MACHINE LEARNING FOR THE CONNECTED CAR

DIETER MAY
DR. ALVIN CHIN, AI AND EMERGING TECHNOLOGY RESEARCHER
BMW GROUP TECH OFFICE USA

IEEE COMSOC OREGON CHAPTER MEETING, FEB. 25, 2021

BMW GROUP

THE NEXT 100 YEARS

Rolls-Royce
Motor Cars Limited

WHY DO WE NEED MACHINE LEARNING FOR CONNECTED VEHICLES?

CONNECTED VEHICLES BRING DIGITALIZATION INTO THE VEHICLE

CLOUD

INFORMATION

BIG DATA & PREDICTIVE ANALYTICS

INTELLIGENCE

PERSONAL SMART DEVICES

ACCESS

THE INTERNET OF THINGS

INTEGRATION

WHY WE NEED MACHINE LEARNING IN THE VEHICLE?

- Improve traffic and road safety
- Autonomous driving
- Integrate with the smart city

- Journey management
- Predictive vehicle maintenance
- Personal preferences

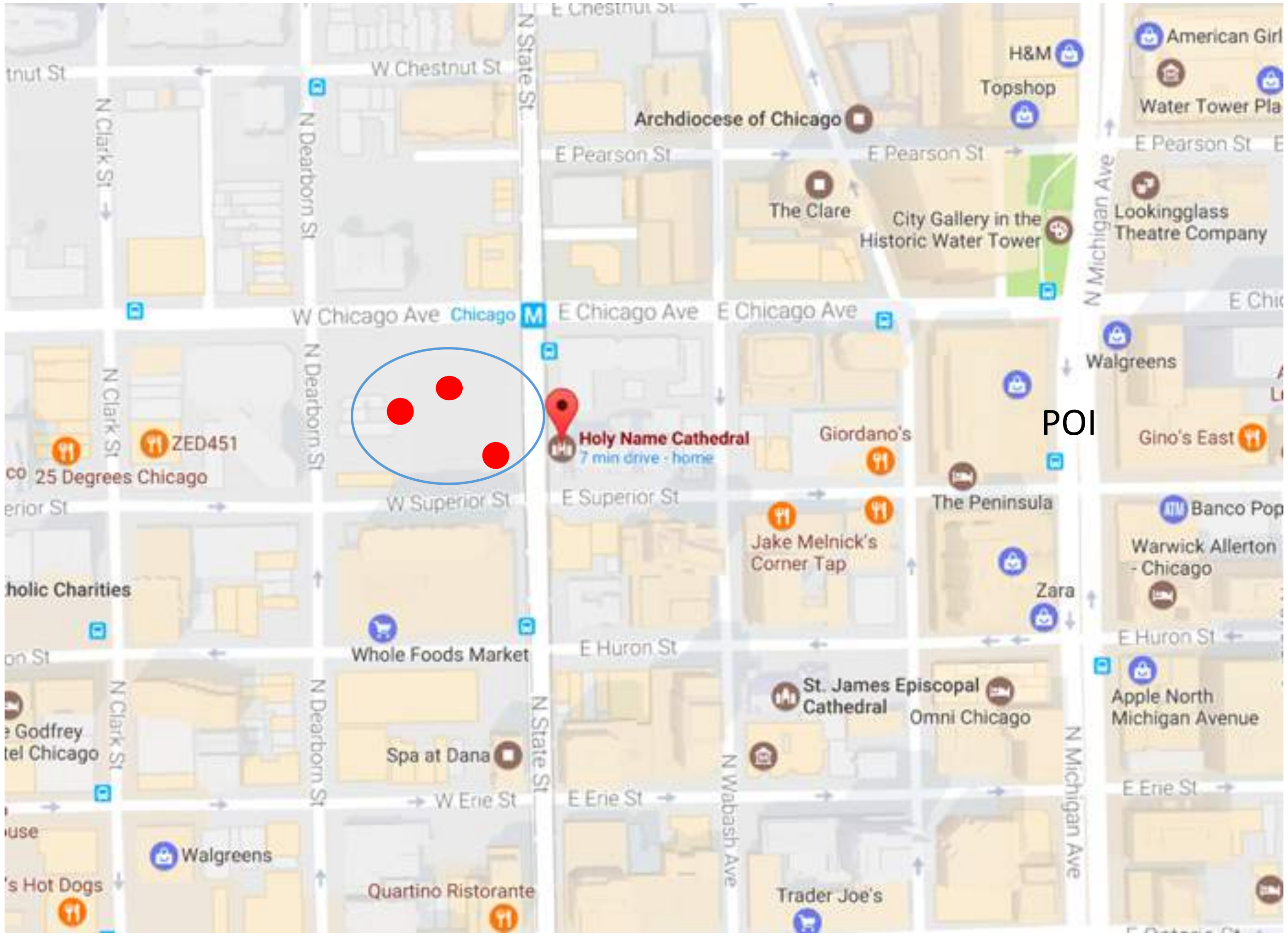
JOURNEY MANAGEMENT

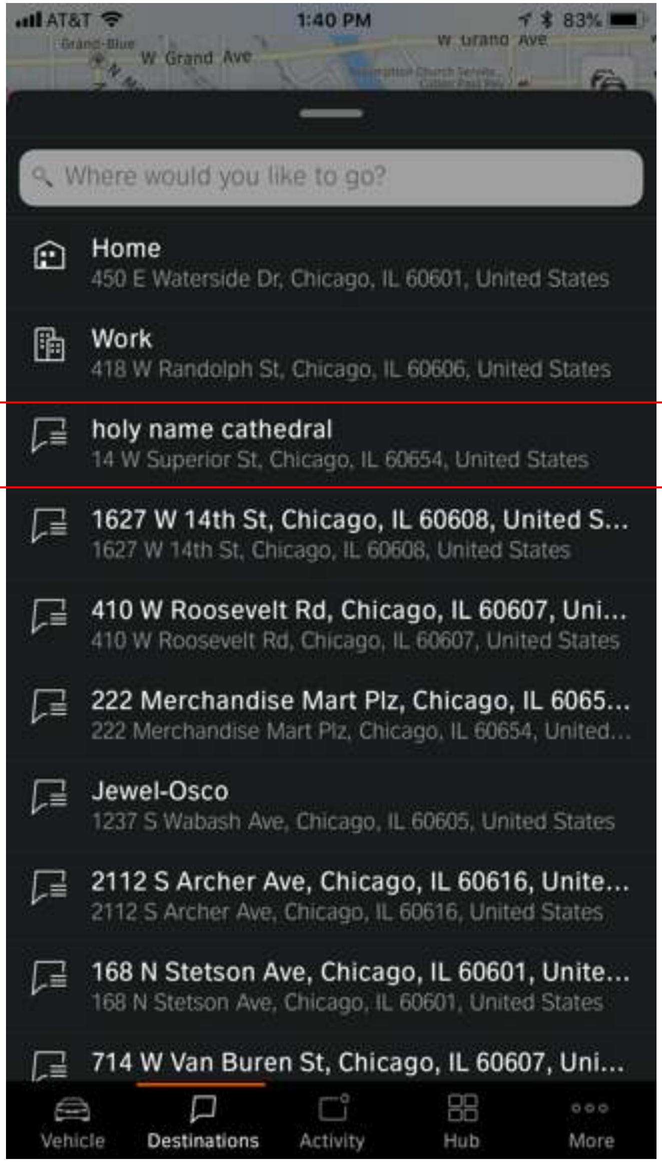
IMPROVING USER AND CAR EXPERIENCE TO MEET CUSTOMERS' INDIVIDUAL MOBILITY NEEDS

BMW CONNECTED – LAUNCHED 2016


GARAGE
ALL
GOOD
Updated from vehicle just now
Combined Range
435 km
MY BMW APP.
CONNECTS YOUR VEHICLE TO YOUR LIFE.

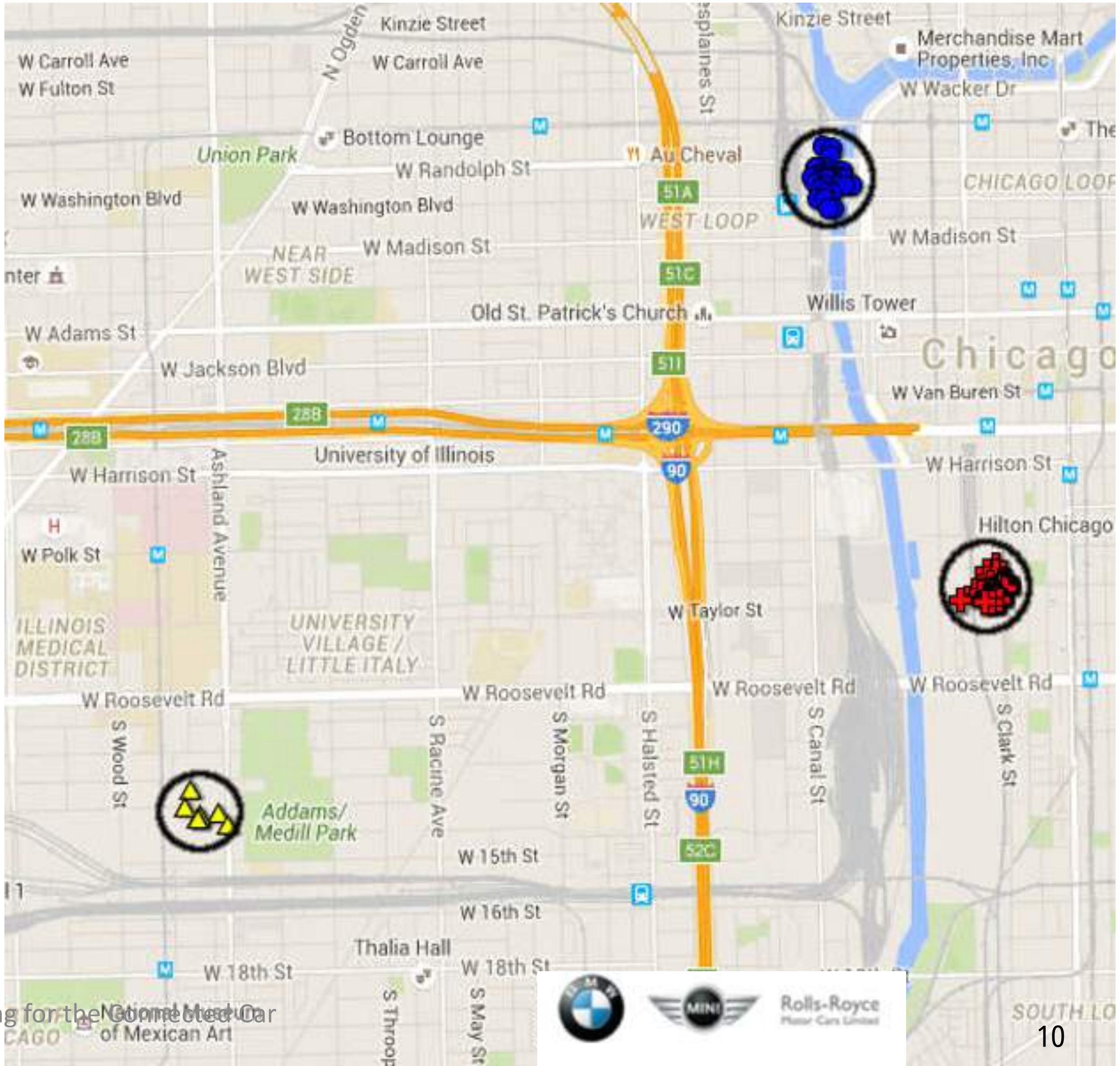
HOW DO WE LEARN A DESTINATION?



