Collaborative Learning on the Edges: A Case Study on Connected Vehicles

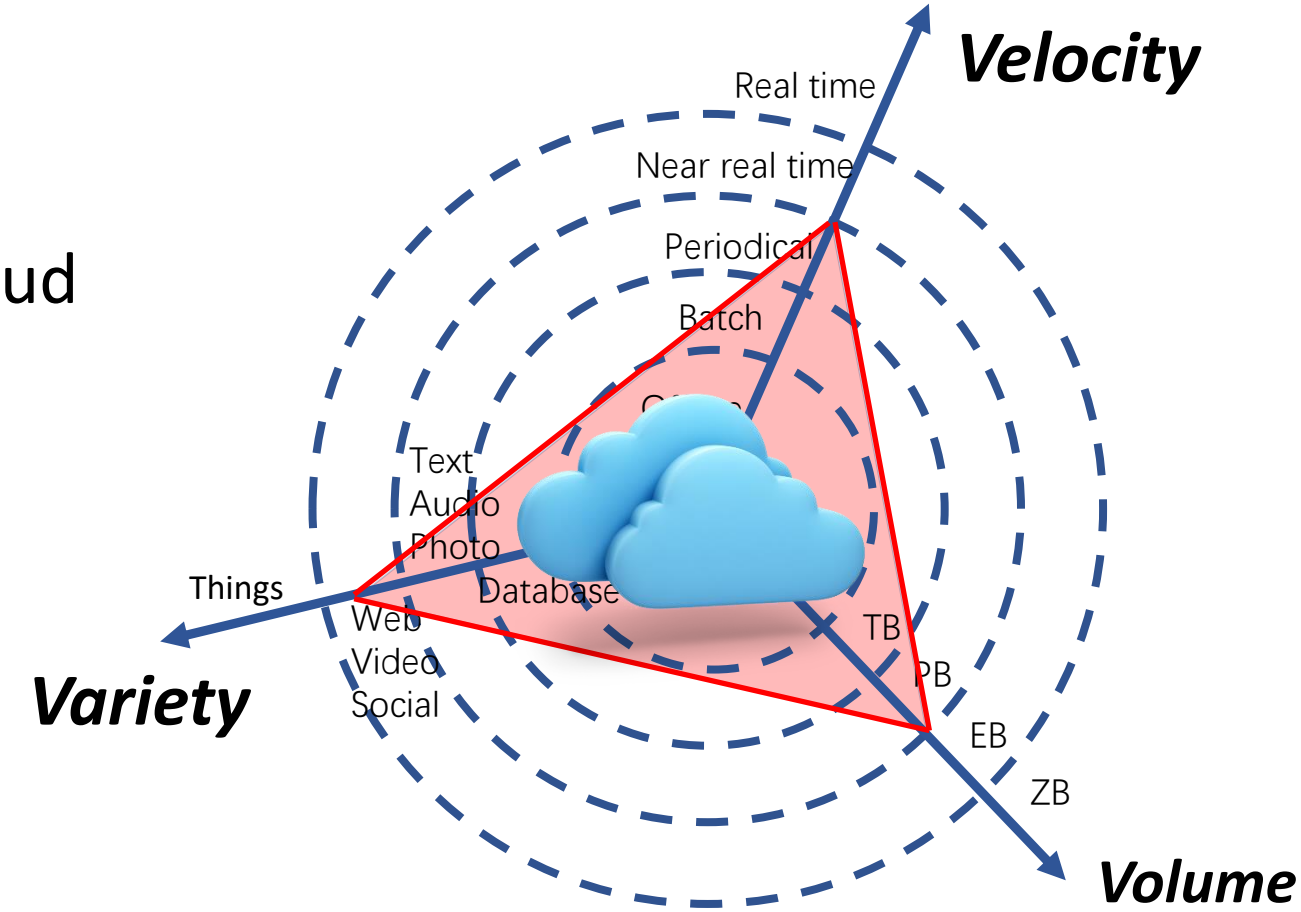
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http://thecarlab.org

