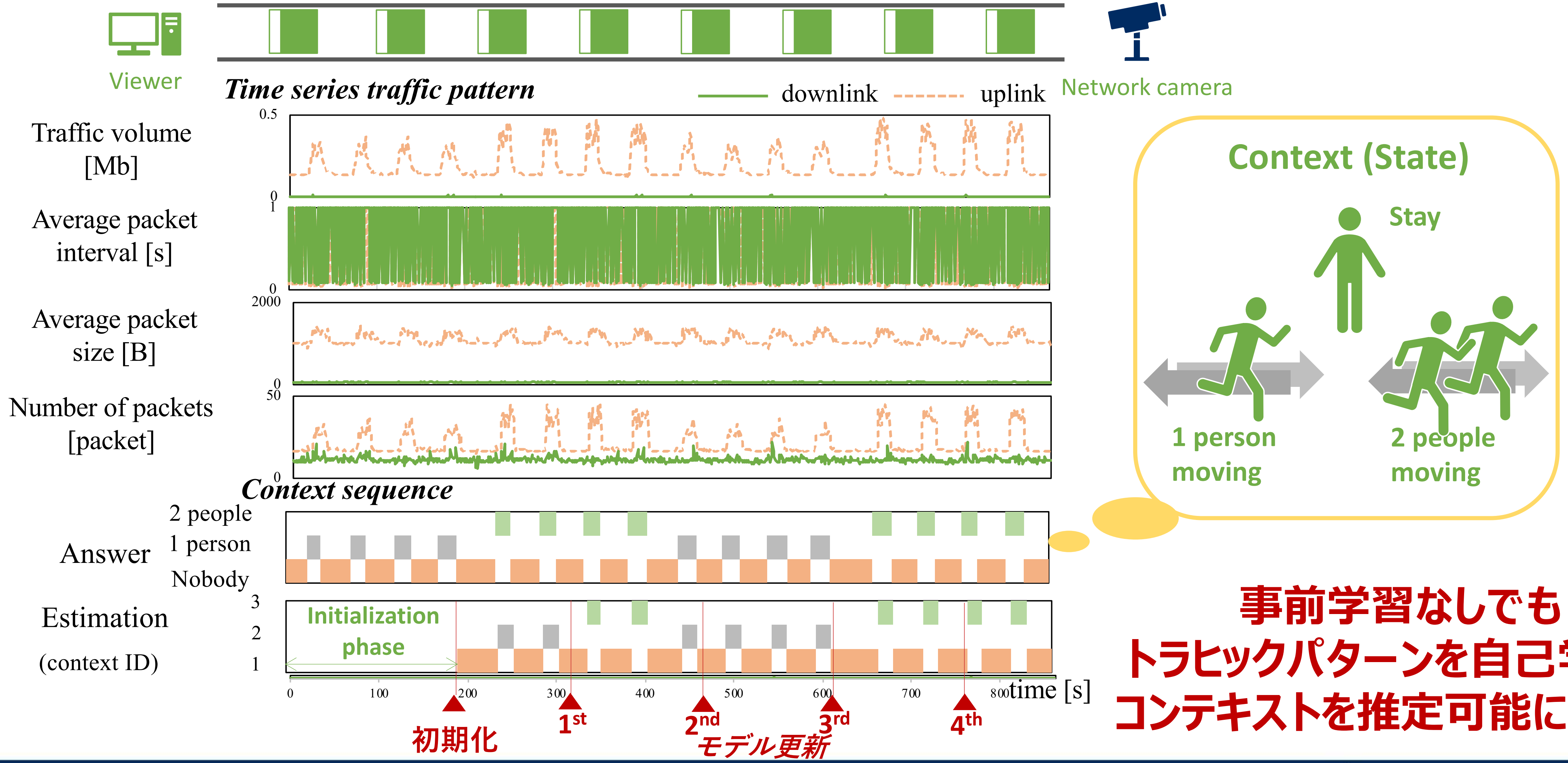


事前学習なしでも
トラヒックパターンを自己学習し
コンテキストを推定可能になる！

A. Sawabe (NEC/UTokyo) , T. Iwai(NEC), K. Satoda (NEC), A.Nakao(UTokyo)

ネットワークカメラの撮影状態推定実験

事前学習なしでコンテキスト（被写体の状態）を推定できるか？



事前学習なしでも
トラヒックパターンを自己学習し
コンテキストを推定可能になる！

A. Sawabe (NEC/UTokyo) , T. Iwai(NEC), K. Satoda (NEC), A.Nakao(UTokyo)

References

- プレスリリース
  - NEC、ローカル5Gを専門家なしで常時高品質に利用可能にする学習型通信分析技術を開発
  - https://jpn.nec.com/press/202005/20200513_01.html

- NOMS 発表
  - Anan Sawabe (University of Tokyo/NEC), Takanori Iwai, Kozo Satoda (NEC), Akihiro Nakao (University of Tokyo), Edge Concierge: Democratizing Cost-Effective and Flexible Network Operations using Network Layer AI at Private Network Edges, NOMS 2020.

Summary:

1. For 5G and Beyond 5G, fine-grained network slicing becomes important as network requirement varies significantly per application. Advanced traffic classification using machine learning (ML) without privacy violation is a viable use case to demonstrate the power of ML.
2. In-Network Machine Learning is powerful means to derive useful high-level information especially in 5G and beyond 5G
   - Traffic User Data
   - Network Operational Data
   - Human behavior Data (Usage of UE, Applications, etc)
3. Tangible example use cases such as traffic classification are simple but suitable and attractive for education purpose (lower barrier to entry to ML/AI application to networking)

Such examples would accelerate research and education on the subject.

ITUEvents

Machine Learning for Wireless LANs + Japan Challenge Introduction

ITU-ML5G-PS-031, ITU-ML5G-PS-032

7 August 2020

ITU

AI/ML in 5G

Challenge

Applying machine learning in communication networks

ai5gchallenge@itu.int

Register here

Join us on Slack

Sponsors

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ITU-ML5G-PS-031, ITU-ML5G-PS-032

29 July 2020

ITU

AI/ML in 5G

Challenge

Applying machine learning in communication networks

ai5gchallenge@itu.int

Register here

Join us on Slack

Sponsors

Organizer

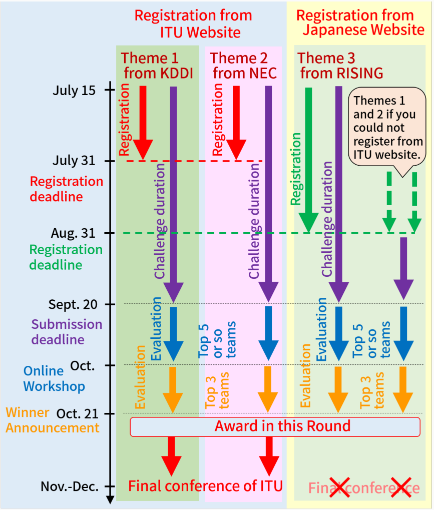
Machine Learning for Wireless LANs

Koji Yamamoto

Graduate School of Informatics, Kyoto University

2020-07-29

- Location estimation from Wi-Fi RSSI (Received Signal Strength Indicator)
- Japan round only
  Not eligible for final conference



This lecture talk

- Our applications of deep supervised learning and reinforcement learning
- For microwave and mmWave WLANs
- Deep (supervised) learning in Part I
- Deep reinforcement learning in Part II

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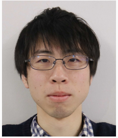
https://www.ieice.org/~rising/jpn/AI-5G/

Part I

Deep Learning for mmWave WLANs

[Nishio+2019] T. Nishio, H. Okamoto, K. Nakashima, Y. Koda, K. Yamamoto, M. Morikura, Y. Asai, and R. Miyatake, "Proactive received power prediction using machine learning and depth images for mmWave networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 11, Nov. 2019

T. Nishio

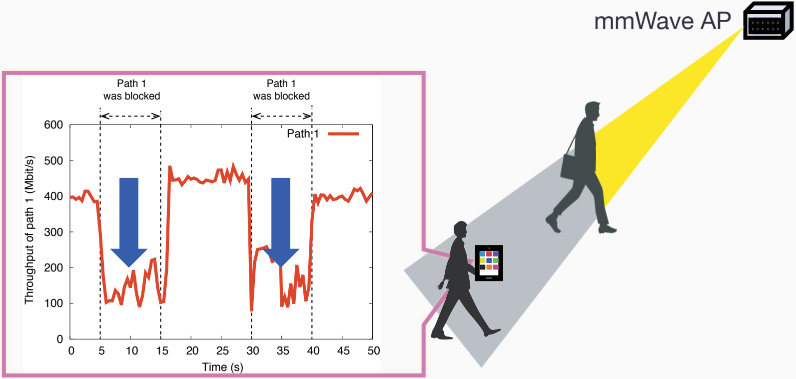


Y. Koda

5G — 28 GHz band

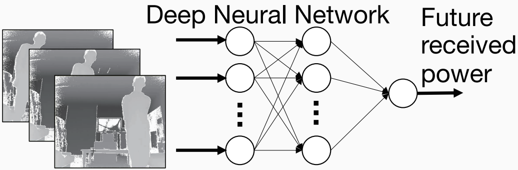
IEEE 802.11ad/ay — 60 GHz band

- Beyond Gbit/s communications using bandwidth of 2.16 GHz or more (IEEE 802.11ad)
- Strong attenuation (15 dB–) when human blocks line-of-sight



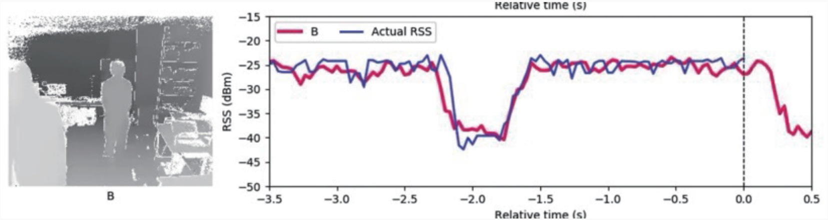
[Nishio+2019]

Key idea: Deep learning and camera images

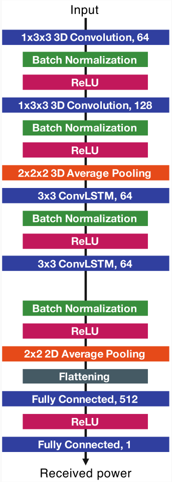


Prediction:

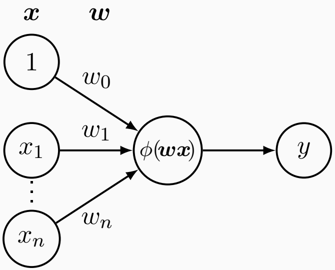
Received power in 500 ms ahead is accurately predicted only from camera images



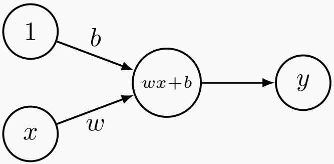
[Nishio+2019]

	(1) Received power prediction (Regression)	(2) Linear regression
Input x	Camera images 	$x \in \mathbb{R}^1$
Output y	Future received power	$y \in \mathbb{R}^1$
NNs		Simple perceptron (NN) with linear activation function

Simple perceptron



$$y = \phi\left(\sum_{i=1}^{n} w_i x_i + w_0\right) = \phi(\boldsymbol{wx})$$



Linear activation function

$\phi(x) = x$

$$y = wx + b$$

```
class Net(torch.nn.Module):
  def __init__(self):
    super(Net, self).__init__()
    self.fc1 = torch.nn.Linear(1, 1)
  def forward(self, x):
    x = self.fc1(x)
    return x
```

(1) Received power prediction

Future power $= f^{(1)}\Big($  $\Big)$

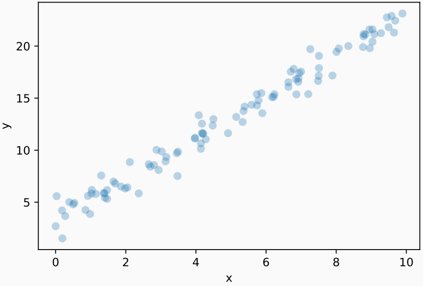
Training $f^{(1)} =$ NN by labeled data set

(2) Linear regression

$$y = f^{(2)}(x) = wx + b$$

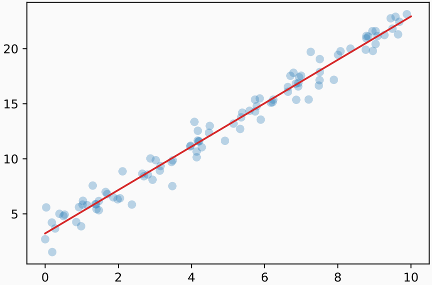
Training $f^{(2)}$, i.e., w and b by labeled data set (x_i, y_i)

$y_i = 2x_i + 3 + \epsilon,\ \epsilon \sim \mathcal{N}(0,1)$



Open in Colab

```
optimizer = torch.optim.SGD(net.parameters(), lr=0.01)
criterion = torch.nn.MSELoss()
(Training)
print(net.fc1.weight) # tensor([[2.0332]], requires_grad=True)
print(net.fc1.bias)   # tensor([2.8885], requires_grad=True)
```

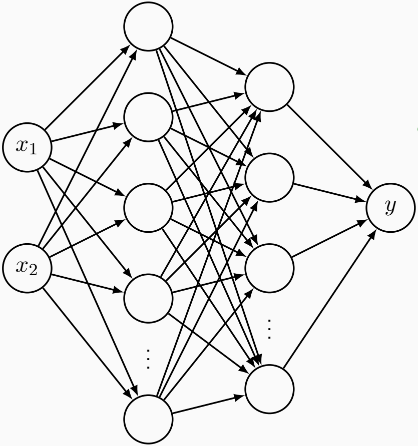


$y = 2x + 3 + \epsilon$: Labeled data (x_i, y_i)

$y = wx + b$: Neural network

Minimum mean-squared error estimation in linear regression

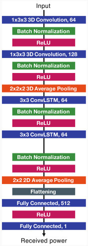
Multiple inputs → Deep networks




```python
class Net(torch.nn.Module):
  def __init__(self):
    super(Net, self).__init__()
    self.fc1 = torch.nn.Linear(2, 64)
    self.fc2 = torch.nn.Linear(64, 32)
    self.fc3 = torch.nn.Linear(32, 1)
  def forward(self, x):
    x=torch.nn.functional.relu(self.fc1(x))
    x=torch.nn.functional.relu(self.fc2(x))
    x=self.fc3(x)
    return x
```

$$f(x) = \mathrm{ReLU}(x) := \max\{0, x\}$$

Depth images				$\cdots$	
Received power	$-50\,\mathrm{dBm}$	$-51\,\mathrm{dBm}$	$-49\,\mathrm{dBm}$	$\cdots$	$-70\,\mathrm{dBm}$
Time	$-60\,\mathrm{ms}$	$-30\,\mathrm{ms}$	$0\,\mathrm{ms}$	$\cdots$	$500\,\mathrm{ms}$

By using this dataset, how can we train the NN 

, i.e., $f^{(1)}$?

Future received power $= f^{(1)}\Big($  $\Big)$

Measured data

$\boldsymbol{x}_1$

Depth images				$\cdots$	
Received power	−50 dBm	−51 dBm	−49 dBm	$\cdots$	−70 dBm y_1
Time	−60 ms	−30 ms	0 ms	$\cdots$	500 ms

$$y = f^{(1)}(\boldsymbol{x})$$

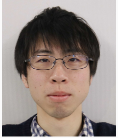
Part II

Deep Reinforcement Learning for WLANs

[Nakashima+2020] K. Nakashima, S. Kamiya, K. Ohtsu, K. Yamamoto, T. Nishio, and M. Morikura, “Deep reinforcement learning-based channel allocation for wireless LANs with graph convolutional networks,” *IEEE Access*, vol. 8, Feb. 2020

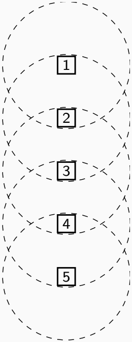
S. Kamiya

[Koda+2020] Y. Koda, K. Nakashima, K. Yamamoto, T. Nishio, and M. Morikura, “Handover management for mmWave networks with proactive performance prediction using camera images and deep reinforcement learning,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, Feb. 2020



Y. Koda

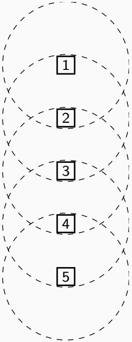
Optimal channel allocation?
Criterion: Aggregated throughput
Number of channels: 2

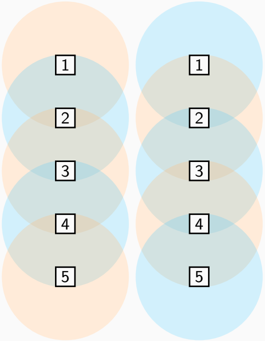


Framework: Combinatorial optimization (NP-hard)

BoE throughput [Liew+2010] is shown for the ease of explanation.

Optimal channel allocation?
Criterion: Aggregated throughput
Number of channels: 2



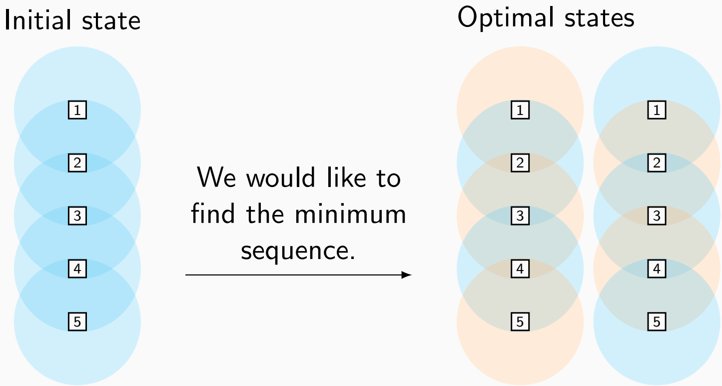


Framework: Combinatorial optimization (NP-hard)

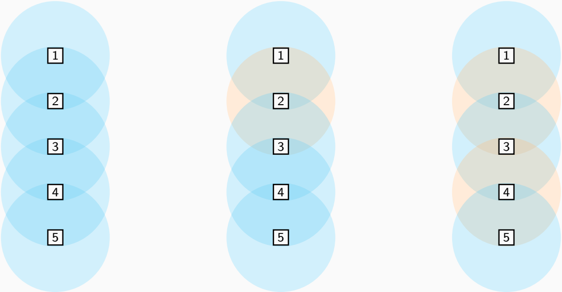
BoE throughput [Liew+2010] is shown for the ease of explanation.

Different problem setting:

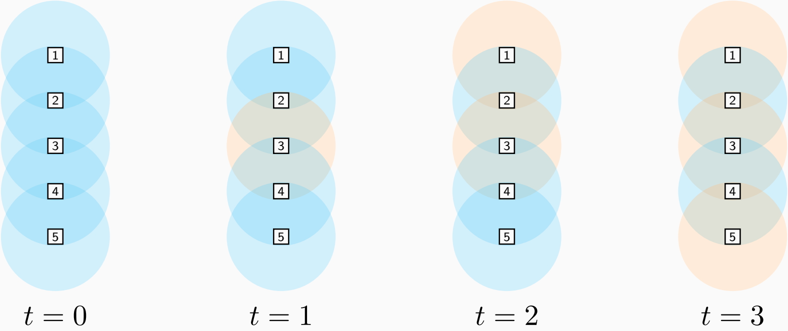
- Finding the minimal *sequence*
- Only one AP can change its channel at a given time
- Throughput can be observed only after channel allocation

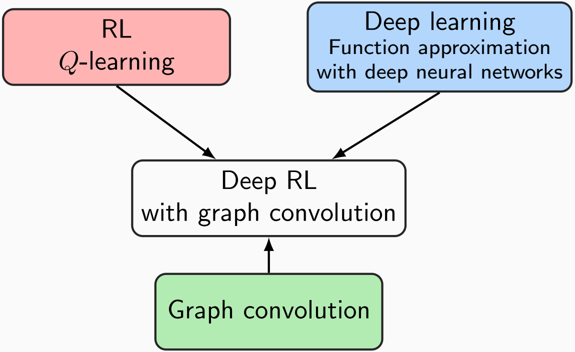


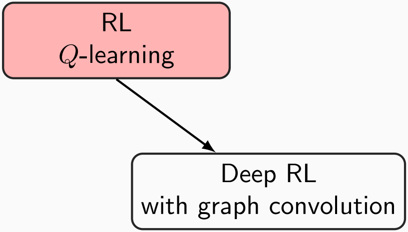
This part is simplified version of [Nakashima+2020]



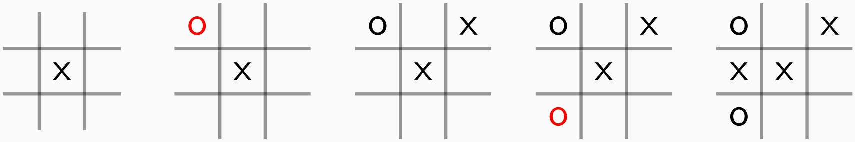
← We want to acquire this sequence based on observed throughput Criterion?