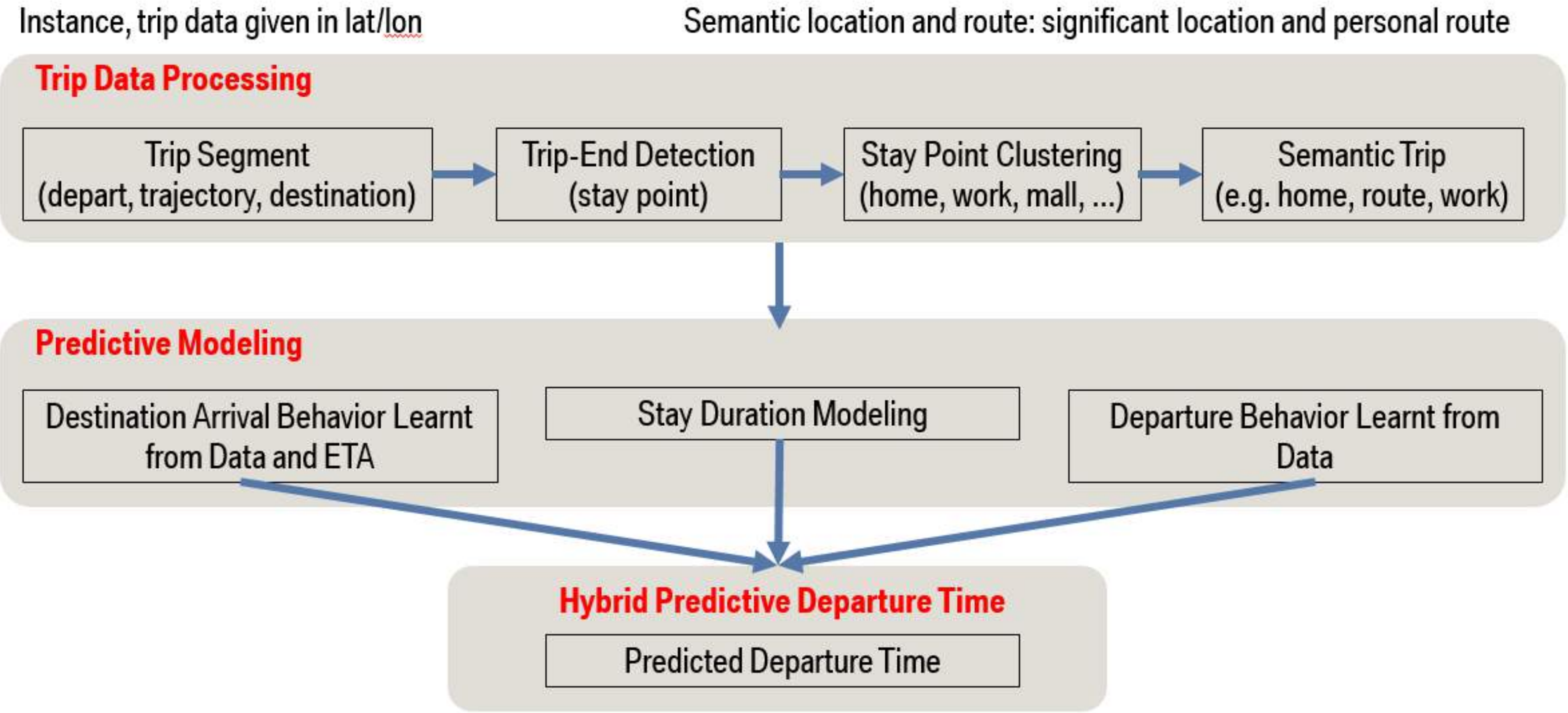


ALGORITHM FOR LEARNED DESTINATIONS

- Process trip data to be completed
- Identify stay points for each trip
- Spatial data clustering of stay points using hierarchical clustering
- Post processing
- Home and work recognition



PREDICTED TRIPS



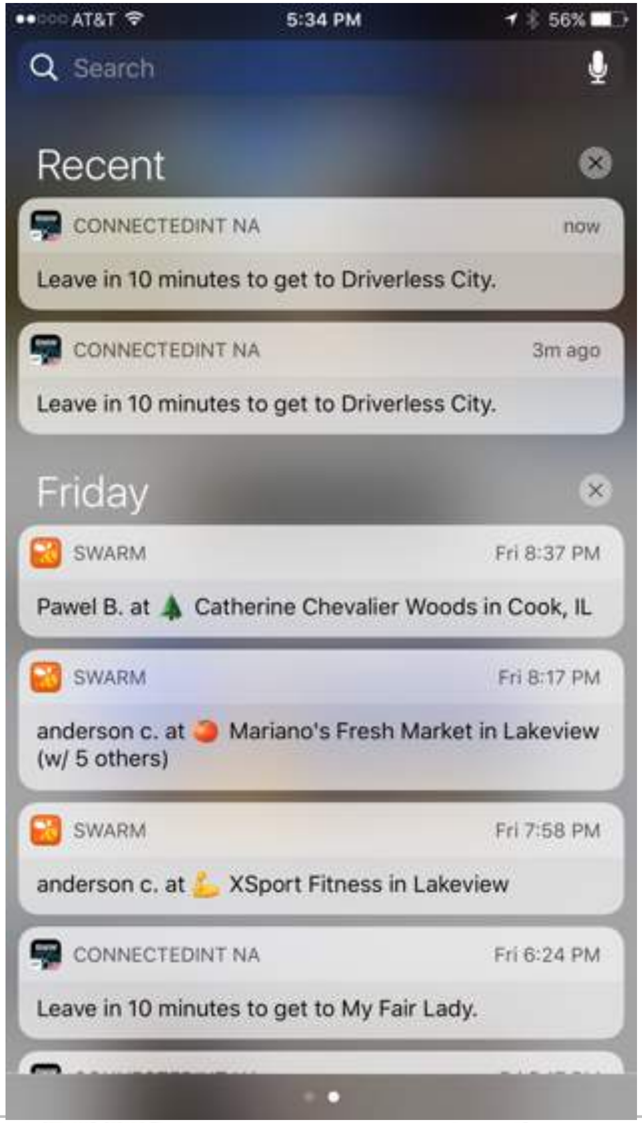
- Must be frequent trip
- Context
  - Last SP, weekday, hour, morning, weekend/workday, morning/noon/afternoon/evening/night
- Method: Contextual association rule mining

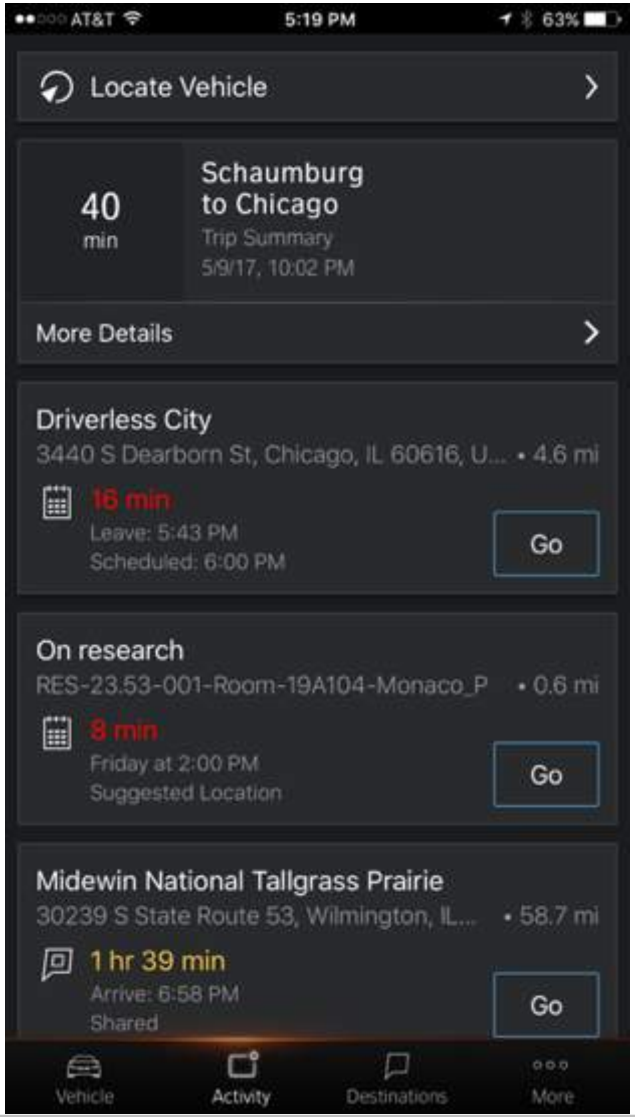
- Contextual association rule mining finds the frequent co-occurring associations among a collection of items in certain context. It is the extension of traditional association rule mining.

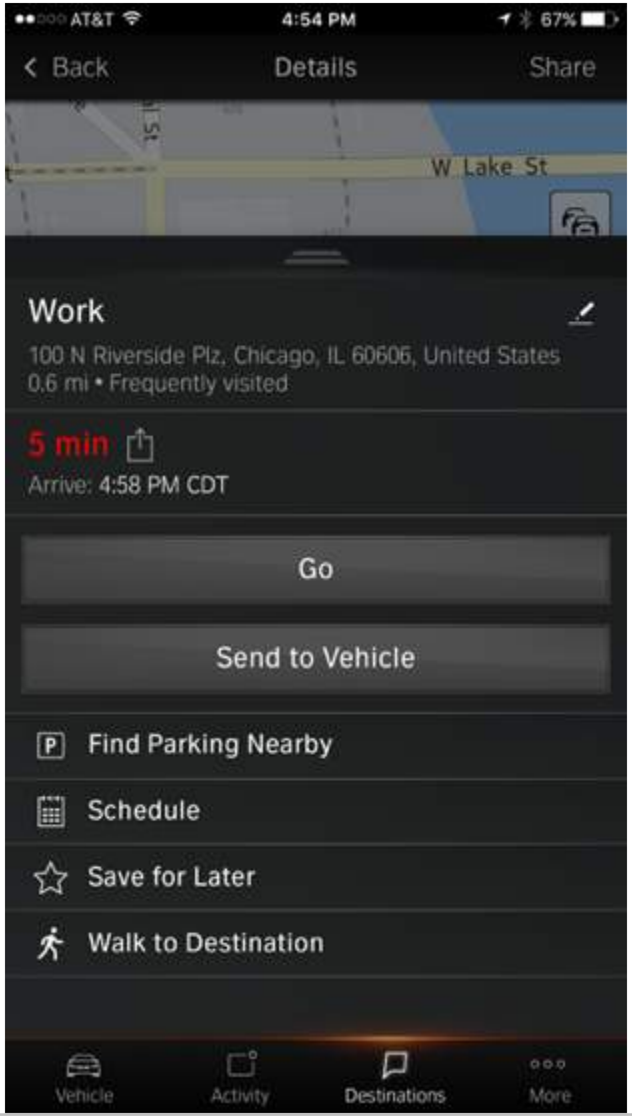
- Example Mined Contextual Rules:

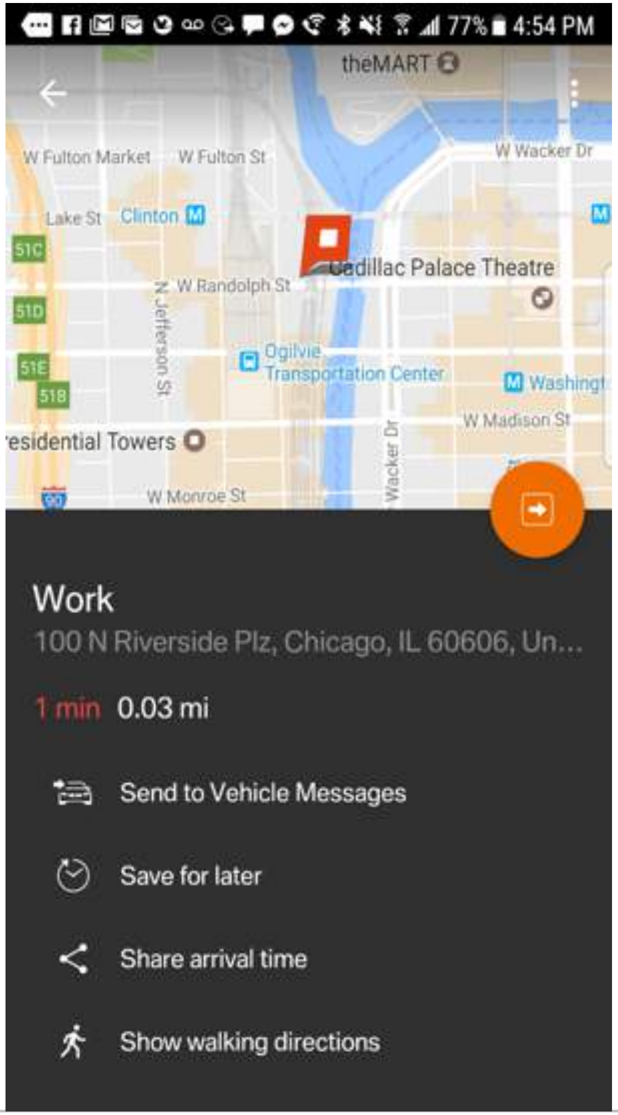
- {(Is Monday: Yes), (time range: AM6:30-7:00)} Home ⇒ Railway station.