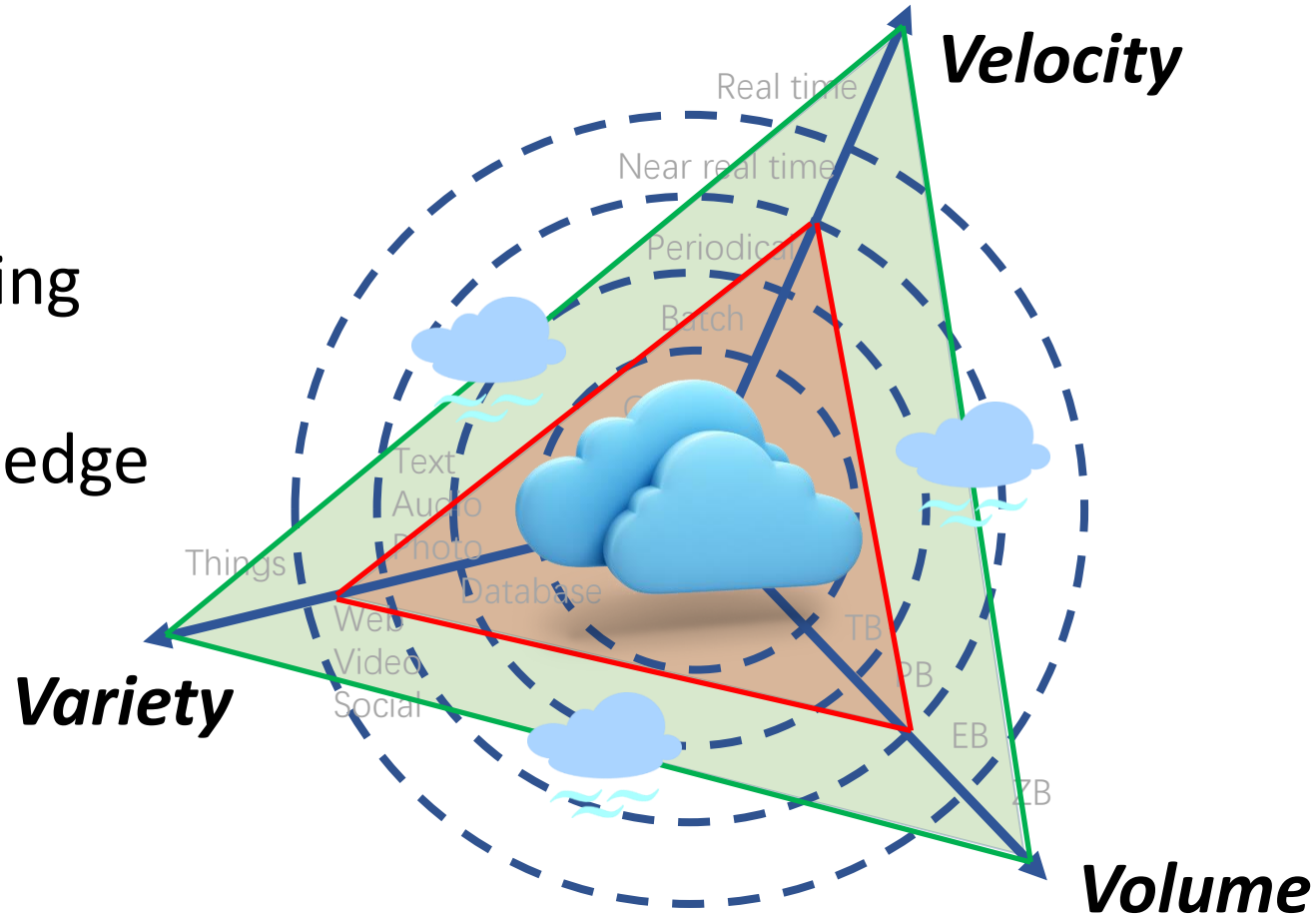
Big Data Processing 1.0 (05-15)

- Push the data to the cloud
- Cloud computing



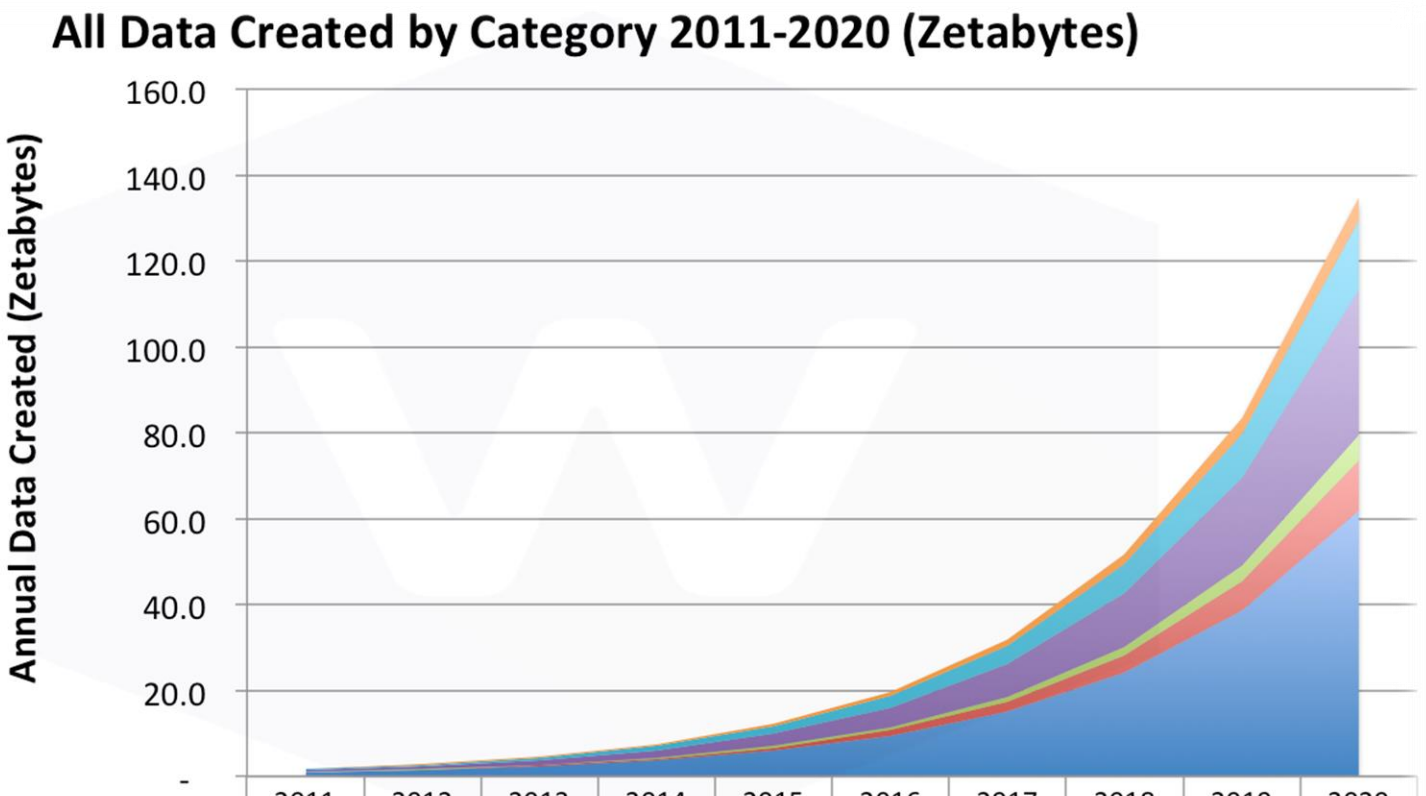
Big Data Processing 2.0 (15-25)