RL
Q-learning
Deep learning
Function approximation
with deep neural networks
Deep RL
with graph convolution
Graph convolution


RL
Q-learning
Deep RL
with graph convolution

Tic Tac Toe — Second player 'o'



State S_0 Action A_0 State S_1 Action A_1 State S_2

The second player observes state S_t and takes action A_t,
then observes the next state S_{t+1},

and gets the reward R_{t+1} — win or loss.

Problem:

Without knowing the rule of the game, i.e.,
only based on the observed sequence $(S_t, A_t, R_{t+1}, S_{t+1})$,
we determine the appropriate action.

Approach:

Reinforcement learning — (Tabular) Q-learning

Action-value function:

Q : State $\times$ Action $\mapsto$ Expected reward

State	A	B	C	D	E	F	G	H	I
⋮									
o | x | · · | x | · · | · | ·								o	
o | · | x · | x | · · | · | ·							o		
o | · | · x | x | · · | · | ·						o			
⋮									

A	B	C
D	E	F
G	H	I

Updating the value of Q table according to observed sequence $(S_t, A_t, R_{t+1}, S_{t+1})$.

Open in Colab

Number of actions:
$3 \times 3 = 9$ cells

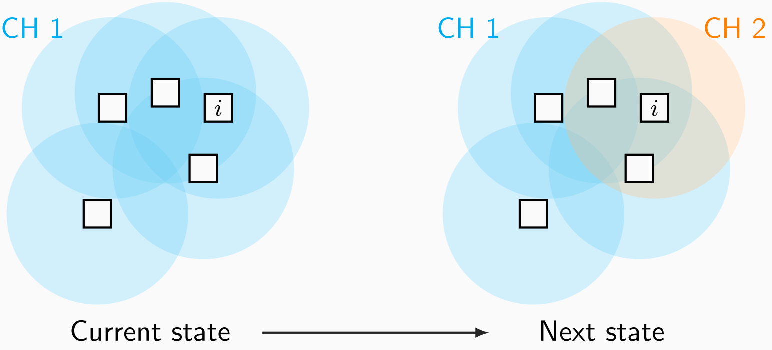
Number of states:
$3^9 = 19683$
blank, o, or x for each cell

Number of elements in Q table:
9×19683 even in this simple problem

To estimate $Q^*(s, a)$, every state-action pair should be visited
When the number of states is huge, training is infeasible — State explosion

Markov decision process

- Agent: Centralized controller of all APs
- State: Channels and contention graph of APs
- Action: Channel selection of one AP
- Reward: Throughput



Action: AP i changes its channel to 2

[Nakashima+2020]

Q table in channel allocation

	Case 1	Case 2
Number of APs	4	10
Number of links between APs	$\binom{4}{2} = 6$	$\binom{10}{2} = 45$
Number of link states	2^6	2^{45}
Number of channels	2	3
Number of channel states	2^4	3^{10}
Number of states	$2^6 \cdot 2^4 = 1024$	$2^{45} \cdot 3^{10} = 2 \cdot 10^{18}$

Tabular Q-learning

$$
\begin{aligned}
Q_{t+1}(S_t, A_t) &\doteq Q_t(S_t, A_t) + \alpha_t\, \delta_{t+1}(Q_t) \\
\delta_{t+1}(Q_t) &\doteq R_{t+1} + \gamma \max_{a' \in \mathcal{A}} Q_t(S_{t+1}, a') - Q_t(S_t, A_t)
\end{aligned}
$$

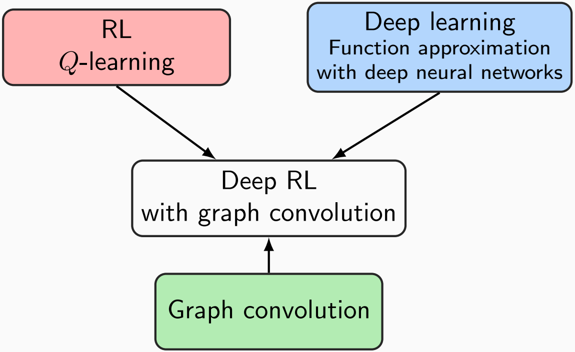
Q-learning with function approximation

Extension to function approximation with a parameterized function $Q_{\boldsymbol{\theta}}$, $\boldsymbol{\theta} \in \mathbb{R}^d$

$$
\begin{aligned}
\boldsymbol{\theta}_{t+1} &\doteq \boldsymbol{\theta}_t + \alpha_t\, \delta_{t+1}(Q_{\boldsymbol{\theta}_t})\, \nabla_{\boldsymbol{\theta}}\, Q_{\boldsymbol{\theta}_t}(S_t, A_t) \\
\delta_{t+1}(Q_{\boldsymbol{\theta}_t}) &\doteq R_{t+1} + \gamma \max_{a' \in \mathcal{A}} Q_{\boldsymbol{\theta}_t}(S_{t+1}, a') - Q_{\boldsymbol{\theta}_t}(S_t, A_t)
\end{aligned}
$$

Deep reinforcement learning

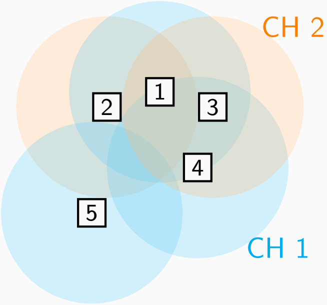
Q-learning with function approximation using deep neural networks


RL
Q-learning
Deep learning
Function approximation
with deep neural networks
Deep RL
with graph convolution
Graph convolution

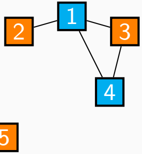
State Design and Feature Extraction [Nakashima+2020]

State: Adjacency of APs and selected channel

Physical expression



Graph expression



Tabular expression
5x7 matrix

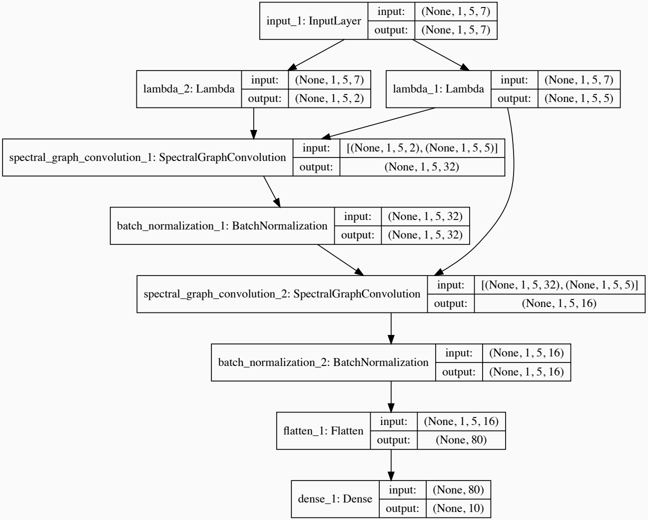
$$\begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{array}{cl} \begin{bmatrix} 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} & \begin{array}{l} \text{Ch 1} \\ \text{Ch 2} \end{array} \end{array}$$

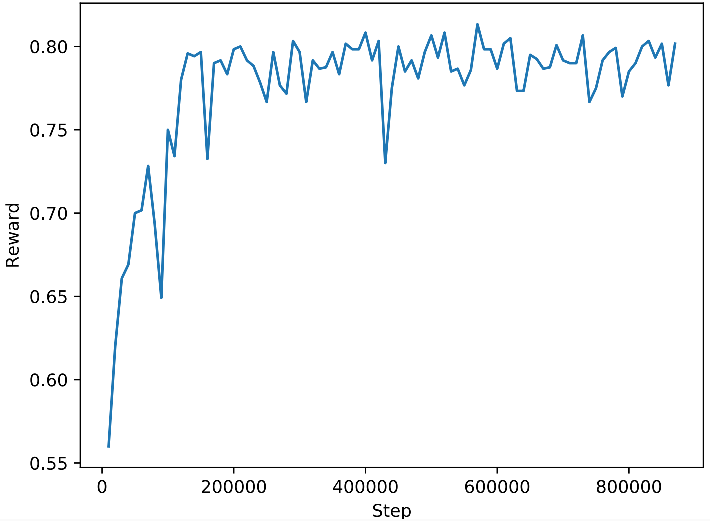
Feature extraction (pre-processing):

Graph convolutional networks	Convolutional neural network (CNN)
Feature extraction for graphs	Feature extraction for images

State: 5x7 matrix



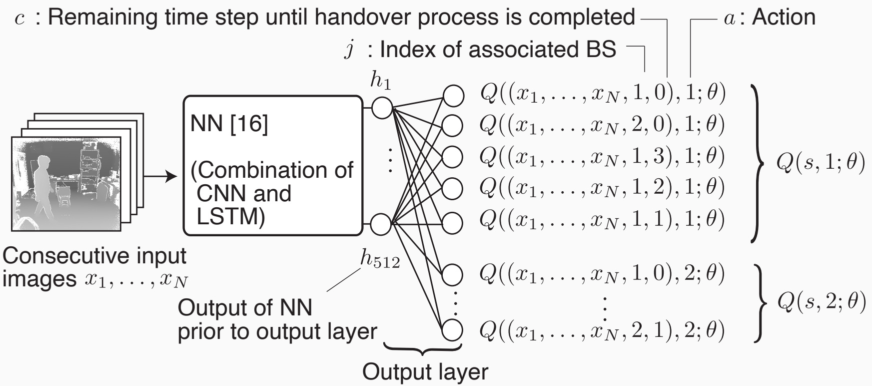
Q-values for 10 actions (5 APs x 2 CHs)

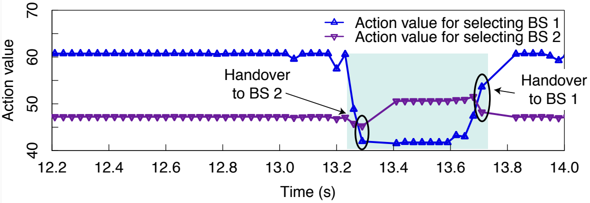


- Five APs are located uniformly and randomly
- Reward: The minimum individual throughput of five APs

Simplified version of [Nakashima+2020]

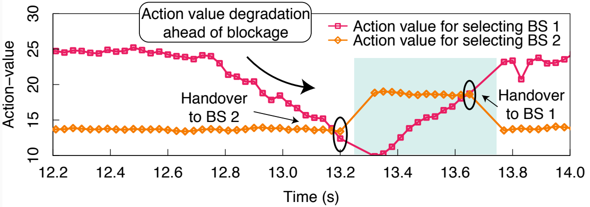
- By using input images, determine one BS from two candidate BSs
- The output of NNs is Q-value for input images





Without camera images

- Because the received power degrades sharply, handover decision is conducted after degradation in general



With camera images

- Usage of camera images extends the state space, and thus proactive handover is enabled

Summary

Part I

- Deep NNs are functions.
- Deep learning successfully predict future received power only from past image sequences.