LEARN YOUR FREQUENT AND PREDICTED TRIPS AND PLAN TRIP

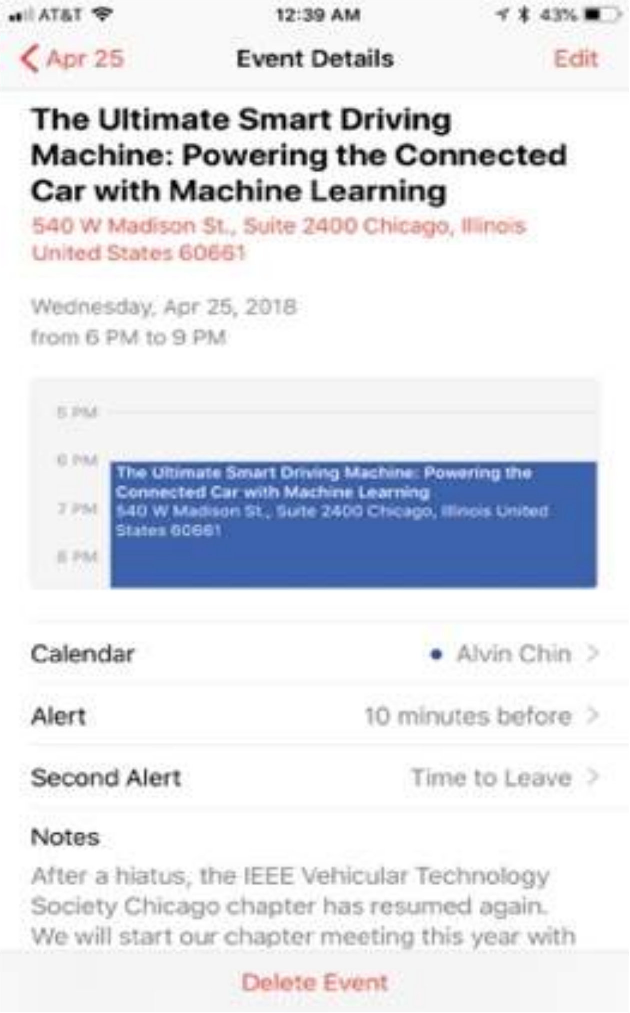


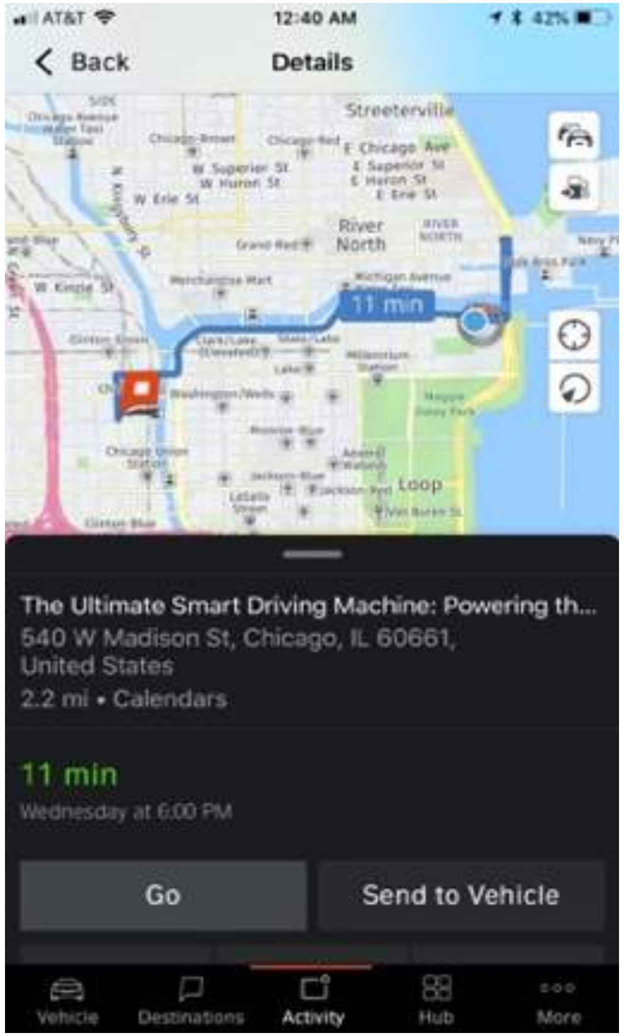


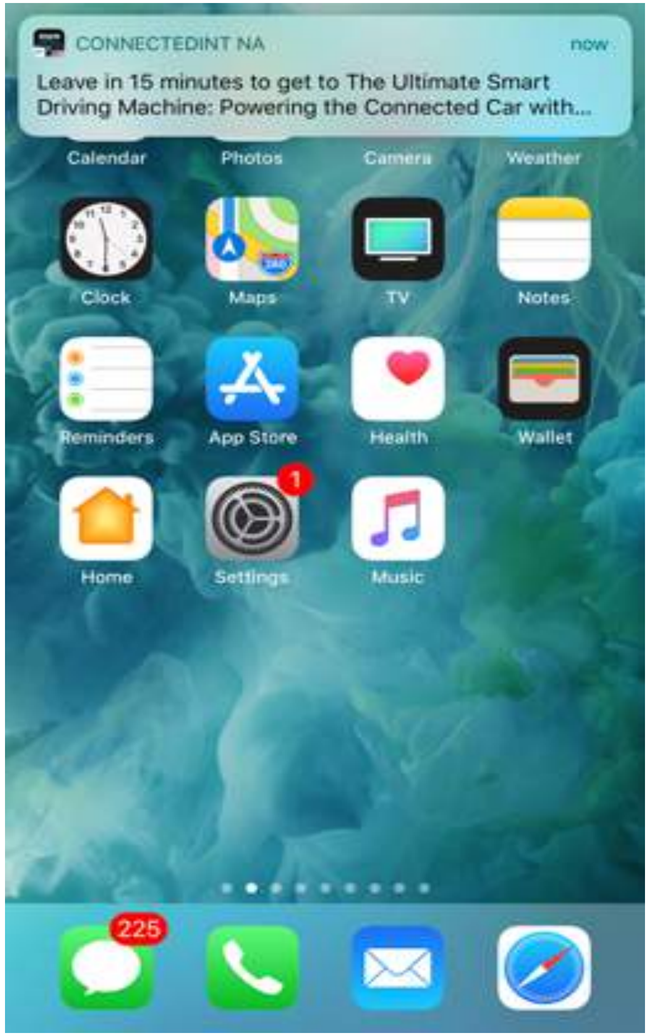




SCHEDULED MEETING AS NEXT TRIP

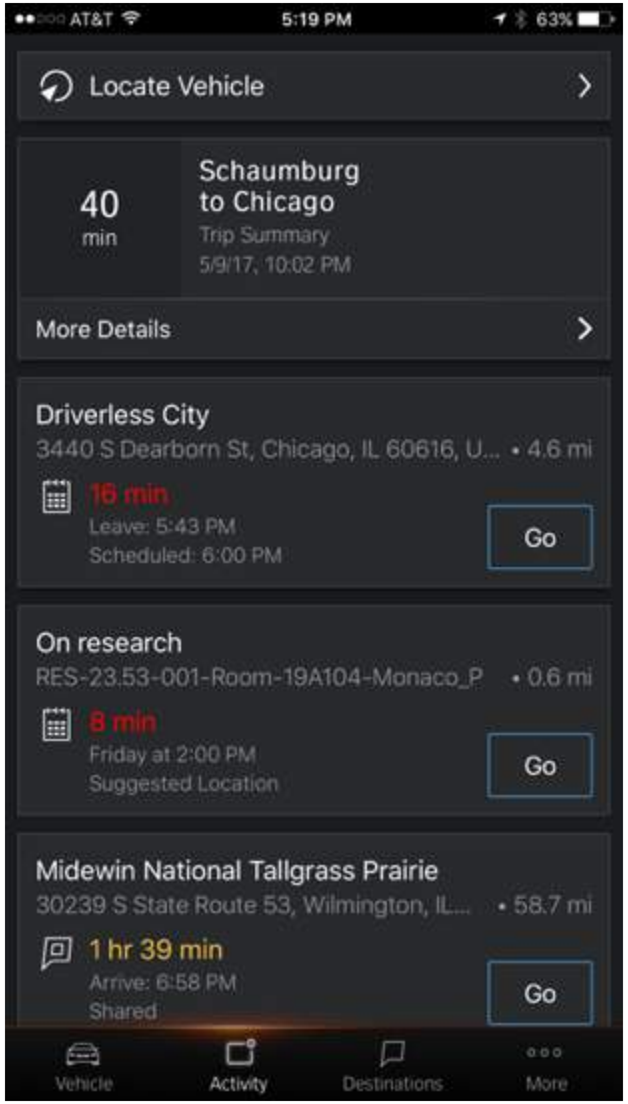


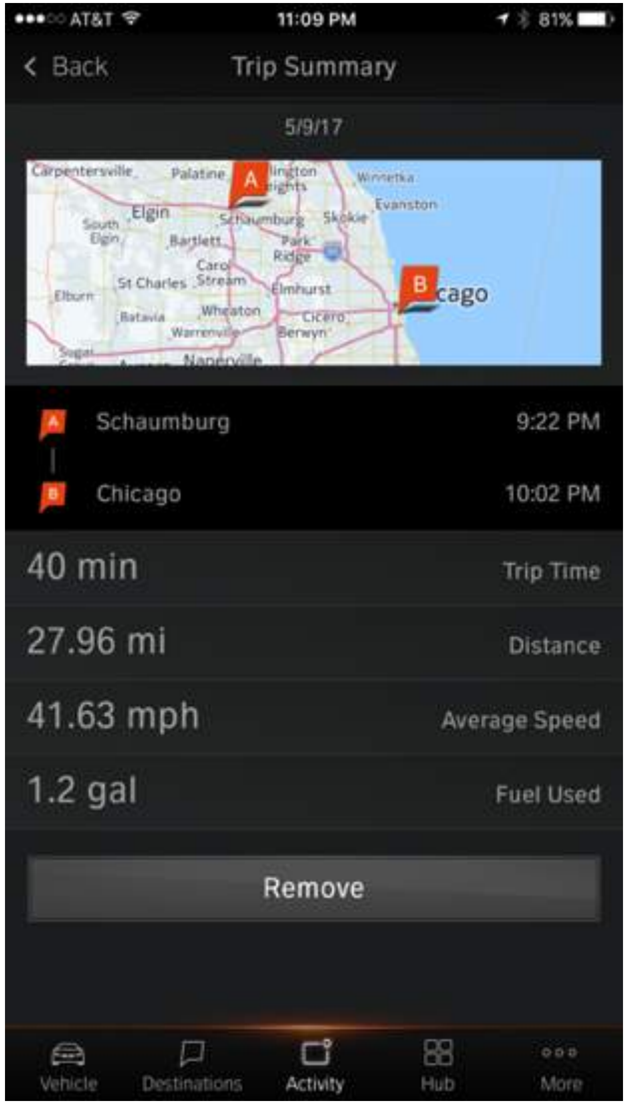




NEXT TRIP SENT TO VEHICLE AUTOMATICALLY SO READY TO GO!