- Enabled by Edge Computing
- Push computation to the edge



Challenges of Edge Computing

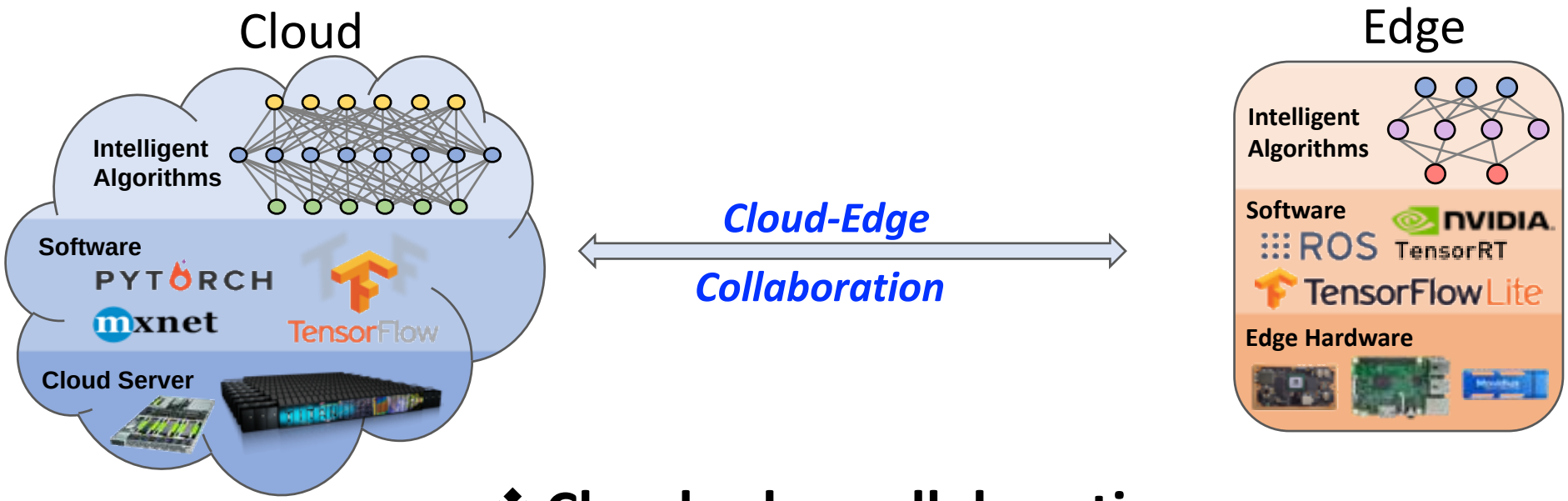
- **Autonomous vehicle**
  - 1 GB data per second
  - 11 TB data per day
- **Challenges**
  - Computation resources
  - Memory resources
  - Stringent latency



	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Consumer Images, Voice & Video	0.1	0.2	0.3	0.4	0.6	1.0	1.5	2.3	3.5	5.4
Entertainment & Social Media	0.3	0.5	0.7	1.1	1.7	2.7	4.3	6.7	10.4	16.2
Data Processing	0.4	0.6	1.0	1.7	2.8	4.6	7.6	12.5	20.5	33.7
Medical	0.0	0.1	0.1	0.2	0.4	0.7	1.2	2.0	3.5	6.1
Internet of Things	0.1	0.2	0.3	0.5	0.8	1.4	2.3	4.0	6.8	11.5
Surveilance	0.9	1.4	2.3	3.7	5.9	9.5	15.1	24.2	38.8	62.0