Part II

- Reinforcement learning is used to acquire the *optimal sequence* to maximize the total reward.
- Deep neural networks are used for function approximation of Q function (deep RL).

References I

[Koda+2020] Y. Koda, K. Nakashima, K. Yamamoto, T. Nishio, and M. Morikura, "Handover management for mmWave networks with proactive performance prediction using camera images and deep reinforcement learning," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, Feb. 2020.

[Liew+2010] S. C. Liew, C. H. Kai, H. C. Leung, and P. Wong, "Back-of-the-envelope computation of throughput distributions in CSMA wireless networks," *IEEE Trans. Mobile Comput.*, vol. 9, no. 9, Sep. 2010.

[Nakashima+2020] K. Nakashima, S. Kamiya, K. Ohtsu, K. Yamamoto, T. Nishio, and M. Morikura, "Deep reinforcement learning-based channel allocation for wireless LANs with graph convolutional networks," *IEEE Access*, vol. 8, Feb. 2020.

[Nishio+2019] T. Nishio, H. Okamoto, K. Nakashima, Y. Koda, K. Yamamoto, M. Morikura, Y. Asai, and R. Miyatake, "Proactive received power prediction using machine learning and depth images for mmWave networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 11, Nov. 2019.

Demonstration of machine learning function orchestrator (MLFO) via reference implementations (ITU-ML5G-PS-024)

Shagufta Henna, LYIT, 31 July 2020

ITUEvents

ITU

AI/ML in 5G

Challenge

Applying machine learning in communication networks

ai5gchallenge@itu.int

Register here

Join us on Slack

Sponsors

Organizer

Analysis on route information failure in IP core networks by NFV-based test environment.

ITU-ML5G-PS-(KDDI)

Agenda

KDDI Research

1. Data set
2. How to use the data set
3. Network configuration for evaluation
4. Use cases of analysis
5. Submission

1. Dataset

KDDI Research

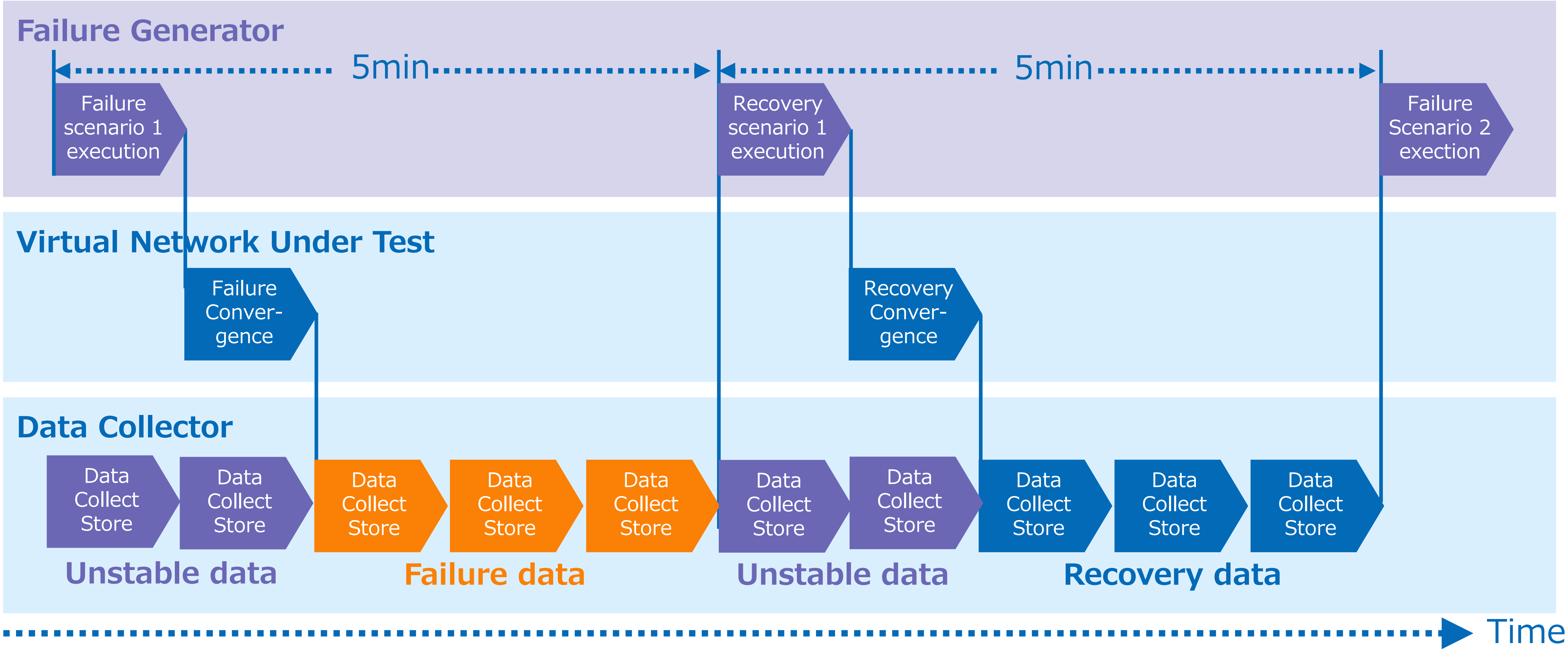
Four types of data sets for learning and evaluation are provided to participants as follows.

Category	File Name	Description	Data format	Time zone (1)
Label	Failure-management	Event date (failure and recovery) and event types, which are listed along the time series	json	UTC
Data	Virtual-Infrastructure	Performance monitoring data sets on instances and virtual network functions gathered from openstack ceilometer, which are listed along the time series	json	JST
	Physical-Infrastructure	Performance monitoring data sets gathered from the physical server under openstack, which are listed along the time series	json	JST
	Network-Device	Performance monitoring information and BGP route information gathered from NEs under the virtual IP network, which are listed along the time series	json	JST

(1) The time zone differs between those of the label and the data due to the system configuration. 9 hours difference exists between UTC and JST.

1. Data collection principles

In order create data sets, the data collector was developed to collects and stores data sets every minute from the network. Once a failure is intentionally caused and recovered, the network indicates a failure or normal status after a period of transition, corresponding to failure data (orange arrows) and recovery data (blue arrows). The period of transition depends on a failure scenario and enough guard time is desired to be considered. The time interval between a failure and a recovery is 5 min.

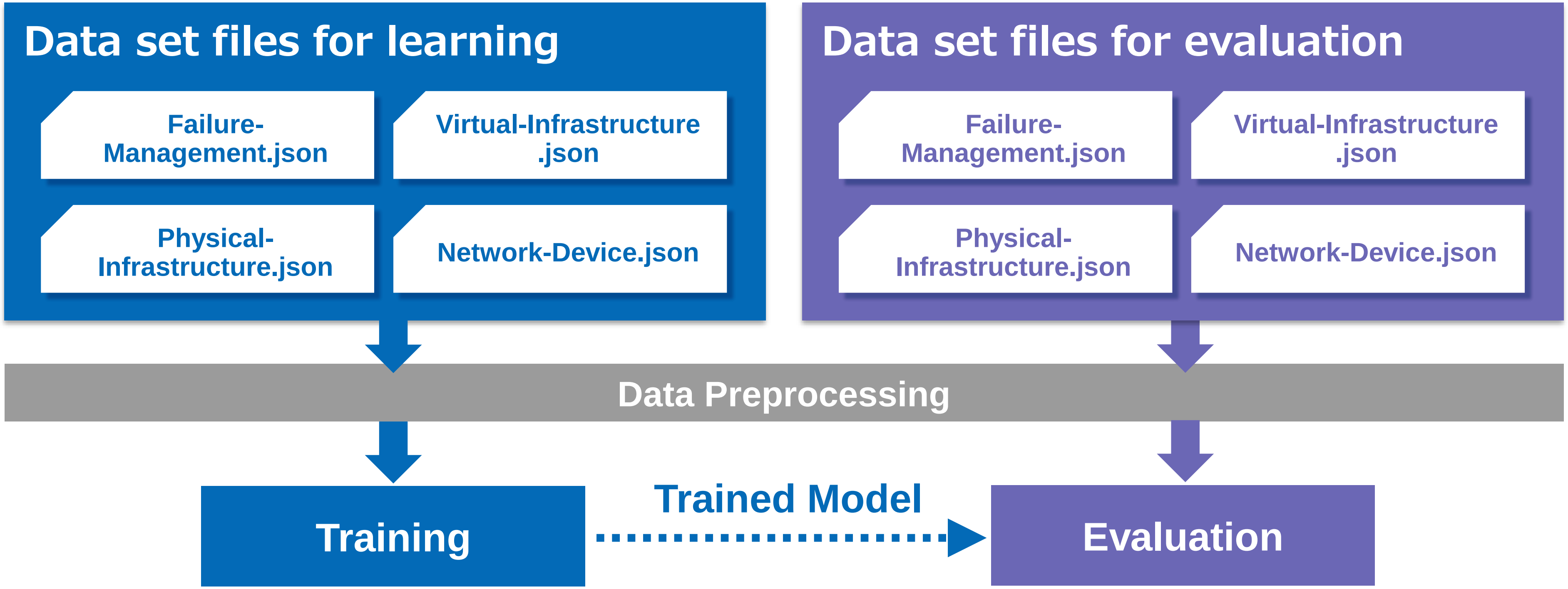


2. How to use the dataset

KDDI Research

Two types of dataset files for learning and evaluation are provided to participants. The dataset files for learning can be used for training AI models, and the dataset files for evaluation can be used for evaluating performance of the trained model.