LEARN YOUR FUEL CONSUMPTION AFTER A TRIP





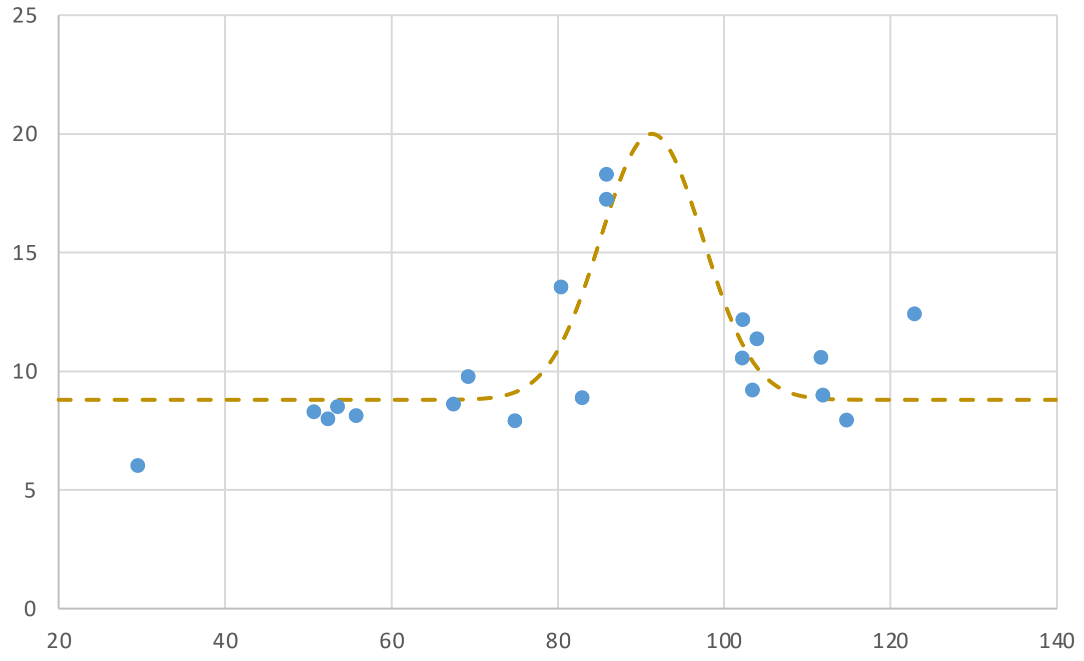
FUEL CONSUMPTION ALGORITHM FOR TRIP SUMMARY

- X-axis: travel speed TS (km/h);
- Y-axis: fuel consumption rate FCR (km/L);
- TS-FCR can be fitted by Gaussian function;
- Travel speed of a trip has impacts on fuel consumption

Eco speed

$$FCR = 8.8 + 11.2 \times e^{-\frac{(TS-91.3)^2}{6.2^2}}$$

Base rate



PREDICTIVE VEHICLE MAINTENANCE

A CLOUD IOT EDGE FRAMEWORK FOR EFFICIENT DATA-DRIVEN AUTOMOTIVE DIAGNOSTICS

DIETER MAY

ALVIN CHIN[1], PETER WP WOLF[2] AND JILEI TIAN[1]

[1]BMW TECHNOLOGY CORPORATION (CHICAGO), [2]BMW GROUP (MUNICH)

09/23/2019

Alvin Chin

BMW GROUP

VTC2019-Fall HONOLULU
Intelligent Connection & Transportation

Rolls-Royce Motor Cars Limited

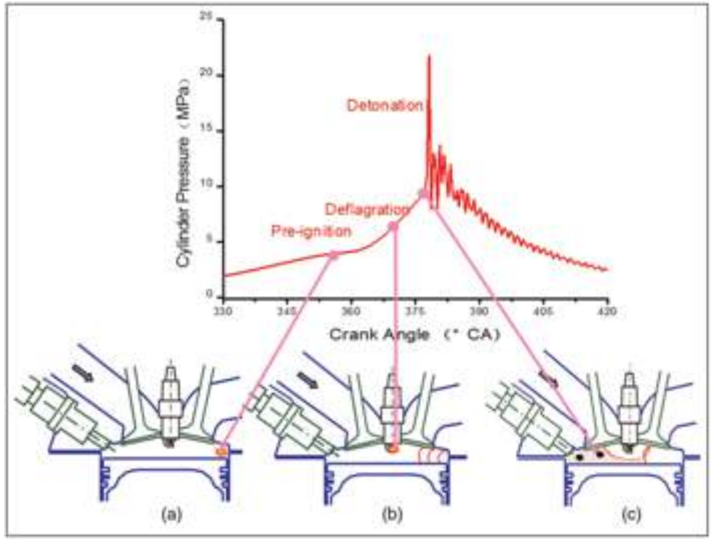
BACKGROUND: DETECTING EARLY FAULTS BEFORE BECOMING FAILURES

- Rule-based and model-based approaches do not work with increasing vehicle complexity and rich data
- Can perform data-driven automotive diagnostics with machine learning and deep learning BUT done off-board and not automated
- Example: Detecting pre-ignitions before causing serious material damage to the engine of a car

PRE-IGNITION

Pre-ignition: A pre-ignition is a combustion of the fuel-air mixture in a cylinder which is not triggered by a spark but by a hot-spot prior to the spark timing.

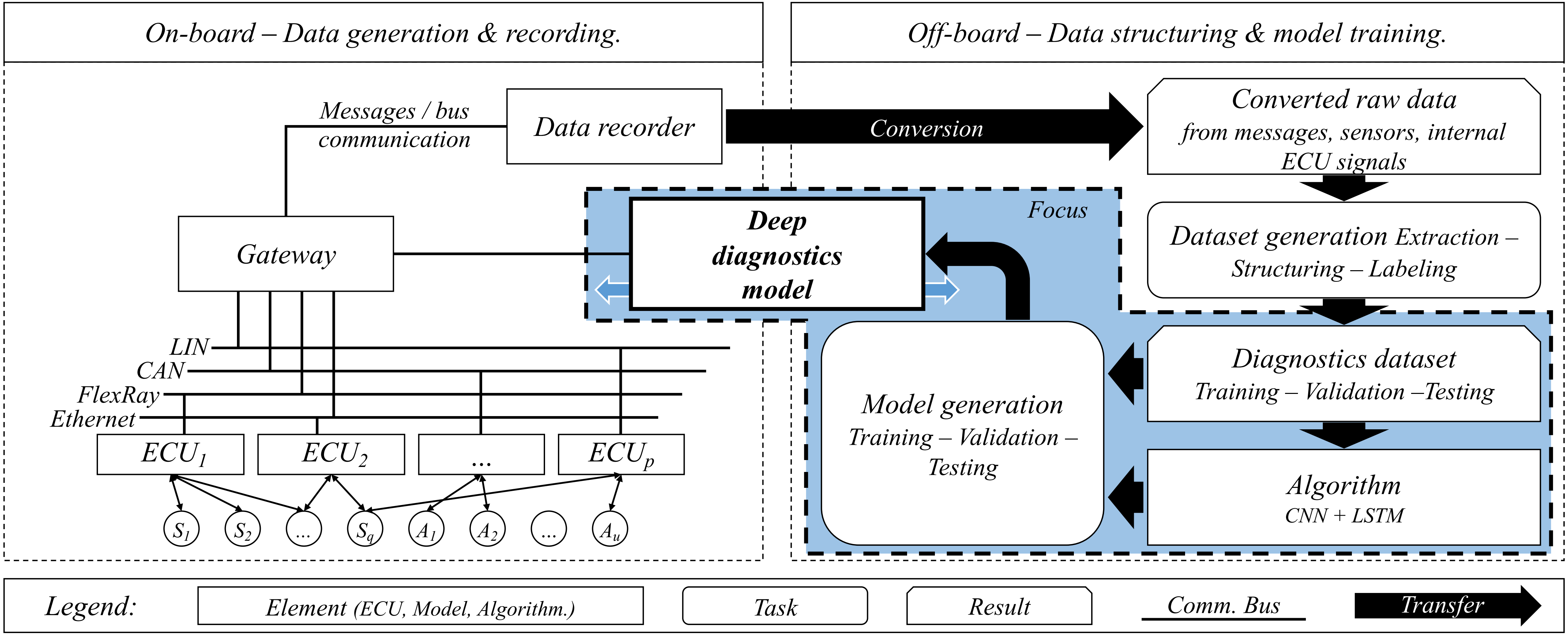
- Occur in high-pressure turbocharged petrol engines.
- The **root causes** of PIs is **not fully understood** but are related to [1]:
  - Lubricating oil.
  - Mix of gasoline/oil.
  - Floated deposit.
  - Gas-phase auto ignition.
  - Fuel properties.
- Can lead **to serious material damage** especially if several **PIs** occur **sequentially**.
- Main aim is to **suppress PI chains**.



Potential process from PI to super-knock: (a) auto-ignition induced by hot-spot, (b) spark ignition and flame, and (c) end-gas detonation induced by hot-spot.[6)]

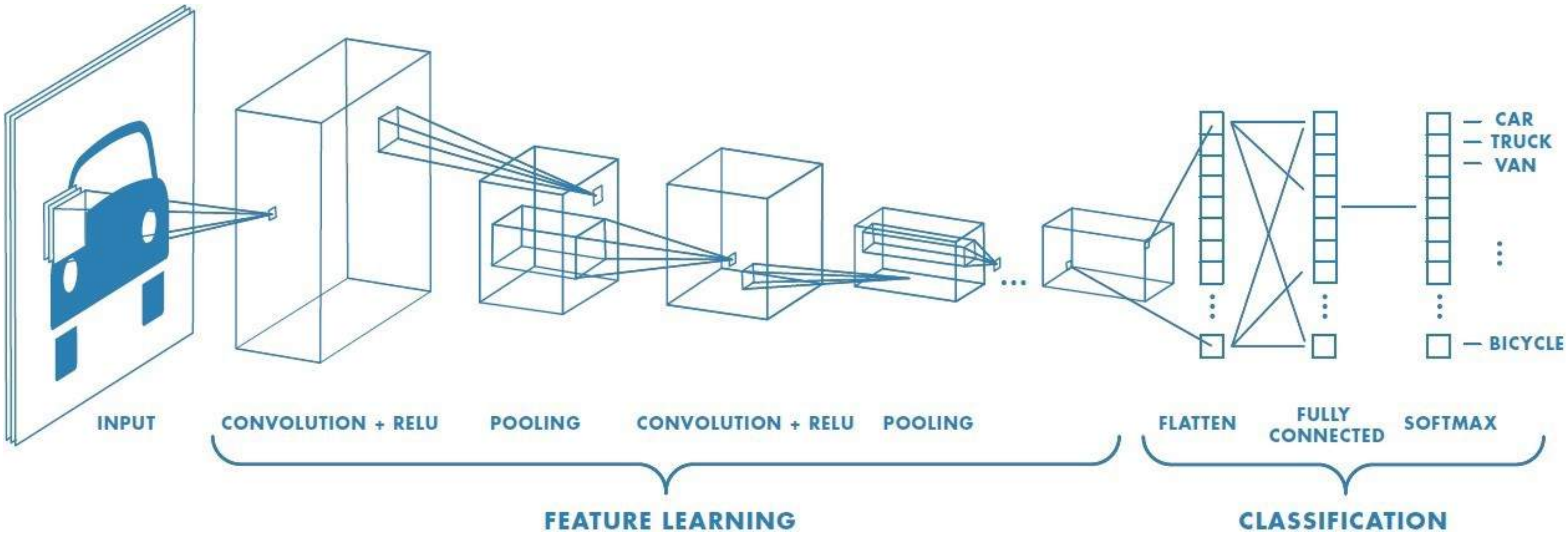
[1] Z. Wang, H. Liu, T. Song, Y. Qi, X. He, S. Shuai, and J. Wang, "Relationship between super-knock and pre-ignition," International Journal of Engine Research, vol. 16, no. 2, pp. 166–180, 2014.