Source: Wikibon 2015, based on Wikibon 2013 projections

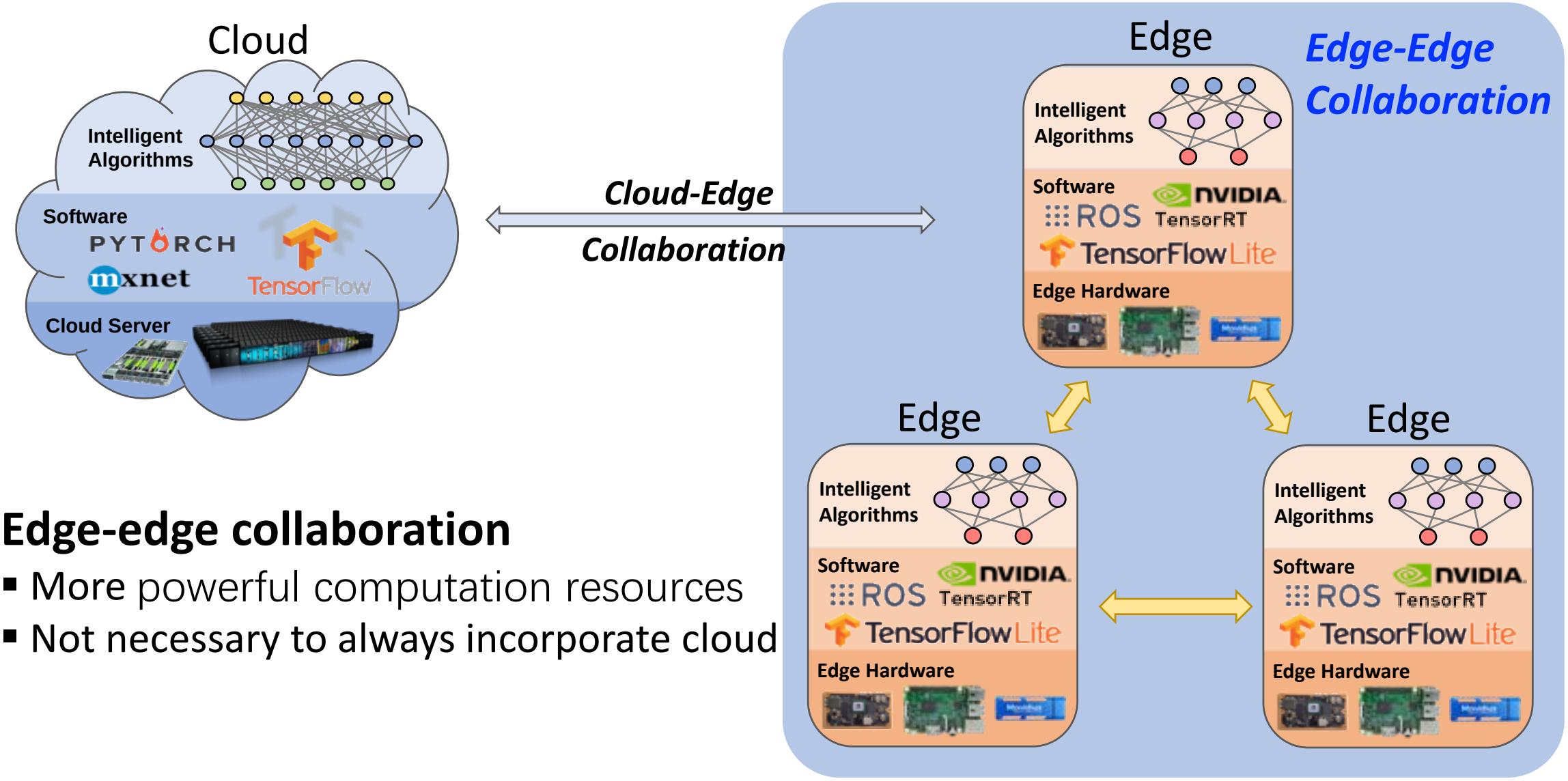
Cloud-edge Collaboration



❖ Cloud-edge collaboration

- Requires sending amounts of data to the cloud
- Data transferring:
  - ✓ Latency bottleneck
  - ✓ High bandwidth cost
  - ✓ Privacy leakage

Edge-edge Collaboration



- **Edge-edge collaboration**
  - More powerful computation resources
  - Not necessary to always incorporate cloud