The dataset files for learning corresponds to use cases when all failure scenarios (shown in Chapter 4) are comprehensively invoked at all possible failure points. The dataset files for evaluation corresponds to the case when a combination of a failure scenario and a failure point is randomly and limitedly generated.

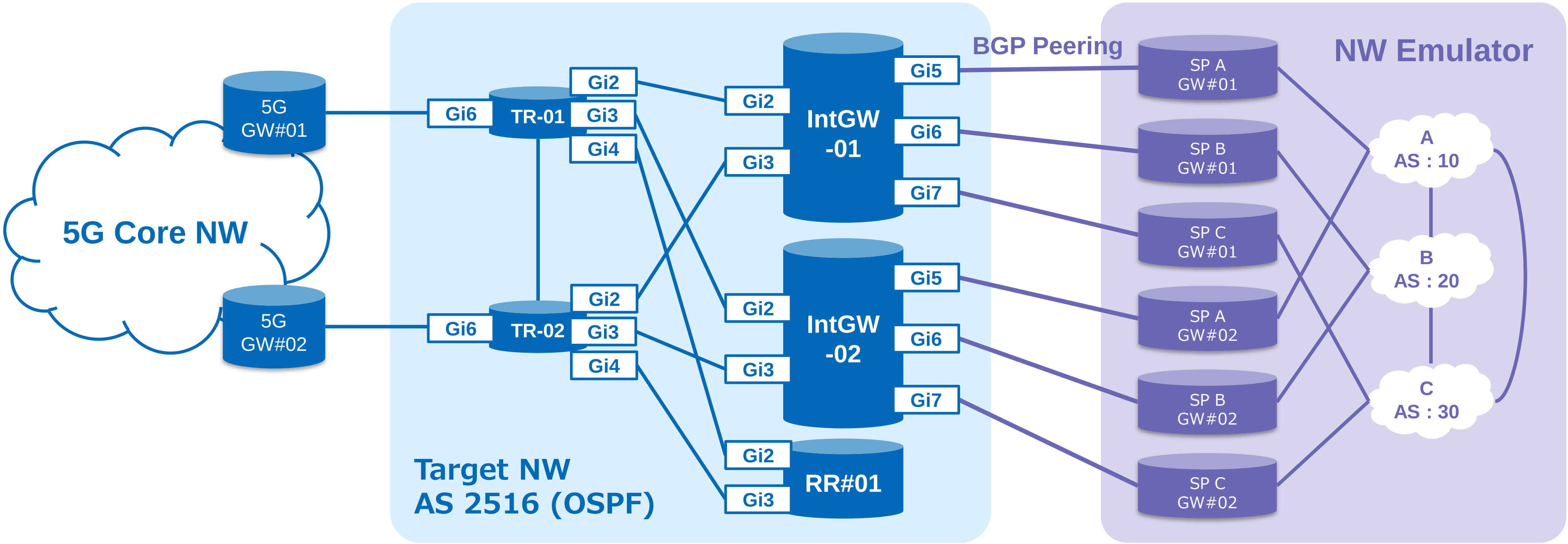


3. Network Topology

KDDI Research

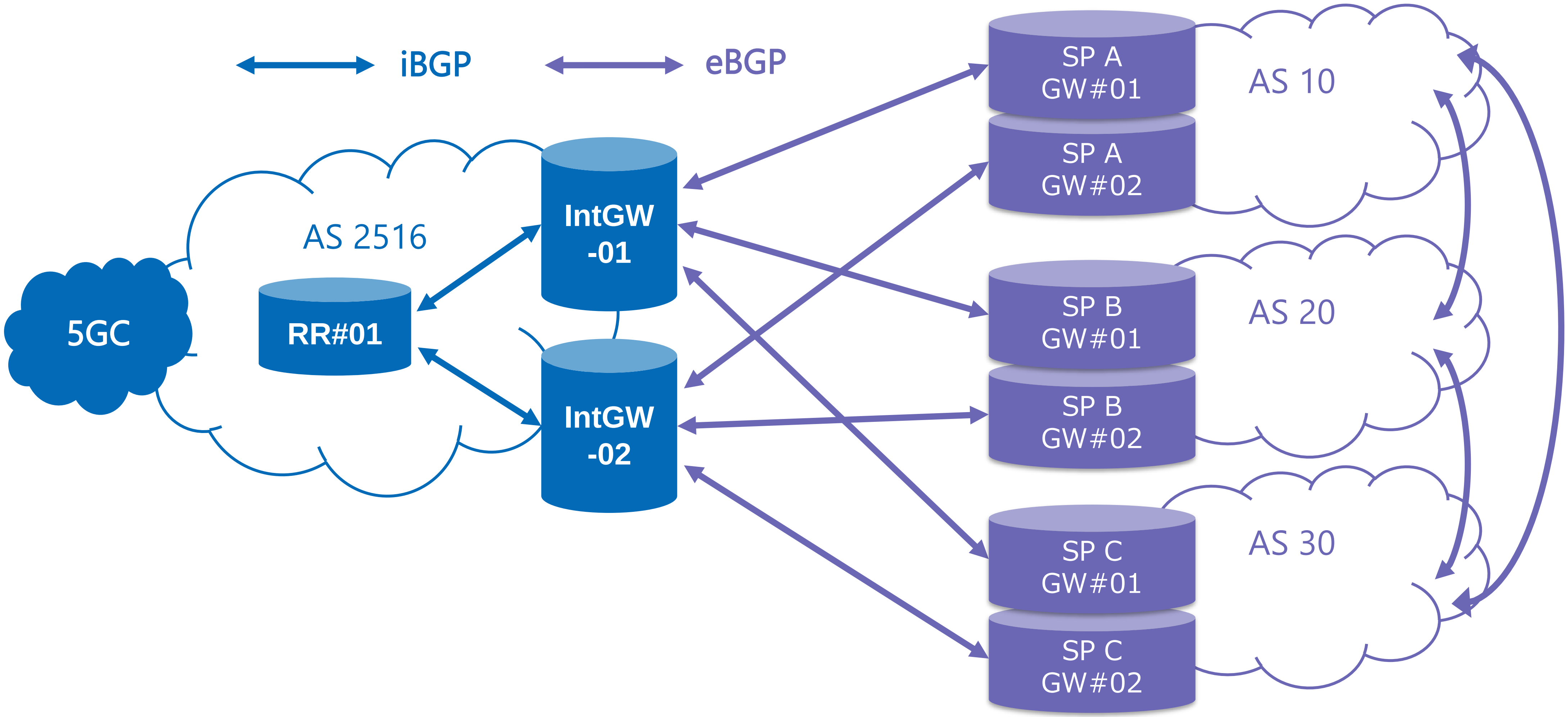
■ Physical topology

The target of data collection is an IP core network, which connects the 5G core network for the Internet connectivity. The IP core network totally consists of 5 network elements, where TR-01, 02 are an IP core node, IntGW-01, 02 are an Internet gateway router peered with other SPs, and RR-01 is a route reflector sharing route information.



KDDI Research

■ Logical Topology (BGP)



4. Use cases

KDDI Research

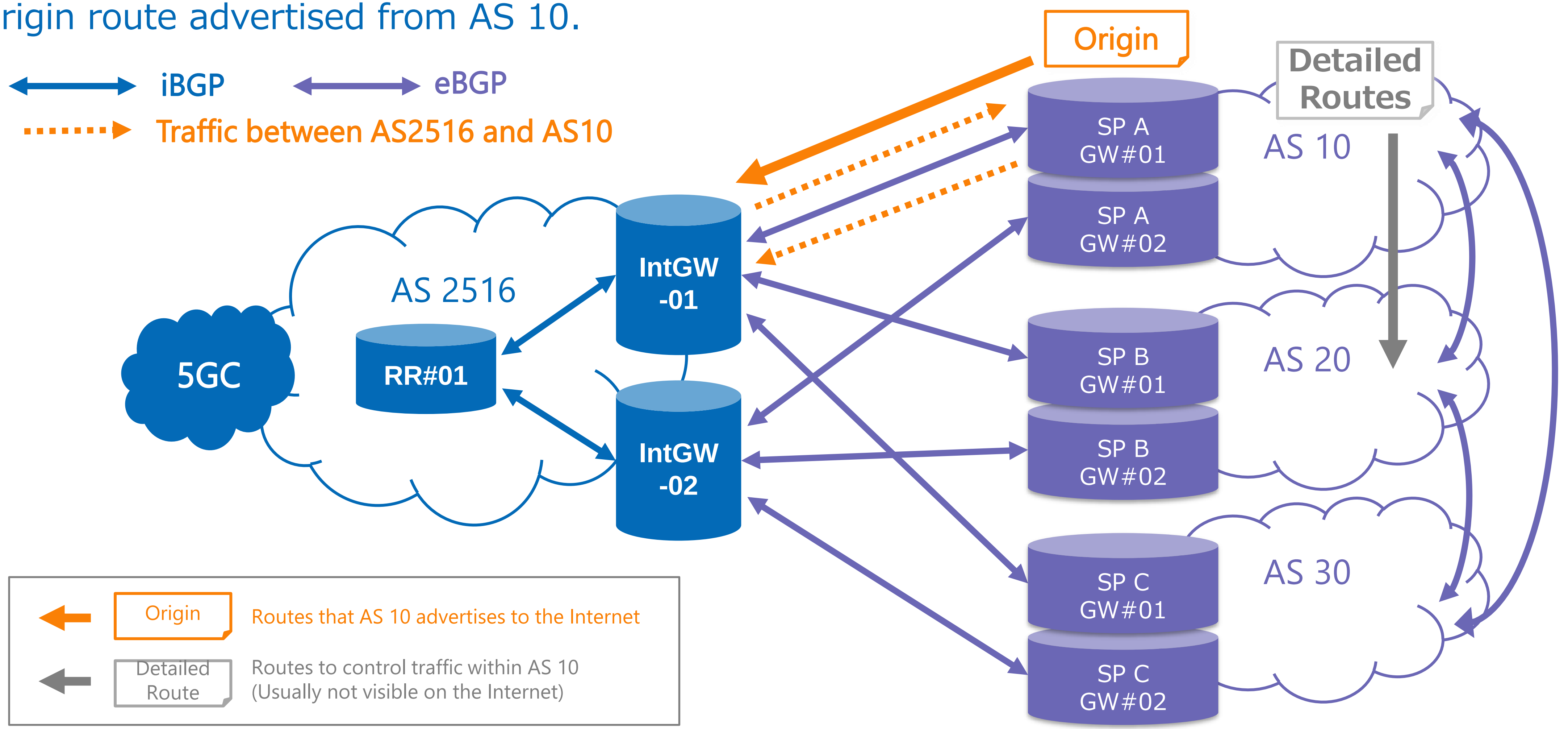
Scenario	UC No.	Use Case Name	Description
Route Information Failure	UC1	BGP Injection	Inject the anomaly route from another SP
	UC2	BGP Hijack	Hijack the own origin route by another SP
Interface Failure	UC3	Interface Down	Cause an interface down
	UC4	Packet Loss	Cause the packet loss on an interface
	UC5	Packet Delay	Cause the delay of packets on an interface
Network Element(NE) Failure	UC6	NE Reboot	Unplanned reboot of a NE