PREVIOUS WORK: DATA-DRIVEN AUTOMOTIVE DIAGNOSTICS PROCESS

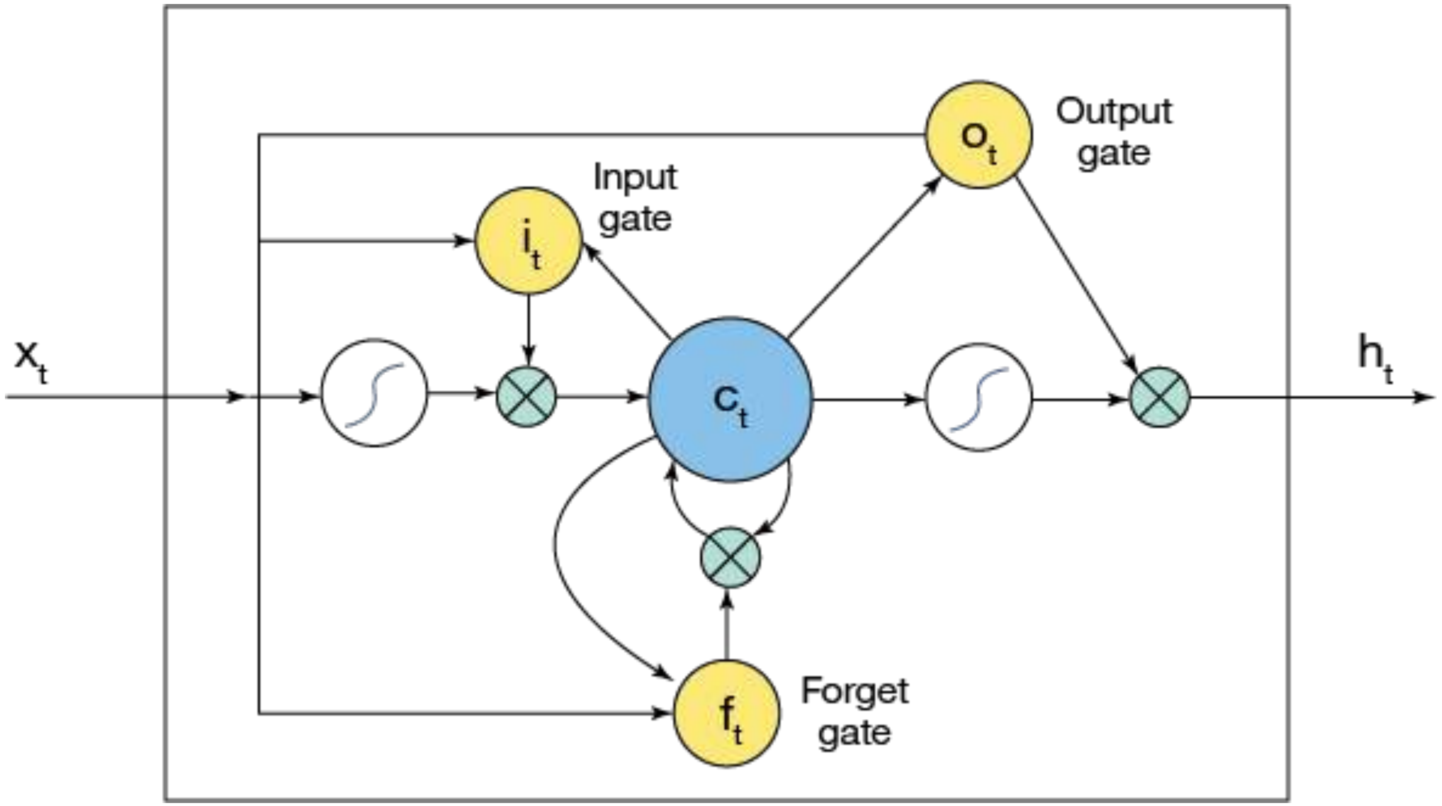


P. Wolf et al., "Pre-ignition detection using deep neural networks: A step towards data-driven automotive diagnostics," in 21st IEEE International Conference on Intelligent Transportation Systems (ITSC), 2018, pp. 176–183.

CONVOLUTIONAL NEURAL NETWORK (CNN)

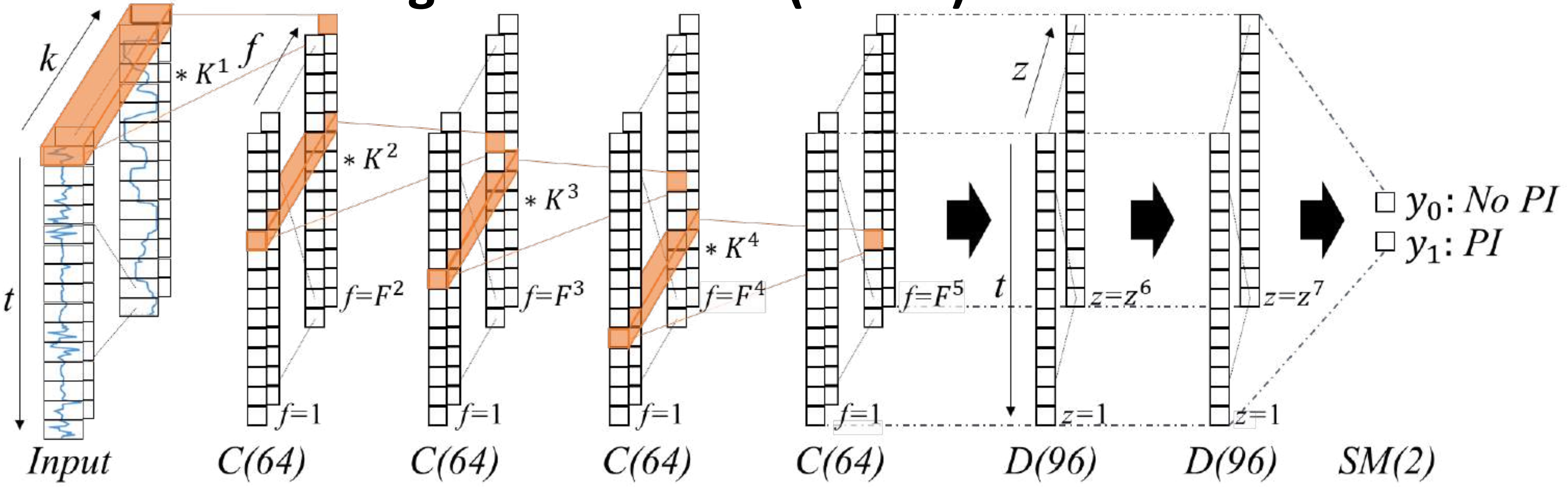


LONG SHORT-TERM MEMORY (LSTM)



THE COMBINATION OF 4 CNNS AND 2 LSTMS HAS BEEN FOUND TO BE THE BEST POSSIBLE ARCHITECTURE FOR PRE-IGNITION DETECTION

Deep Automotive Diagnostics Model (DADN)



Proposed architecture of DADN comprising four CNN layers (64 filters) for feature learning, two LSTMs layers with 96 cells per layer to learn temporal relationships, and a softmax layer.

$C(F^l)$: convolutional layer l with F^l feature maps (and kernel K^l).*
$D(z^l)$: recurrent (LSTM) layer l with z^l cells.
$SM(n)$: softmax layer with n neurons (classes).

DADN for pre-ignition detection through classification.

* Subscripts of kernels are omitted due to a clearer visualization.

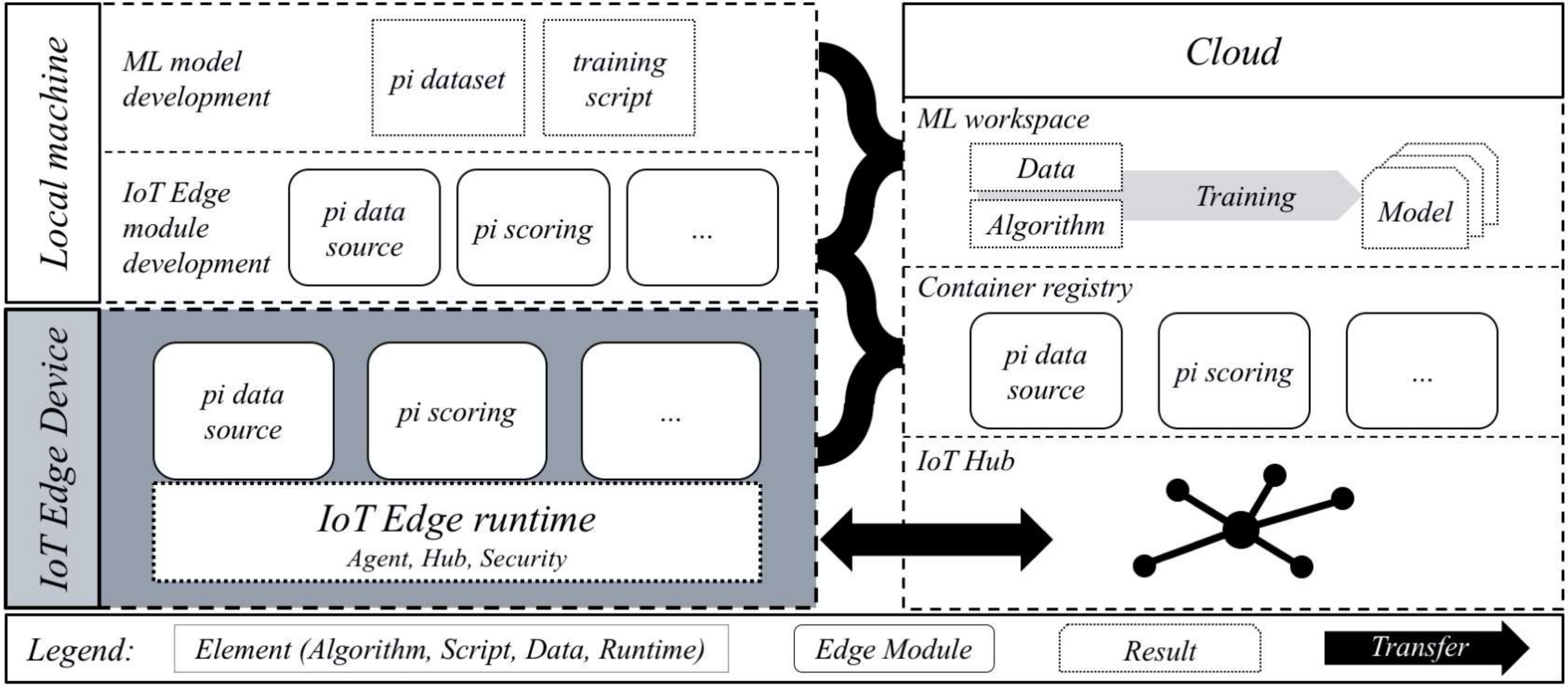
PROBLEM AND MOTIVATION

- How to run the model in the car where resources are constrained in the embedded environment?
- How to develop, manage and deploy the model to thousands of cars easily?
- We want to run an efficient, scalable model without sacrificing performance and accuracy

OUR SOLUTION AND CONTRIBUTIONS

- We create an end-to-end framework using enterprise cloud and IoT edge technologies for training, testing and deploying to thousands of vehicles
- We evaluate performance of Data-driven Automotive Diagnostics Network (DADN) with other models varying number of CNNs and LSTMs

CLOUD IOT EDGE FRAMEWORK FOR DATA-DRIVEN AUTOMOTIVE DIAGNOSTICS



PRE-IGNITION DATASET

PI Data used in this work:

- 1600+ test drives with special gasoline
- Internal engine ECU signals extracted by data recorders
- Input matrix $I_{X,0}$:
  - High dimensional: 1681 features.
  - High frequency: >20 Hz
- Hypothesis testing identified 484 statistically relevant features
- Labels: PI indicators extracted by expert analysis
- Experiments: use **top 50% (242) and top 5% (24)**
- Preprocessing includes:
  - Slice relevant sequences using a pragmatic undersampling approach
  - Split data to generate dataset: 70% training data, 15% validation data, 15% test data
  - Sliding window approach

DEVELOPMENT AND IMPLEMENTATION

- Using Raspberry Pi 3+ to simulate vehicle head-unit
- Training the models using Python and Microsoft Azure Machine Learning Service
- Executing the predictive models using Python, Docker and Azure IoT Edge
- Visualizing the results using Microsoft Power BI