CLONE: Collaborative Learning on the Edges



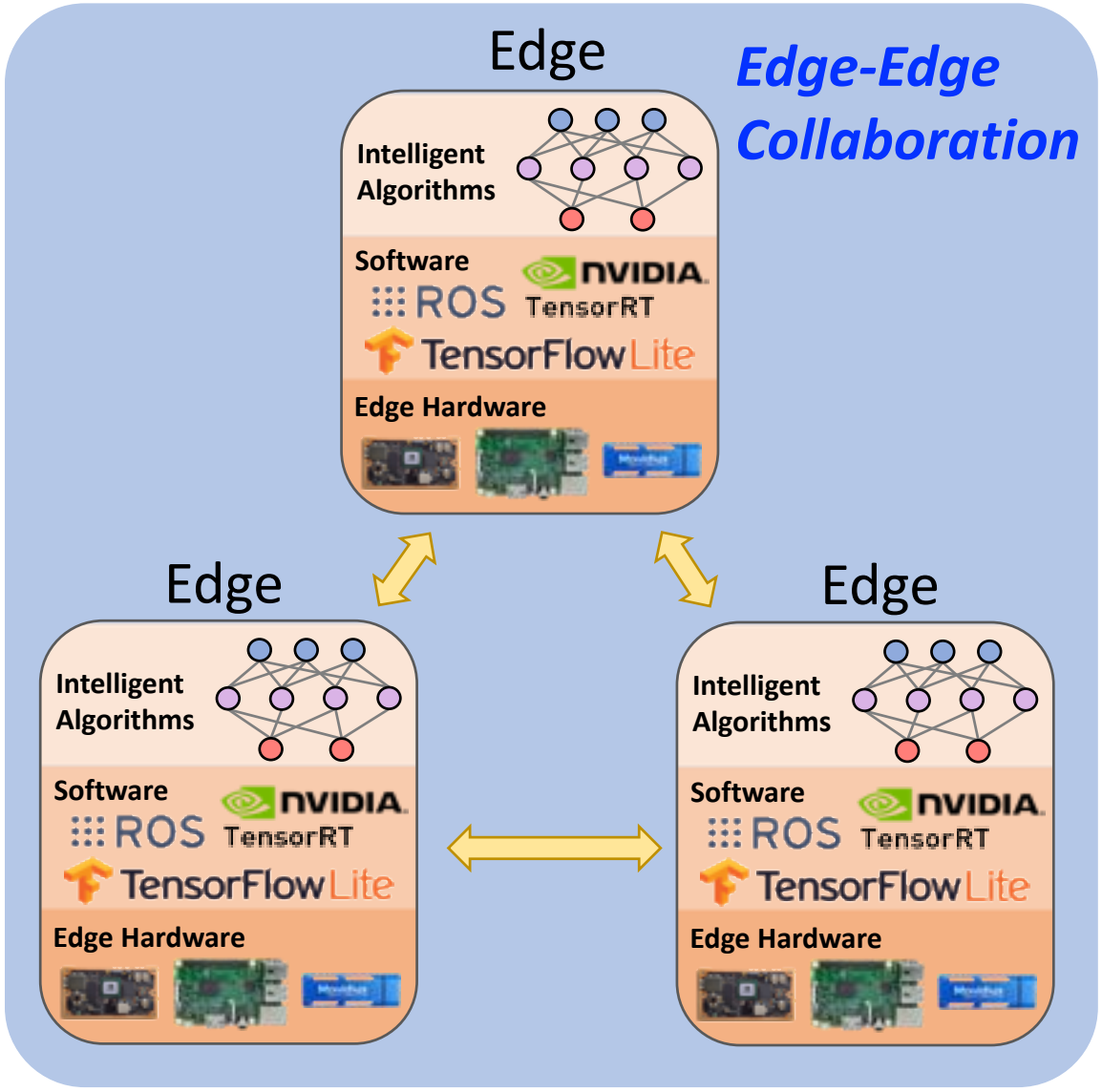
Latency Reduction



Privacy-Preserving



User Personalization



Key Contributions

- **CLONE**: a collaborative learning framework on the edges
- Demonstrate the **applicability** of CLONE in the *battery failure prediction of electric vehicles (EVs)*
- Experiment results:
  - **Reduce training time** significantly without sacrificing **algorithm performance**
  - Adding **driver behavior metrics** could improve the prediction accuracy

EV Battery Failure Prediction

❖ Early failure detection for **EV battery and associated accessories** is essential

- **Popular transportation system**
  -- Tesla reaches milestone of 100,000 Model 3 EVs
  -- Nissan Leaf surpass 400,000 sales of EVs
  -- Chevy Bolt produce 499,000 EVs
  -- Many bus and shuttles are EVs



- **Battery costs 1/3 of an EV**

- **Largely determines the safety and durability of EVs**

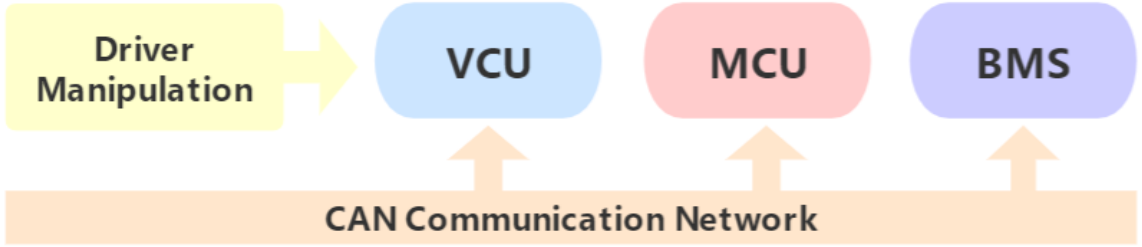
Data Description

- **Dataset**
  - Three different models of EVs
  - Reported every 10 milliseconds
  - 6-hour collection period





- **Three core control systems**
  - Vehicle control unit (VCU)
  - Motor control unit (MCU)
  - Battery management system (BMS)



Selected Attributes

Voltage	Temperature	Power & Energy
BMS_BattVolt	InCar_Temp	BMS_BattSOC
BMS_CellVoltMax	Environment_Temp	BMS_MaxChgPwrCont
BMS_CellVoltMax_Num	BMS_BattTempAvg	BMS_MaxChgPwrPeak
BMS_CellVoltMin	BMS_Inlet_WaterTemp	BMS_MaxDchgPwrCont
BMS_CellVoltMin_Num	BMS_Outlet_WaterTemp	BMS_MaxDchgPwrPeak
MCUF_Volt	BMS_MaxTemp	VCU_Batt_Comp_Pwr
MCUR_Volt	BMS_MinTemp	VCU_Batt_PTC_Pwr
Current	BMS_TempMaxNum	**Error Info**
BMS_BattCurr	BMS_TempMinNum	BMS_BatterySysFaultLevel
MCUF_Curr	MCUF_Temp	BMS_Low_SOC
MCUR_Curr	MCUR_Temp	VCU_PTC_ErrSta