UC1 : BGP Injection

KDDI Research

■ Route Information in a normal state

Detailed routes of AS 10 are exchanged only with AS 20 by the coordinated operation between AS 10 and AS 20, therefore the traffic between AS2516 and AS 10 are transported following the origin route advertised from AS 10.

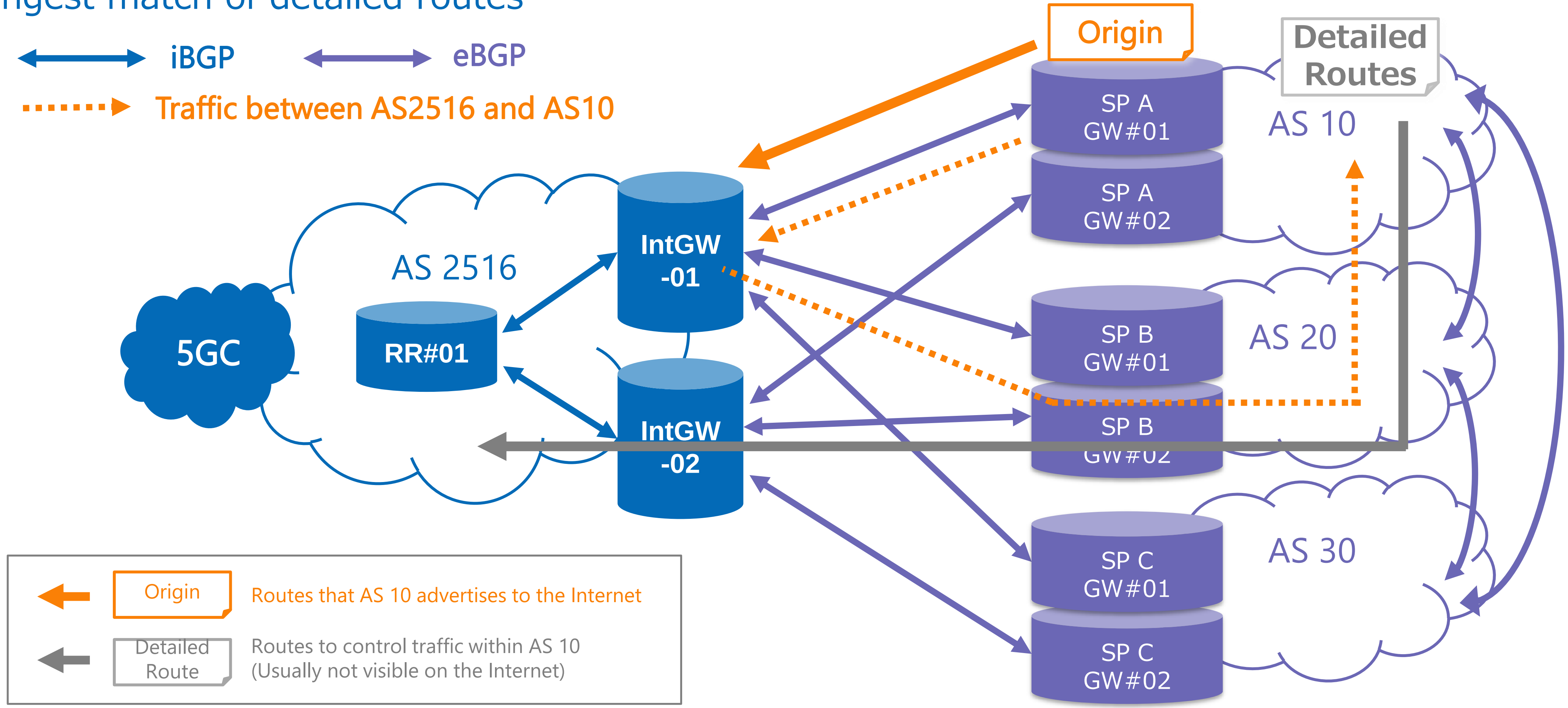


UC1 : BGP Injection

KDDI Research

Route Information in an anomaly state

AS 20 happens to send detailed routes of AS 10 to AS 2516 due to an operational mistake. The traffic is switched from the direct route to the AS 10 to bypass route via AS 20 according to the longest match of detailed routes

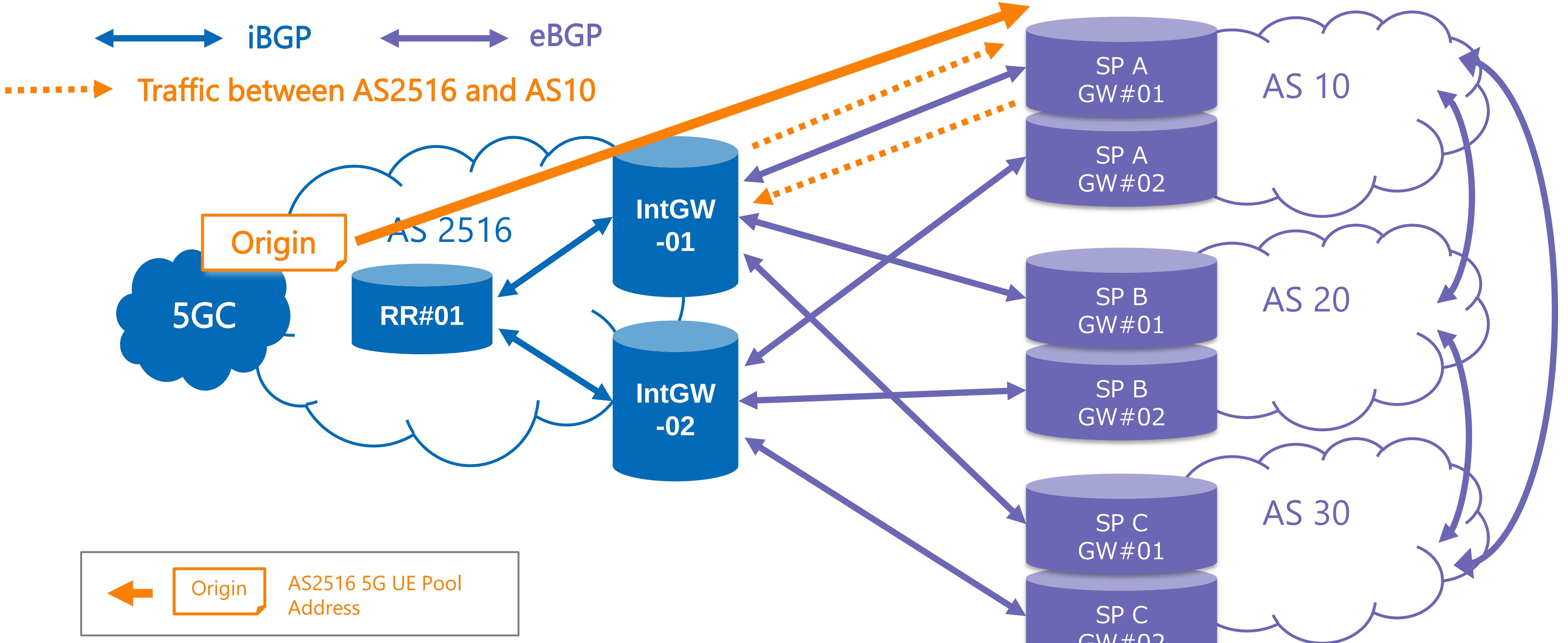


UC2 : BGP Hijack

KDDI Research

■ Route Information in a normal state

The traffic between AS 2516 and AS 10 is transported according to the advertised origin routes of AS 2516.