SELECTING WHICH MODELS TO USE FOR EXPERIMENTS: HIGHEST F1 -SCORE

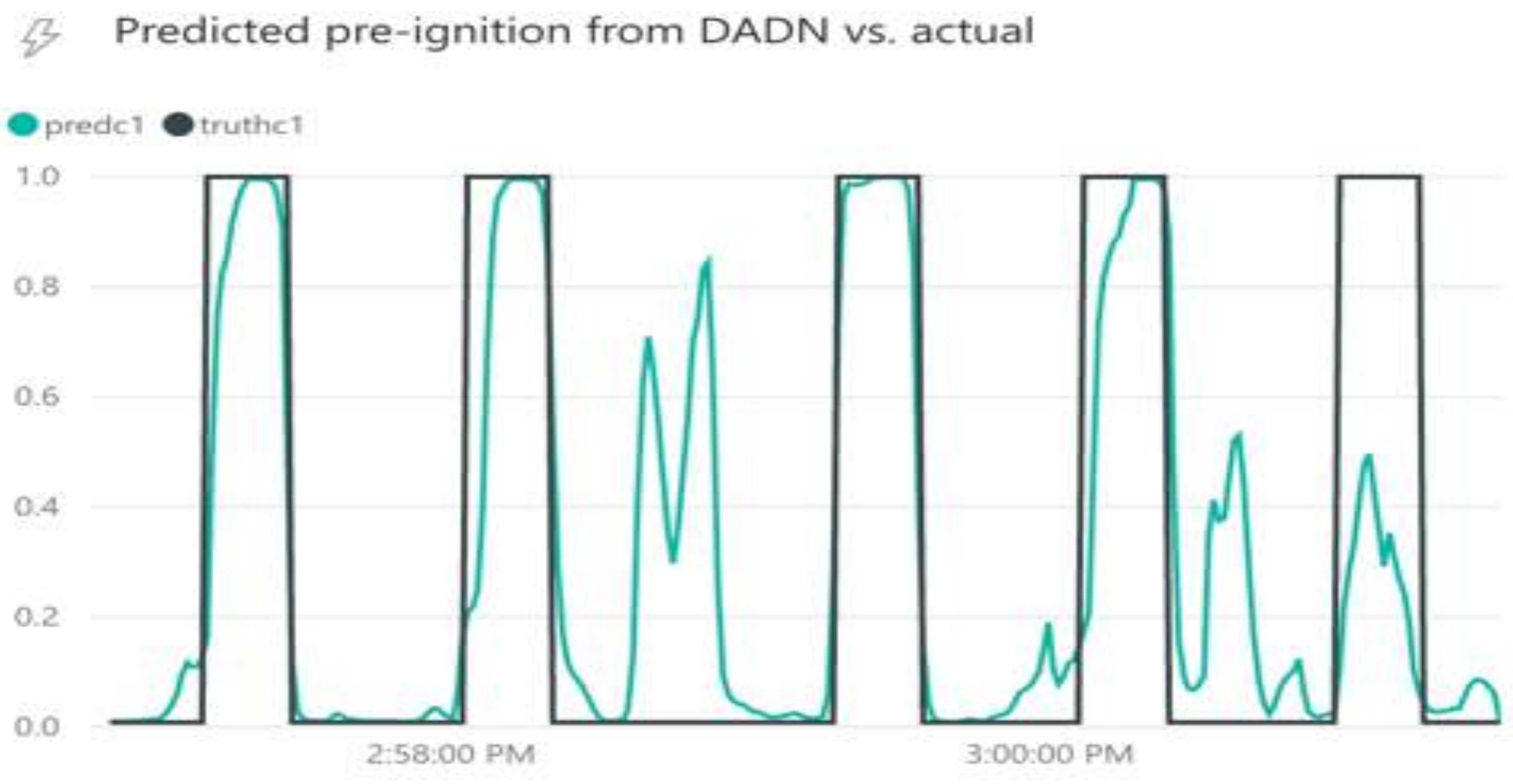
Model	F1-score and network parameters for model	
	F1-score	*# of network parameters*
4 CNN, 2 LSTM	0.893	173570
6 CNN, 0 LSTM	0.891	42754
2 CNN, 2 LSTM	0.888	165250
2 CNN, 0 LSTM	0.885	26114
0 CNN, 2 LSTM	0.882	213890
0 CNN, 1 LSTM	0.876	139778
1 CNN, 0 LSTM	0.872	21954

Highest F1-score for various models for top 50% of input features on the PI dataset

PERFORMANCE RESULTS FOR PREDICTION MODELS (TOP 50%)

Model	Performance results (prediction time, memory used) and F1-score ranked by prediction time				
	F1-score	*Mean predicted time (ms)*	*Standard deviation for predicted time*	*Memory overhead for setup (MB)*	*Memory for second prediction (MB)*
LDA-LR	0.692	12.4	5.08	71.4	0
1 CNN, 0 LSTM	0.872	22.7	8.84	160	2.4
2 CNN, 0 LSTM	0.886	28.4	13.6	161	1.9
6 CNN, 0 LSTM	0.892	37.7	14.9	166	1.8
0 CNN, 1 LSTM	0.876	75.4	115	176	8.2
4 CNN, 2 LSTM	0.893	104	43.7	196	14.7
0 CNN, 2 LSTM	0.882	126	50	191	11.6
2 CNN, 2 LSTM	0.888	128	51.1	193	4.7

ACCURACY OF PREDICTED PRE-IGNITION FROM DADN



PERSONAL PREFERENCES

TOWARD CONTEXTUAL AND PERSONALIZED INTERIOR EXPERIENCE IN A VEHICLE: PREDICTIVE PRECONDITIONING

DIETER MAY

ALVIN CHIN[1], JILEI TIAN[1] AND JOHANN PRENNINGER[2]

[1]BMW TECHNOLOGY CORPORATION (CHICAGO), [2]BMW GROUP (MUNICH)

Nov 18-Dec 16, 2020

Alvin Chin

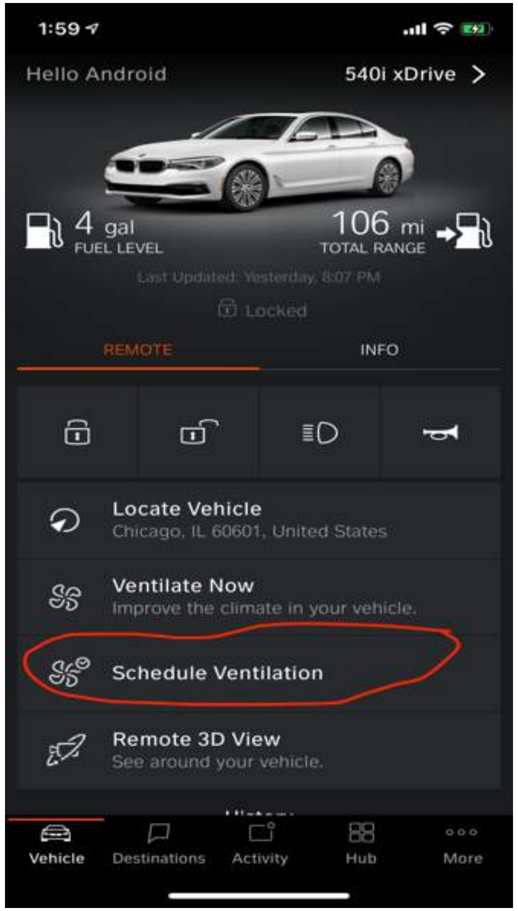
BMW GROUP

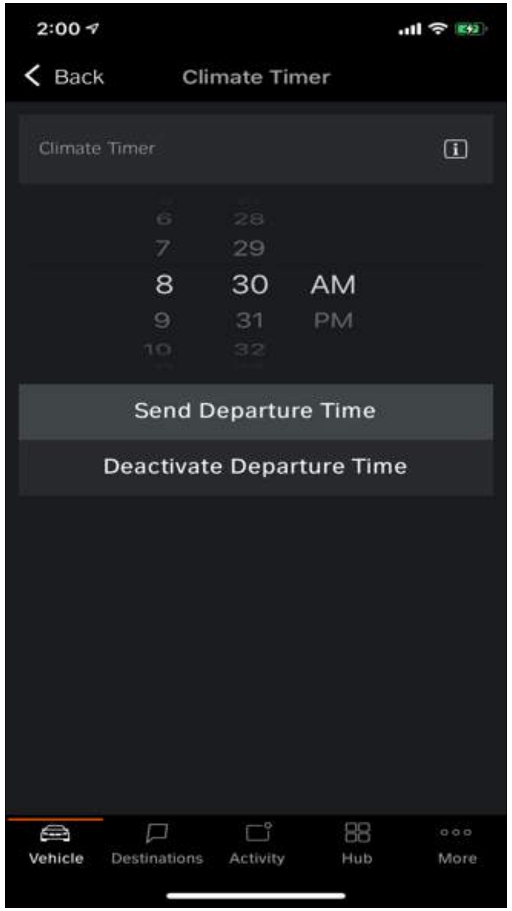
VTC2020-Fall
VICTORIA
Intelligent Mobile Connections

Rolls-Royce Motor Cars Limited

BACKGROUND: PERSONALIZED INTERIOR OF A VEHICLE

- Personalization exists in vehicle but based on explicit driver preferences





PREVIOUS WORK

- Automatically waking up vehicle and performing preconditioning before requested departure time [US Patent US20110153140A1, GM]
- Remotely starting engine of vehicle depending on temperature [US Patent US20100235046A1, GM]
- Infotainment [Rogers et al., 1997], recommending personalized audio content [Arnason et al., 2014]
- Personalized ADAS [Hasenjager and Wersing, 2017]
- **Automatically learning seat heating preferences [Laudy et al., BMW, 2018]**

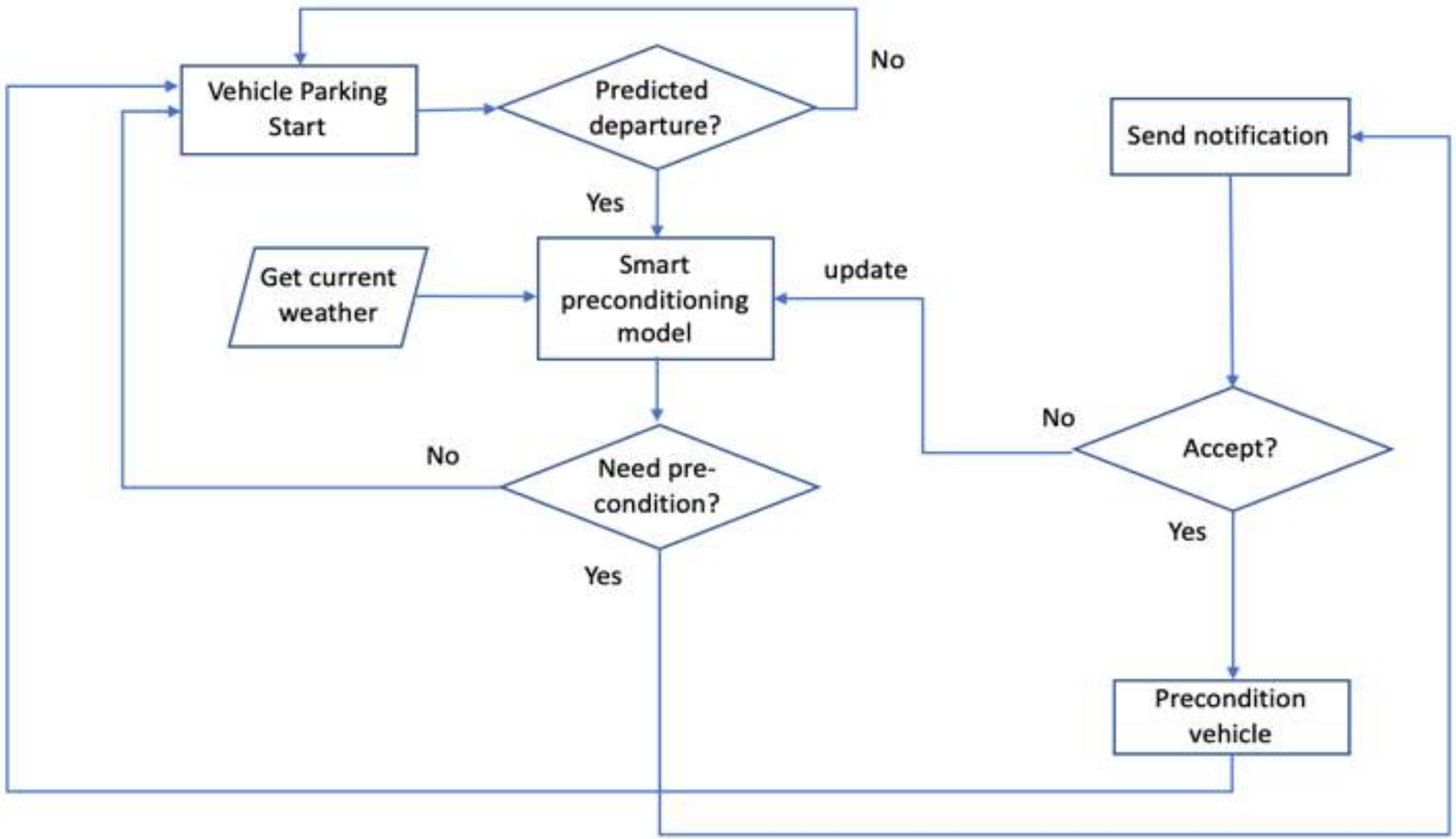
PROBLEM AND MOTIVATION

- How to create a system for personalized smart interior that can provide a proactive and comfortable user experience?
- For predictive preconditioning, how can we recommend and notify drivers when to precondition their vehicles, depending on vehicle's parking environment, user behavior, departure time and weather?