Driver Behavior	VehicleSpeed	Acceleration	Steering
	YawRate	WheelSpeedFL	WheelSpeedFR
	WheelSpeedRL	WheelSpeedRR	Emergency_Stop
	AccPedalPosition	BrakePedalPosition	

❖ **EIC attributes**

-- electric, instrumentation, and computer control system

- Voltage
- Current
- Temperature
- Power and Energy
- Error Information

❖ **Driver behavior metrics**

Stand-alone Learning



Intel fog reference design (Intel FRD)

	EIC Attributes	Driver Behavior Metrics
ED Group	31 attributes	11 metrics
E Group	31 attributes	NONE

		Precision	Recall	Accuracy	F-measure
ED Group	**RF**	0.7492	0.7814	0.7833	0.7469
	GBDT	0.7905	0.8500	0.8234	0.8192
	LSTM	0.9420	0.9500	0.9430	**0.9460**
	Average	0.8272	0.8605	0.8499	**0.8434**
E Group	**RF**	0.6615	0.6900	0.7008	0.6755
	GBDT	0.6975	0.7500	0.7294	0.7228
	LSTM	0.8924	0.9000	0.8738	0.8962
	Average	0.7505	0.7800	0.7680	**0.7648**

❖ Goal

- Suitable algorithm to predict failures
- Influence of the driver behavior metrics on EV failure prediction

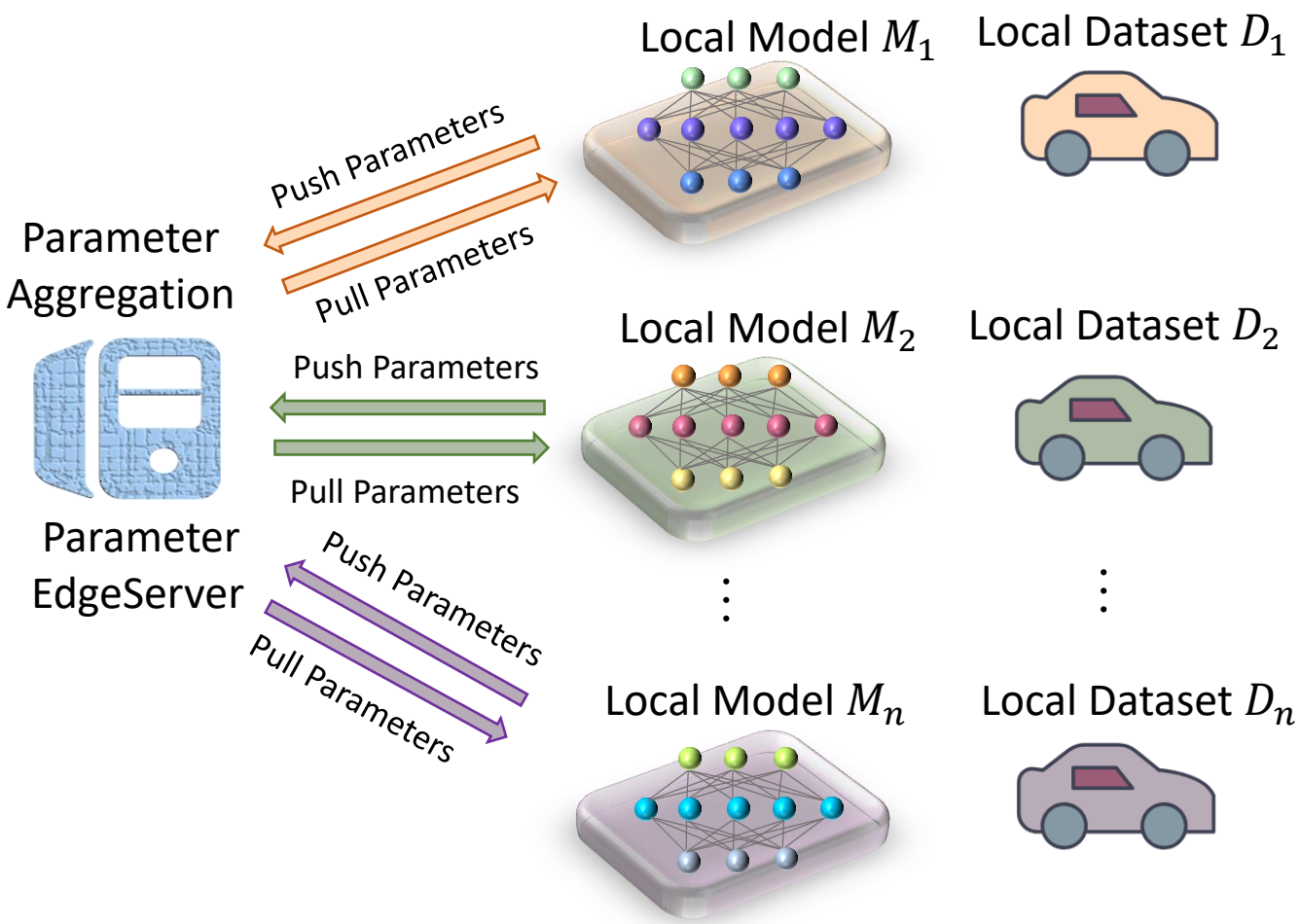
❖ Three methods

- Random Forest (RF)
- Gradient boosted decision tree (GBDT)
- Long short-term memory networks (LSTMs)