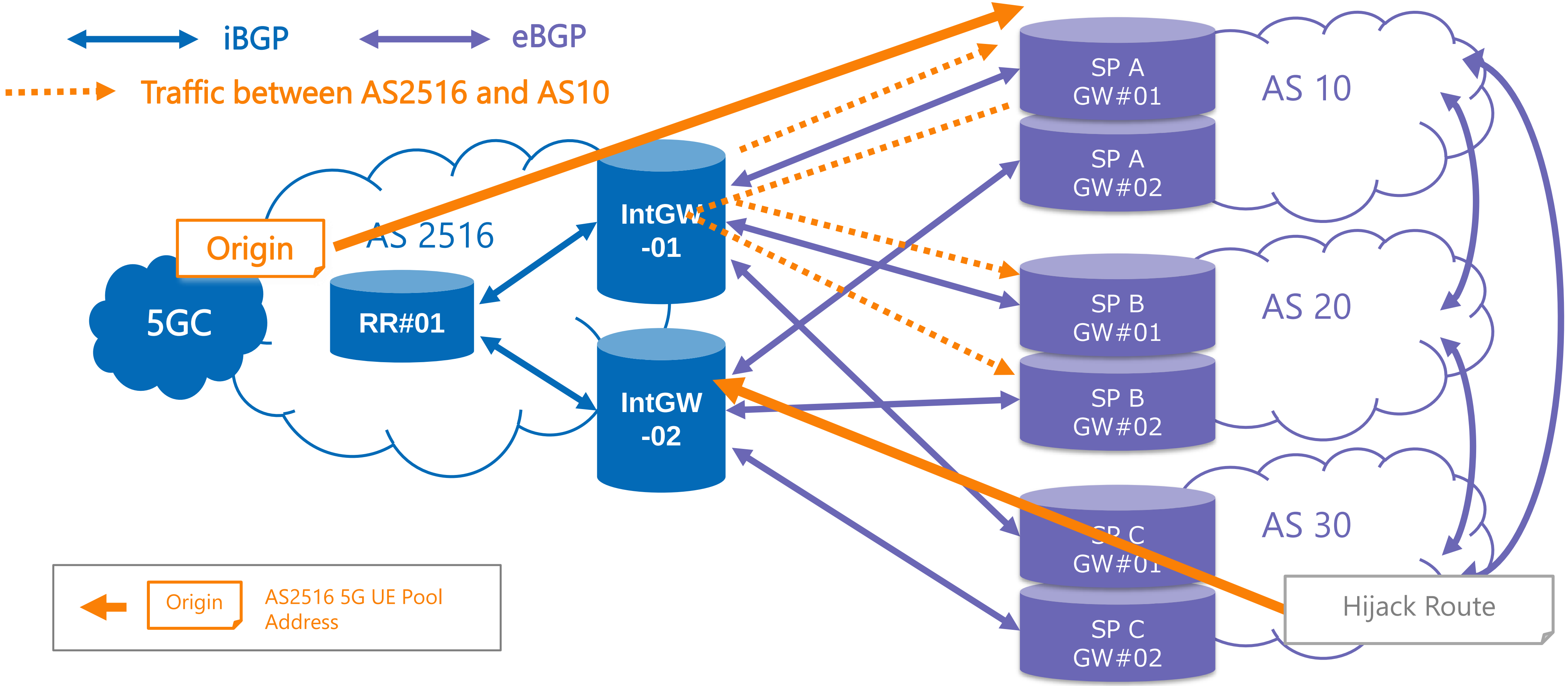


UC2 : BGP Hijack

KDDI Research

■ Route Information in an anomaly state

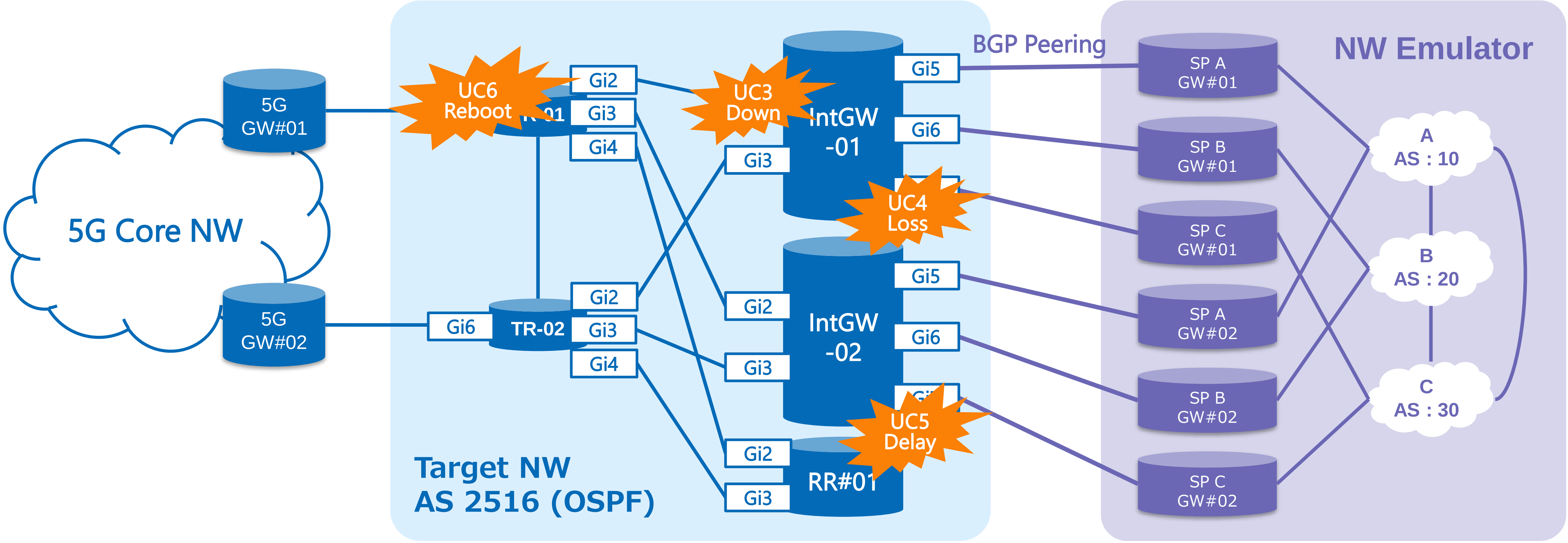
Malicious SP C intentionally advertised a part of the IP address space allocated to 5G terminals in AS 2516 for route hijack, and caused traffic disruption from other operators to AS 2516.



KDDI Research

■ Use case detail

Interface failures (packet loss, packet delay, down) and node failures (reboot) are comprehensively (for learning) and randomly (for evaluation) caused.



failure-management sample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Unique Key

Failure scenario

Failure execution start/end date and time

virtual-infrastructure sample

KDDI Research

Unique Key


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physical-infrastructure sample