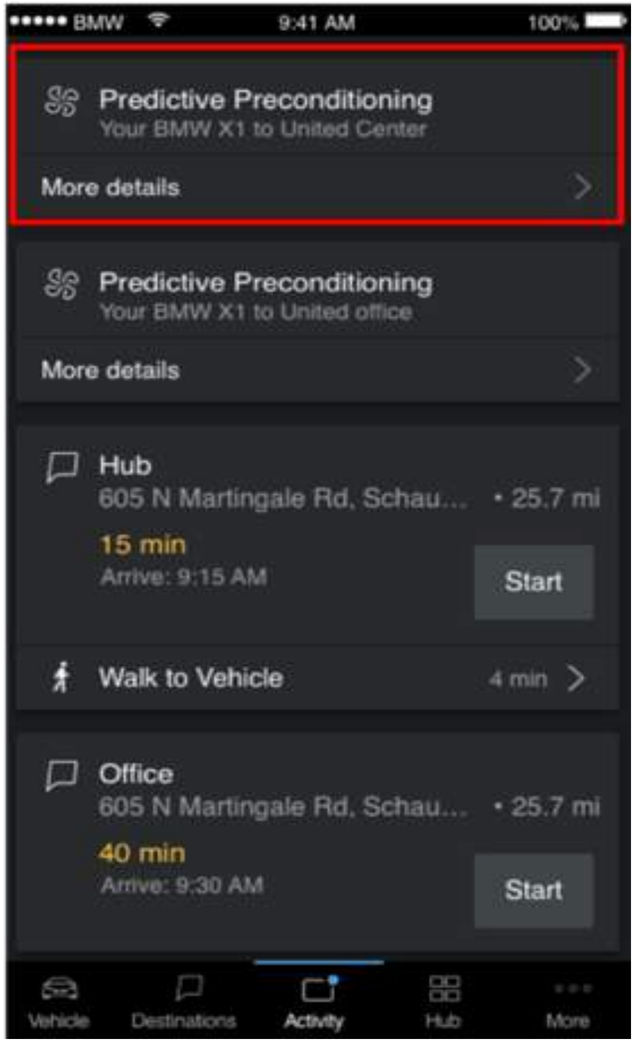
OUR SOLUTION AND CONTRIBUTIONS

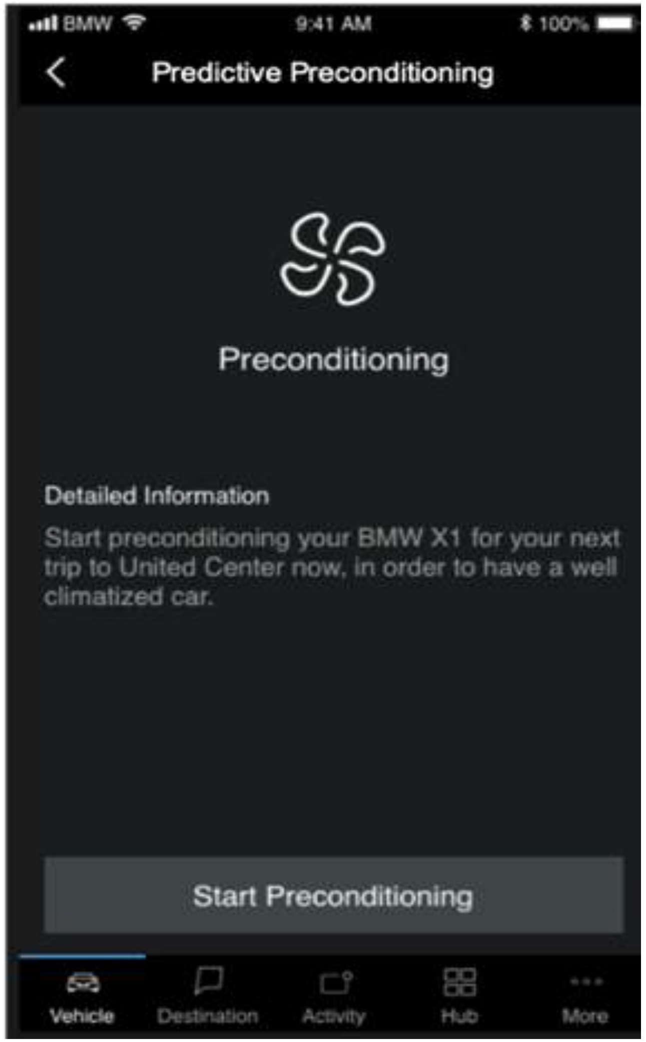
- We create a machine learning framework for smart interior that supports predictive preconditioning
- We recommend and notify drivers about preconditioning by considering weather, departure time, user behavior and parking
- We implement the framework in a real production environment
- We evaluate the performance and effectiveness of the predictive preconditioning algorithm through data analytics and user feedback

PREDICTIVE PRECONDITIONING FLOW



PREDICTIVE PRECONDITIONING NOTIFICATION





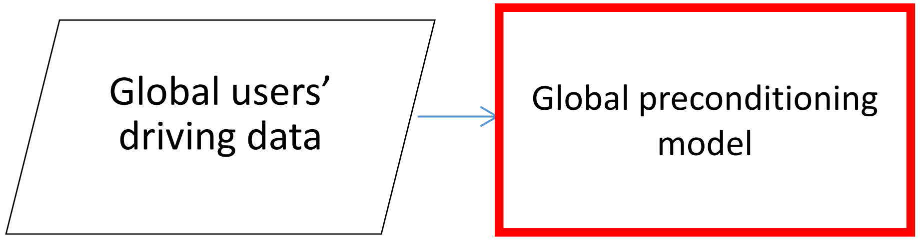
PREDICTIVE PRECONDITIONING MODEL: 1. COLLECT PERSONAL DRIVING DATA

Global users' driving data

Collect all the history driving data about the user

- Location data
- Exterior temperature: T_{out}
- Interior temperature: T_{in}
- Weather temperature: W

PREDICTIVE PRECONDITIONING MODEL: 2. CREATE GLOBAL MODEL



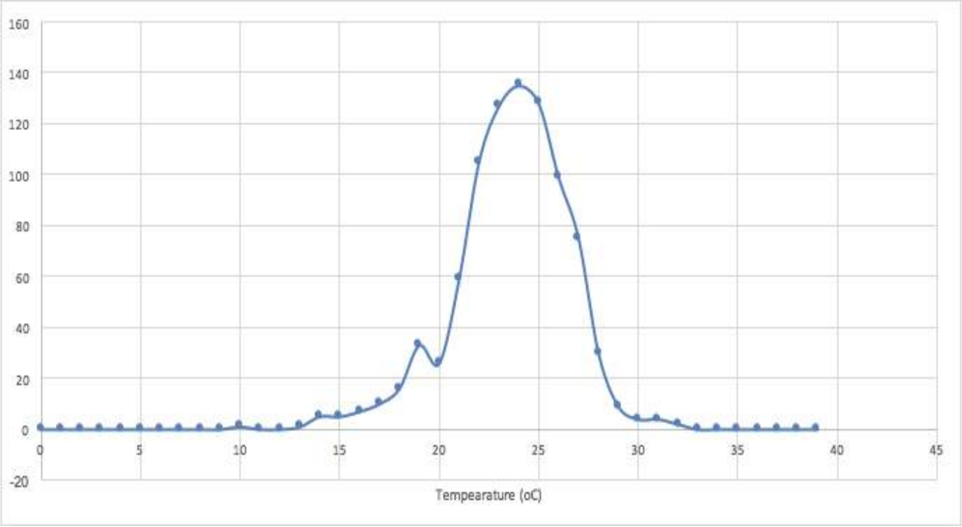
(i) Feature extraction

- Exterior temperature (first x records) criteria (et_j) set as 1, if any or average $T_{out_i} < \alpha_{cold}$ for where $i \le x$., otherwise as 0
- Wait time (wt_j): duration between first car record and first record with temperature T_{out_1}
- Max difference of interior temperature and exterior temperature for the first x records (md_j): $\max\left(abs(T_{out_i}, \quad T_{in_i})\right), for\ i \le x$
- Interior temperature (first x records) criteria (it_j), set as 1, if any or average $T_{in_i} < \beta_{cold}$ for where $i \le x$. Otherwise as 0

(ii) Outdoor parking probability

$$Tp_j = f(et_j,\ wt_j,\ md_j,\ it_j)$$

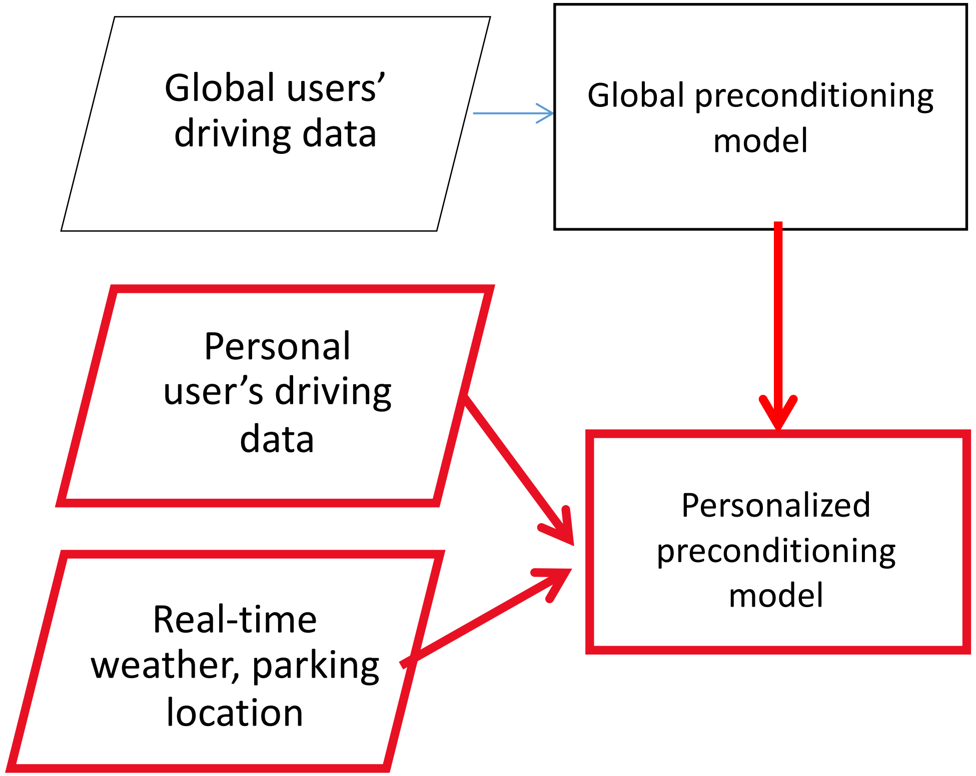
(iii) Global comfortable temperature model



(iv) Global preconditioning model

- Combine above to label trip by parking type, use outdoor temp
- Predict whether there should be preconditioning or not based on the global comfortable temperature model
- Supervised learning to learn the relationship between preconditioning, exterior temperature and wait time

PREDICTIVE PRECONDITIONING MODEL: 3. CREATE PERSONALIZED MODEL



(i) Bi-logistic regression

$$Pre = \frac{1}{1+e^{-(wea*\alpha_1+\beta_1)}} \times \frac{1}{1+e^{-(sd*\alpha_2+\beta_2)}} - \frac{1}{1+e^{-(wea*\alpha_3+\beta_3)}} \times \frac{1}{1+e^{-(sd*\alpha_4+\beta_4)}} + \varepsilon$$