❖ Observations

- Excluding driver behavior metrics results in around 8% reduction in the average F-measure
- LSTMs outperform RF and GBDT in both two groups

The CLONE Framework



❖ **LSTMs-based collaborative learning approaches on edges**

-- EIC attributes + driver behavior metrics

❖ **Model Description**

- **Privacy Preserving**
  -- raw data is always kept in the device
- **Latency / Bandwidth Reduction**
  -- upload parameters instead of dataset
- **Driver Personalization**
  -- update local model by the private data

Aggregation Protocol

❖ **Loss Function**

$$Loss = \sum_i \left[\hat{y}_{(i)} * log(y_{(i)}) + (1 - \hat{y}_{(i)}) * log(1 - y_{(i)})\right]$$

Predicted output Desired output

❖ **Aggregation Protocol**

$$\begin{cases} P(p) \leftarrow \frac{Loss(v)}{Loss(p)+Loss(v)} P(p) + \frac{Loss(p)}{Loss(p)+Loss(v)} P(v) \\ Loss(p) \leftarrow Loss(v) \end{cases}$$

P: the value of a parameter

$Loss$: the value of the loss function

p: Parameter EdgeServer

v : a specific vehicle

- **More accurate results** (lower value of loss function):

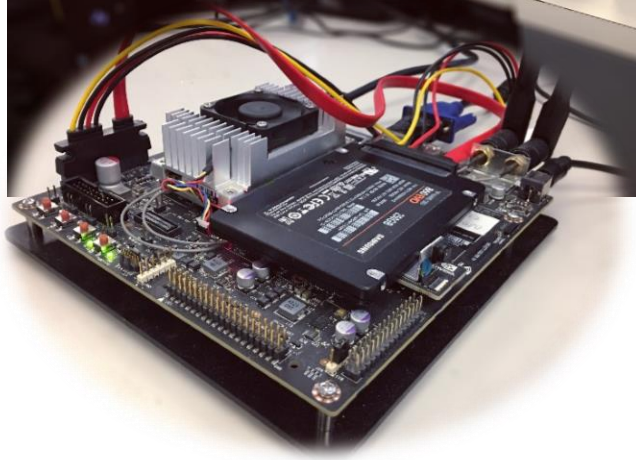
-- Assign a **higher weight**

-- **Minimized required training time** to reach a certain accuracy level

Experiments Setup



Intel FRD



Jetson TX2

- **Heterogeneous hardware cluster**
  - Parameter EdgeServer: Intel FRD
  - Edge nodes:
    -- One Jetson TX2
    -- Two Intel FRD

	Intel FRD	Jetson TX2
CPU	Intel Xeon E3-1275 v5	ARMv8 + NVIDIA GPU
Frequency	3.6 GHz	2 GHz
Cores	4	6
Memory	32 GB	8 GB
OS	Linux 4.13.0-32-generic	Linux 4.4.38-tegra

Evaluation

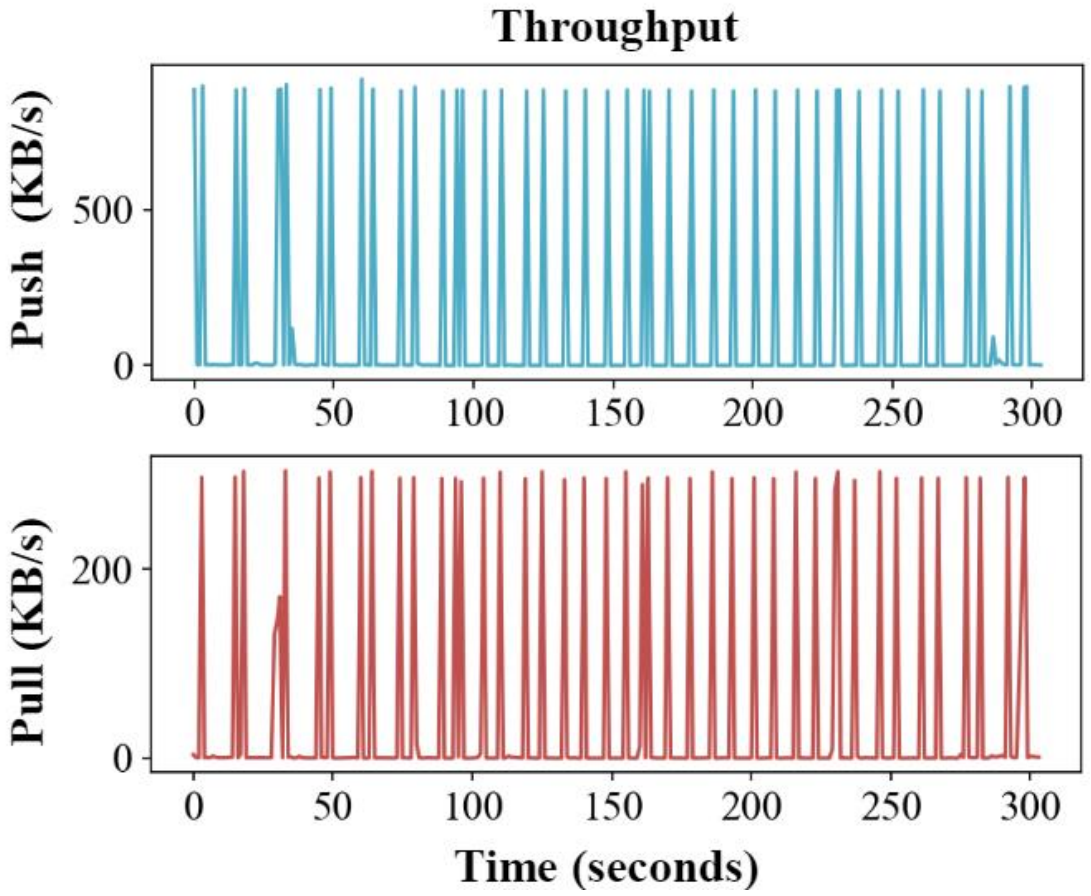
❖ Model Parameters

- 297,700 parameters

❖ Throughput

- the maximum throughput for push and pull process is around 750 KB/s and 250 KB/s