Unique Key


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```

Network-Device sample

KDDI Research

Unique Key


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{
  "_index": "network-device-bgpnw-20200301",
  "_type": "_doc",
  "_id": "2020-03-01T12:01:00+0900",
  "_version": 1,
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                    }
                  },
```

5. Submission

KDDI Research

Create and train a model of AI/ML by the data set for learning and verify the performance of the derived model by the data set of evaluation in terms of anomaly detection and root cause analysis.

Submit a power point file with a pdf format indicating the results and a demonstration video showing predicting performance.

Contact information

info_itu5G_jp@lists.cc1g.kddi-research.jp

KDDI
KDDI Research

Orchestrating a brighter world NEC

ITU AI/ML in 5G challenge

【ITU-ML5G-PS-031】
Network State Estimation by Analyzing Raw Video Data

2020/7/29

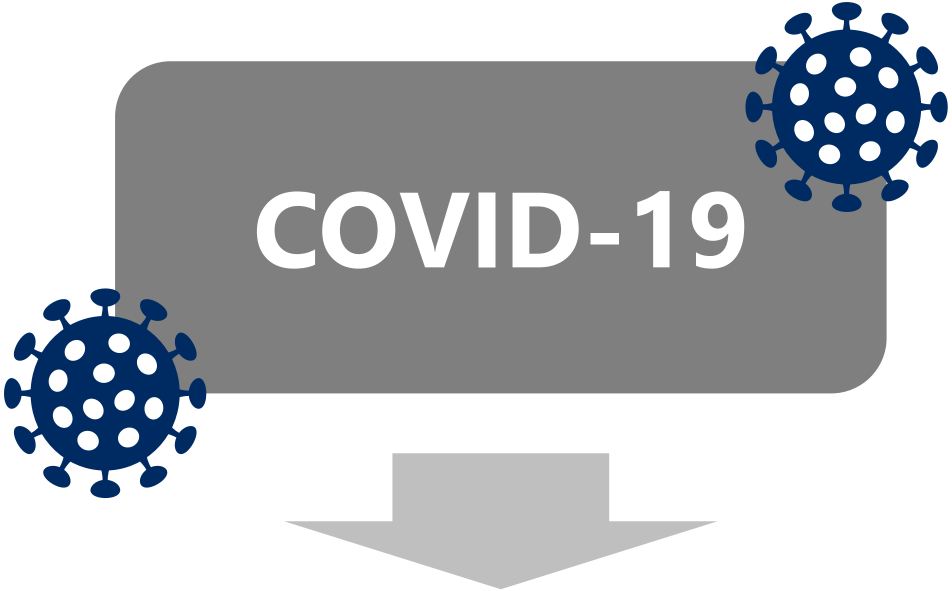
NEC Corporation, Japan

Agenda

1. Introduction
2. Challenge
3. Dataset
4. Information

1. Introduction

Background – COVID19 pandemic

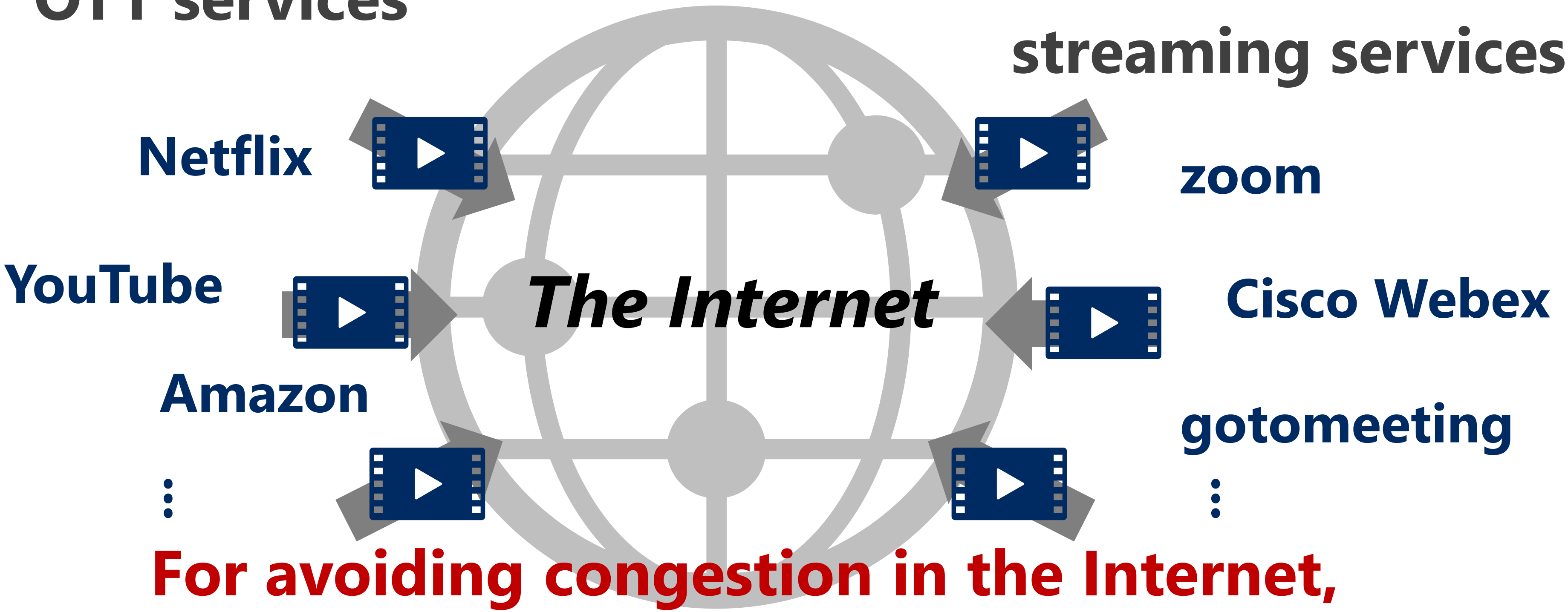


The importance of *interactive live video streaming services*,
e.g., telework system, is increasing!!

Social problem

OTT services

Interactive video streaming services



For avoiding congestion in the Internet, video traffic reduction is required!!

Difference between OTT services and interactive services

Service provided by OTT

OTT providers,
e.g., Netflix and YouTube

Standard resolution
720p → 480p

Deliver

Consumers

Interactive services

Consumer

Resolution depends on *player setting*

e.g., zoom
video volume depends on player's display size

Consumer

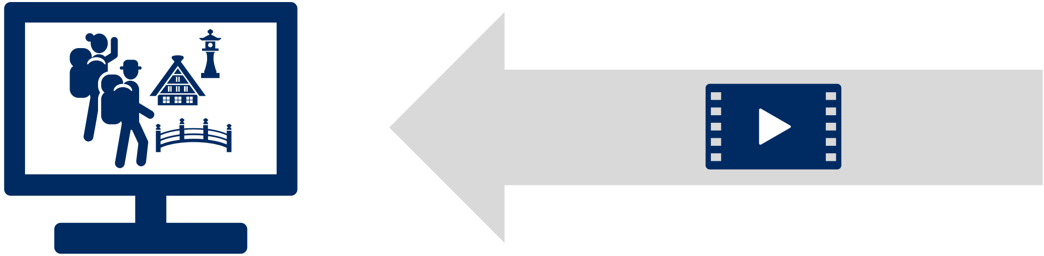
Who needs to know network state?

Service provided by OTT	Interactive services
OTT providers **need to know network states.**	***Consumers*** **need to know network states.**

Interactive video streaming services force network state estimation for control video traffic to consumers.

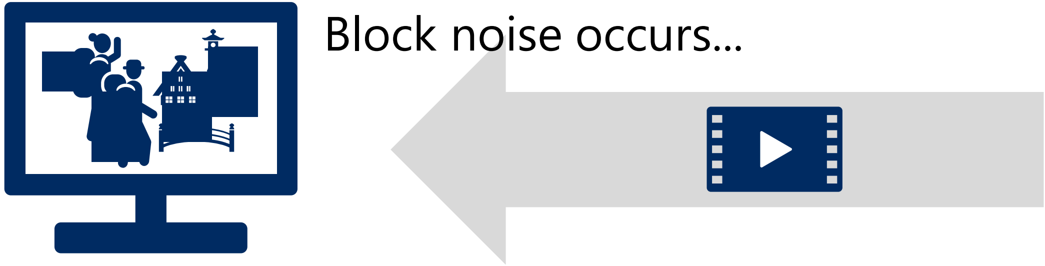
Relationship between network state & video images

Good network condition



Bad network condition

Block noise occurs…



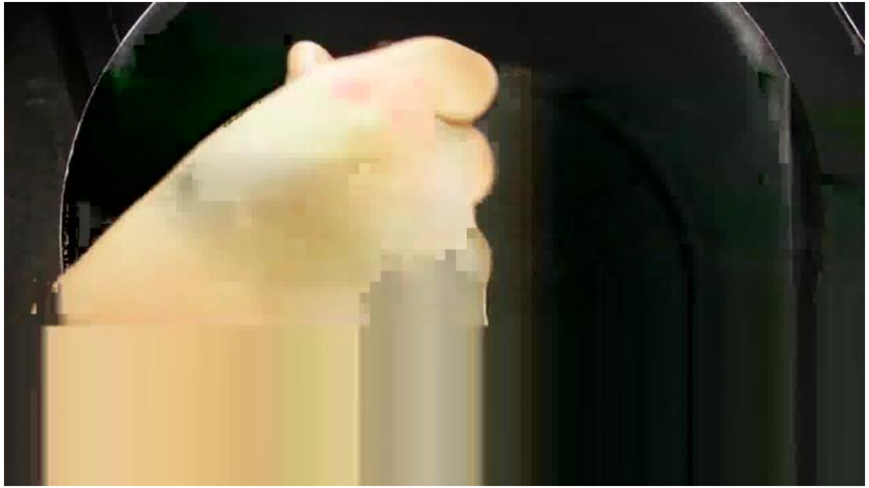
Streaming server

What happens in the network???

Example (Original vs Received)

Original video

Received video



Network state

Throughput: 1100kbps
Loss rate: 0.1%

Background

Conventional approach

KPI is important for evaluate their (researcher's) approaches.

e.g., bit rate

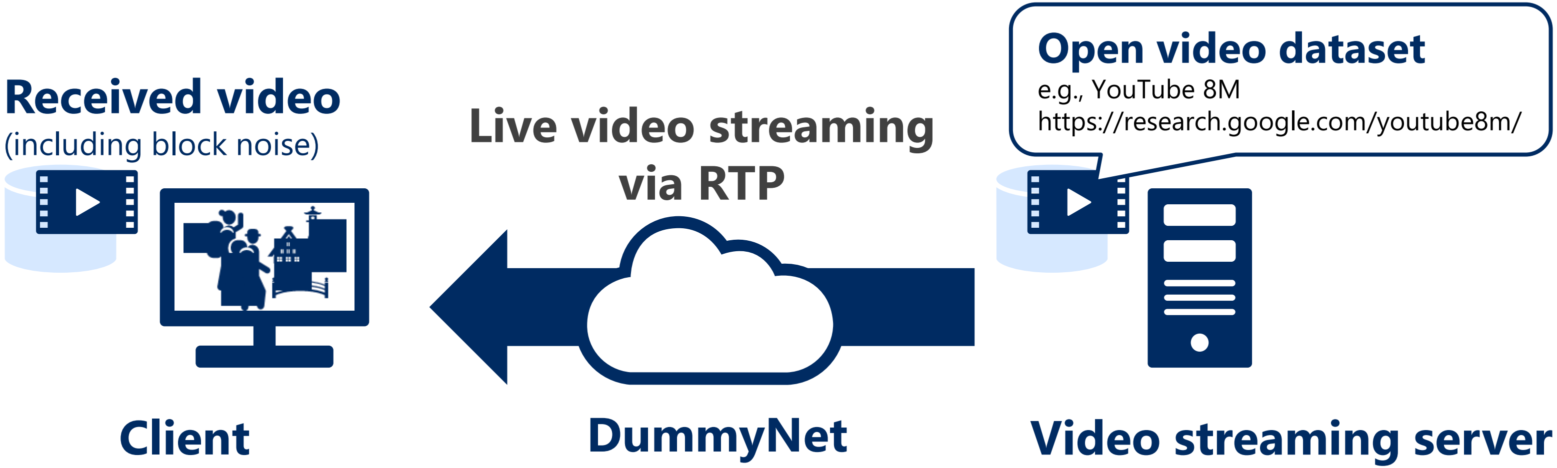
Practical case

Raw video image is important.

This challenge is the first step to understand relationship between raw video images and network state.

2. Challenge

Understanding network state from raw video



Provided dataset

Original video data (.mp4)
Received video data (.mp4)

Task for participants

Estimate network state, i.e., throughput/loss ratio.
Train their ML-based method by using given dataset.
Performance measure is MAE.

Training/test process

Training phase

Original video (.mp4)

Received videos (.mp4)

	Network condition
	1100kbps, 0.001% loss
	1200kbps, 0.001% loss
⋮	
	2000kbps, 0.001% loss

ML

Test phase

Original video (.mp4) **Received video (.mp4)**

↓ **Input** ↓

Trained ML

↓ **Output**

Network condition

1100kbps, 0.001% loss

3. Dataset

Dataset

Provided dataset

One original video data (.mp4)
Many received video data (.mp4)

Original video

original.mp4

Received video

videoid_1100kbps_001.mp4

videoid_1200kbps_001.mp4

⋮

Dummynet configuration

- Traffic rate: from 1100kbps to 2000kbps at 100kbps intervals
- Packet loss ratio: 0.001%, 0.01%, 0.025%, 0.05%, 0.1%

Dataset

You can download our dataset from RISING web site.

- https://www.ieice.org/~rising/AI-5G/dataset/theme2-NEC/dataset_and_issue.tar.gz

Dataset (dataset_and_issue.tar.gz, 24GB) includes following files.

- dataset
  - original: original videos for training
  - received: received videos named <video_id>_<bandwidth>_<loss ratio>.mp4 for training
- issue
  - original: original videos for network state estimation
  - received: received videos for network state estimation
- README.md

Performance measure

- **For each of throughput and loss ratio, MAE is calculated as performance measure. (n is the number of test videos)**

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\mathrm{Estimation} - \mathrm{Answer}|$$

** IMPORTANT ** - Submission

Participants need to submit only ***report***.

- Report includes the following items at least.
  1. Explanation of your method/approach
  2. Evaluation results (MAE, See “Evaluation criteria”) for provided data set
  3. Consideration
- Report format: A4 size, pdf, 4 pages at most.

All submissions will be evaluated in terms of

1. Performance measure (MAE)
2. Technical excellence

4. Information

Information

Detailed information

- https://www.ieice.org/~rising/AI-5G/
- *Updated problem statement is shown in the web page!!*

Contact by e-mail

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