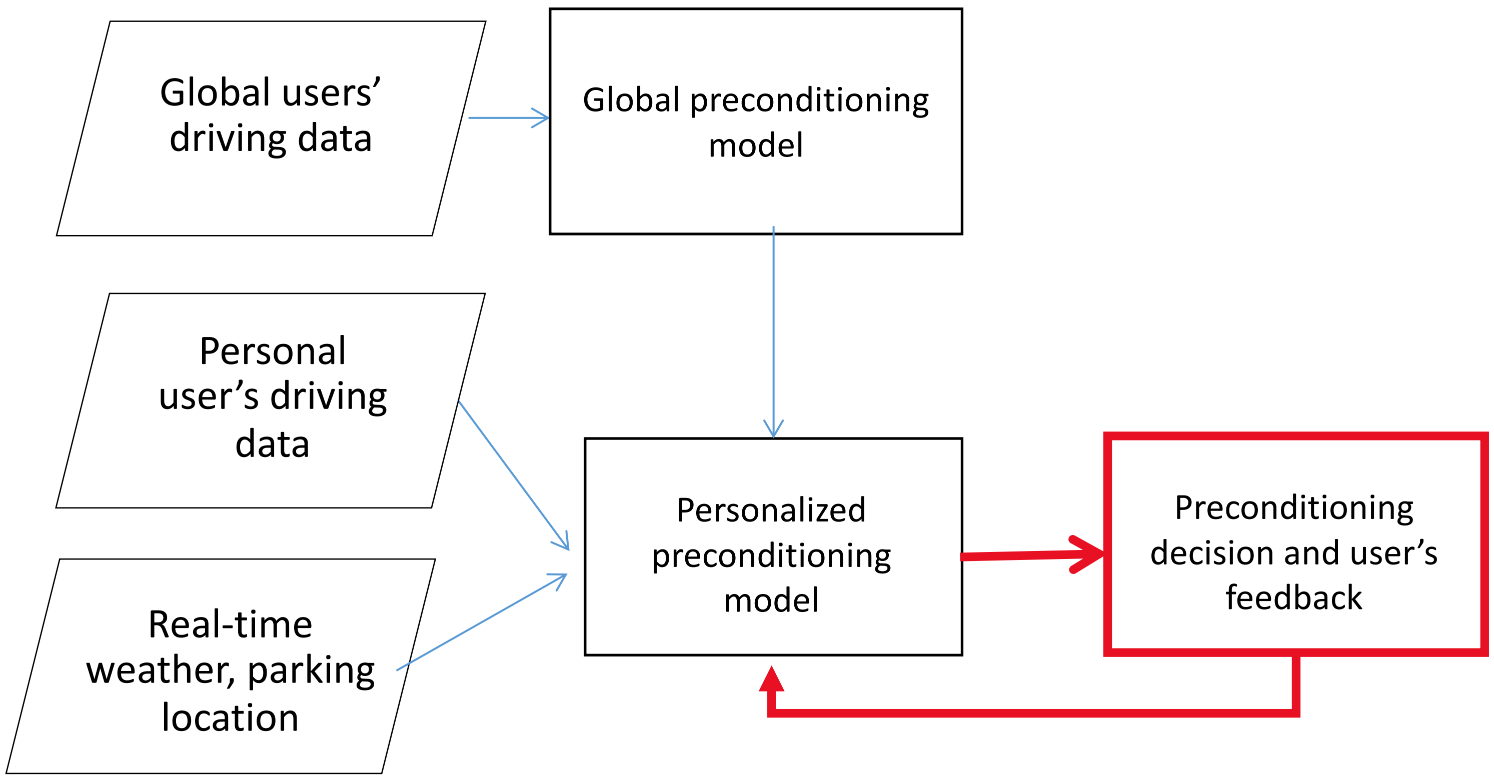
(ii) Find personalized parameters $w = \{\alpha_i, \beta_i, \varepsilon\}$, $i = 1,..,4$

$$E(w) = W_e \{Pre(wea, sd, w) - Y\}^2 + \frac{\tau}{2} \|w\|^2$$

(iii) Optimize w

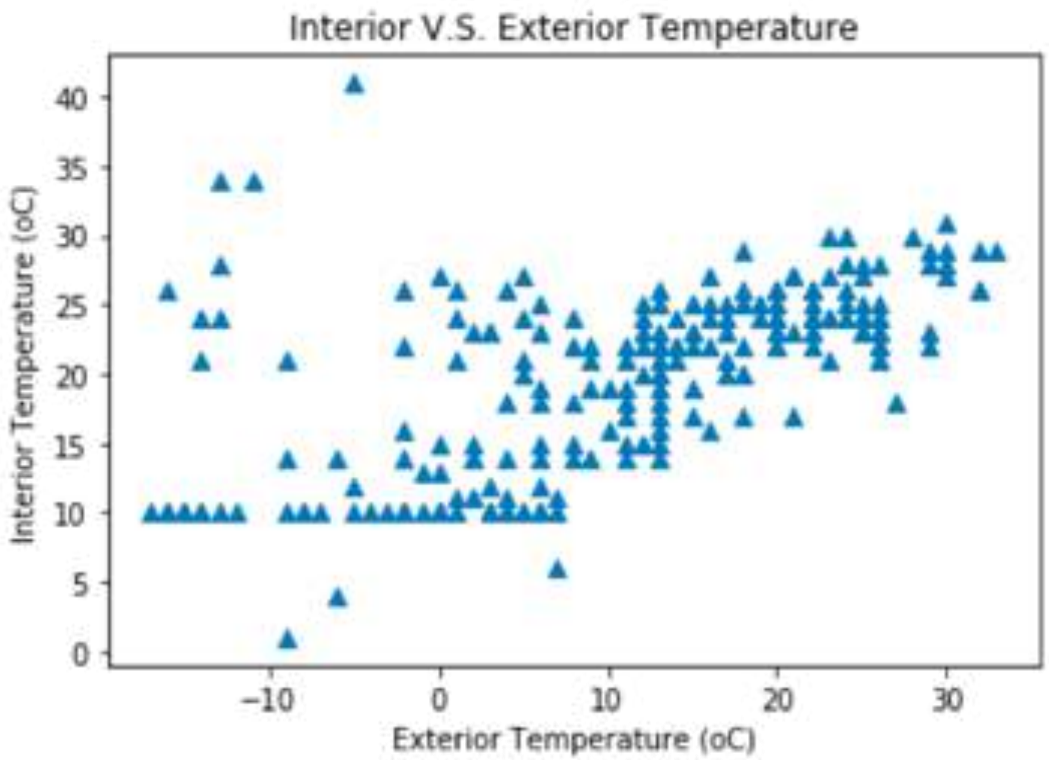
$$w_{k+1} = w_k - lr_k \cdot \nabla E(w_k)$$

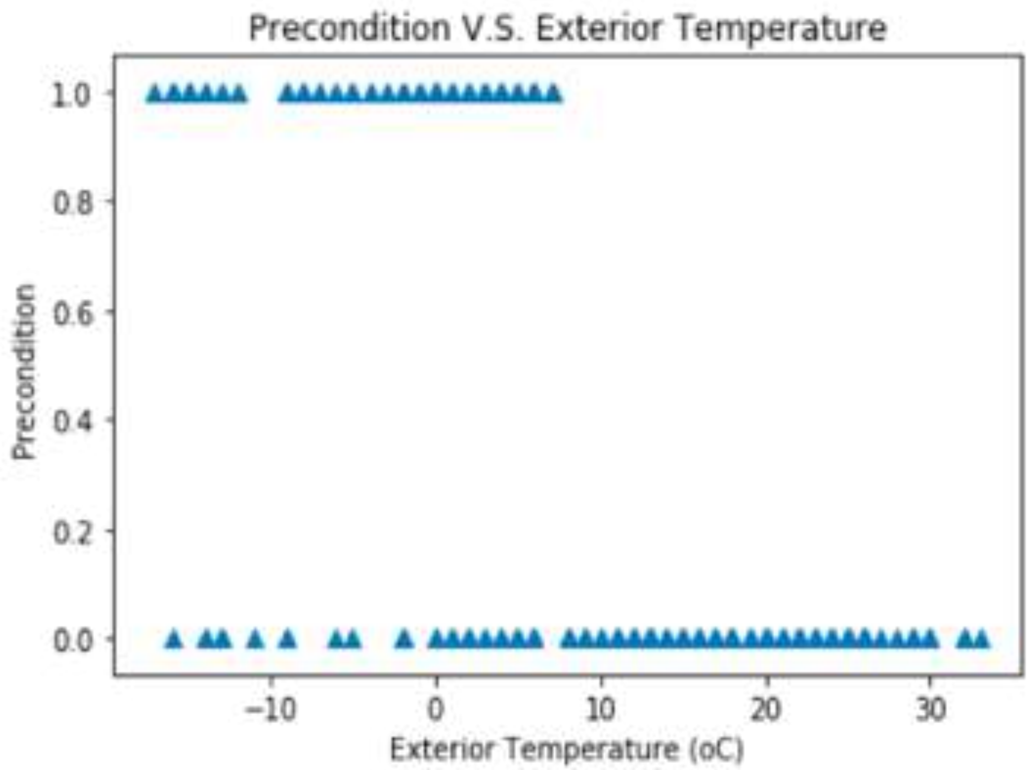
PREDICTIVE PRECONDITIONING MODEL:
4. PREDICT DECISION AND GET USER FEEDBACK



- Precondition decision is made based on the model output
- If high confidence level, automatically precondition vehicle
- If very low confidence level, do nothing
- Otherwise, notify user and let user choose whether a precondition is needed
- Feedback used to update model parameters and adapt personalized preconditioning model

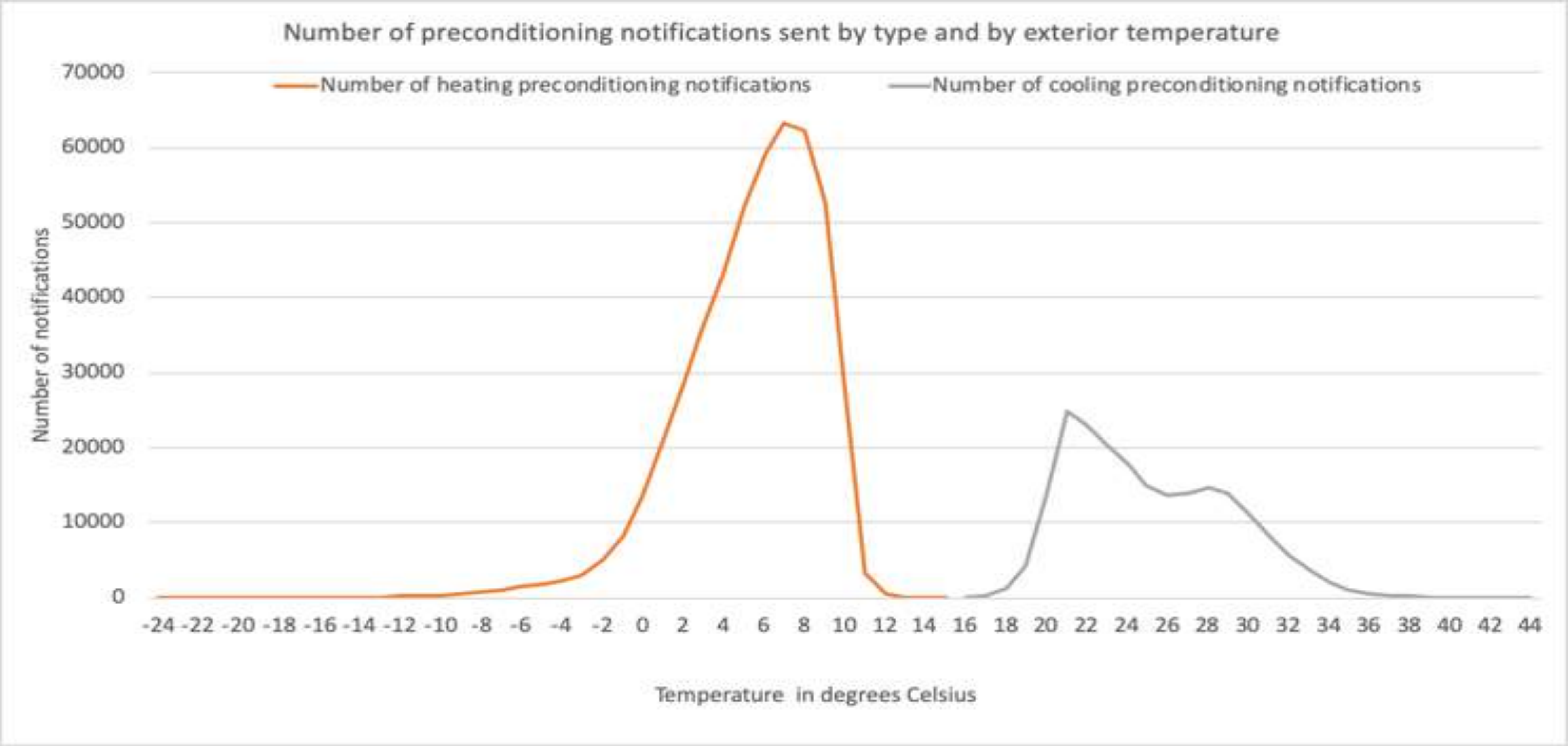
ALGORITHM EVALUATION





From 240 trips, accuracy = 91%, precision = 76%, recall = 89%

SYSTEM PERFORMANCE AND ANALYTICS INSIGHT



Active user, on average, executes cooling, heating or ventilation at least twice in a week from the preconditioning notifications sent

SUMMARY

- Machine learning can be used to learn driver behavior patterns for journey management
- Machine learning can be used to predict faults of components in a vehicle before they become failures for predictive maintenance
- Machine learning can be used to learn user's personal preferences for personalization in the vehicle
- Machine learning can be used to make The Ultimate Smart Driving Machine

THANKS!

Dr. Alvin Chin

AI and Emerging
Technology Researcher
IT Innovation and Research
Silicon Valley (FG-AM-7MV)
BMW Group Tech Office USA

E-mail: alvin.chin@bmwna.com
Web: http://www.alvinychin.com