Layers	Variable	Shape
First layer (lstm_1)	lstm_1/kernel	(16, 400)
	lstm_1/recurrent_kernel	(100, 400)
	lstm_1/bias	(400,1)
Second layer (lstm_2)	lstm_2/kernel	(100, 400)
	lstm_2/recurrent_kernel	(100, 400)
	lstm_2/bias	(400,1)
Third layer (dense_1)	dense_1/kernel	(100, 24)
	dense_1/bias	(24,)

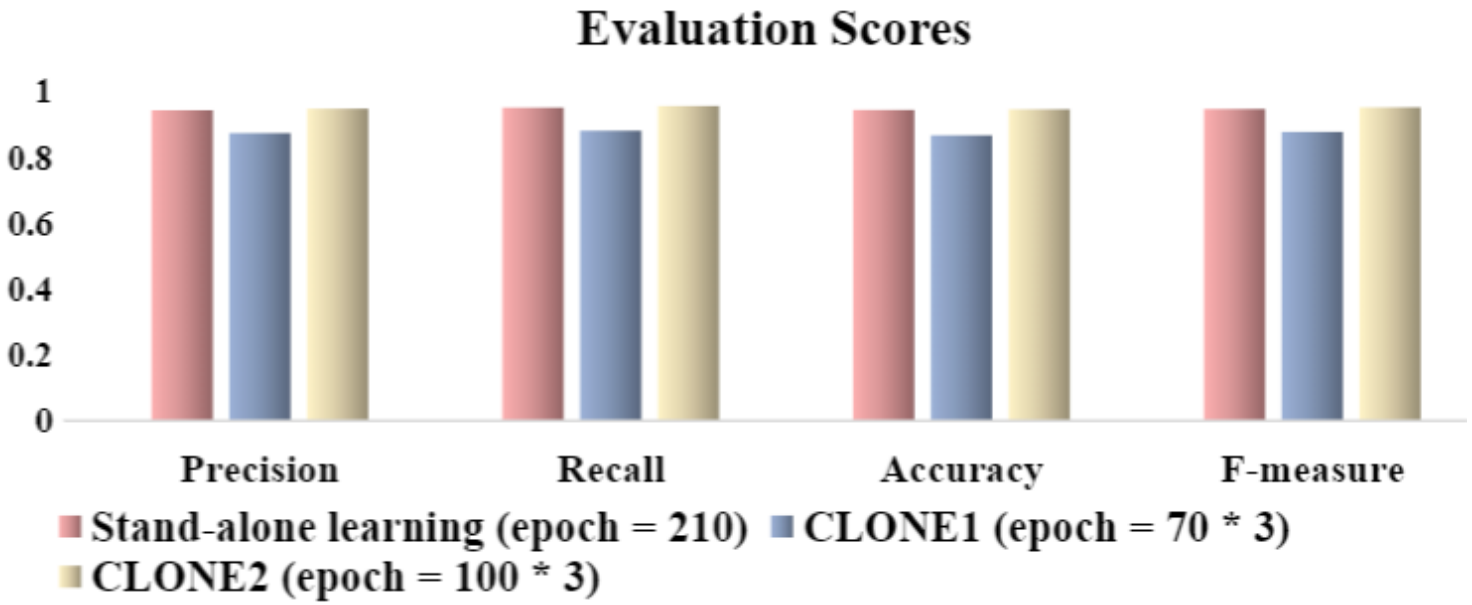


CLONE *vs.* Stand-alone learning

❖ Training Time Comparison (seconds)

	Intel FRD1	Intel FRD2	Jetson TX2
Stand-alone learning (epoch = 210)	1183	1573	1497
CLONE1 (epoch = 70× 3)	657	734	765
CLONE2 (epoch = 100× 3)	928	1036	1158

❖ Evaluation Score Comparison



❖ CLONE2 *vs.* Stand-alone learning

- Higher evaluation scores
- Less training time

❖ CLONE

- Reduce model training time significantly
- Achieve equal or even higher accuracy

Conclusion

- **CLONE**: a collaborative learning framework on the edges
  - Latency reduction
  - Privacy-preserving
  - User personalization

- Demonstrate the **applicability** of CLONE in the battery failure prediction of electric vehicles (EVs)

Discussion Topics

❖ **Expected feedbacks**

Possible use cases

❖ **Controversial points**

Global prediction accuracy may be influenced by the weak edge nodes

❖ **Open issues**

- The most suitable aggregation protocol
- Limitation of the bandwidth

❖ **Circumstances the whole idea might fall apart**

No network: each edge node will build the model alone

Thank You

Q & A

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