# MACHINE LEARNING FOR THE CONNECTED CAR

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#### IEEE COMSOC OREGON CHAPTER MEETING, FEB. 25, 2021



# WHY DO WE NEED MACHINE LEARNING FOR CONNECTED VEHICLES?







# CONNECTED VEHICLES BRING DIGITALIZATION INTO THE VEHICLE







Machine Learning for the Connected Car



#### 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







Machine Learning for the Connected Car





### Dinner with Robert

- 15 The Embarcadero San Francisco, CA 94111

#### **BMW CONNECTED – LAUNCHED 2016**

Next Trip





# CONNECTS YOUR VEHICLE TO YOUR LIFE.

#### **HOW DO WE LEARN A DESTINATION?**



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THE NEXT

100 YEARS









## **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.

Instance, trip data given in lat/lon

- Example Mined Contextual Rules:
- {(Is Monday: Yes), (time range: AM6:30-7:00)} Home  $\Rightarrow$  Railway station.







Semantic location and route: significant location and personal route

#### LEARN YOUR FREQUENT AND PREDICTED TRIPS AND PLAN TRIP

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| SWARM   | Fri 8:37 Pf                     | Leave: 5:43 Pl<br>Scheduled: 6: | 4<br>00 PM             | Go                        | 1000                 | Go                       |                |  |         |
| Pawel B. at 🎄 Catherin  | ne Chevalier Woods in Cook, IL  |                                 |                        |                           |                      |                          |                | Work                                       |         |
| SWARM   | Fri 8:17 Pf                     | On research                     | oom-19A104-Monaco      | P • 0.6 mi                |                      | Send to Vehicle          |                | 100 N Riverside Plz, Chicago, IL 60606, Un |         |
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| SWARM   | Fri 7:58 Pf                     | Suggested Lo                    | cation                 |                           | Schedule             |                          |                | Send to Vehicle Messages                   |         |
| anderson c. at 💪 XSpo   | ort Fitness in Lakeview         | Midewin Nation                  | al Tallgrass Prairie   |                           | ☆ Save for L         | .ater                    |                | 🖄 Save for later                           |         |
|   | Fri 6:24 P!                     | 30239 S State Ro                | ute 53, Wilmington, IL | . • 58.7 mi               | r  Walk to D         | estination               |                | Share arrival time                         |         |
| Leave in 10 minutes to  | get to My Fair Lady.            | Arrive: 6:58 Pl                 |                        | Go                        |                      |                          |                |  |         |
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#### **SCHEDULED MEETING AS NEXT TRIP**

| 🔹 TATA 🕪 | 12:39 AM      | 🕈 🛊 43% 🔳 🔿 |
|----------|---------------|-------------|
| Apr 25   | Event Details | Edit        |

#### The Ultimate Smart Driving Machine: Powering the Connected Car with Machine Learning

540 W Madison St., Suite 2400 Chicago, Illinois United States 60661



#### Notes

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After a hiatus, the IEEE Vehicular Technology Society Chicago chapter has resumed again. We will start our chapter meeting this year with

#### **Delete Event**

THE NEX

100 YEARS







#### **NEXT TRIP SENT TO VEHICLE AUTOMATICALLY SO READY TO GO!**









#### **LEARN YOUR FUEL CONSUMPTION AFTER A TRIP**

| •≈• AT&T 🗢  | 5:19 PM  | <b>⊀</b> ∦ 63% 🗖 ⊃           |
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#### 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











## **PREDICTIVE VEHICLE MAINTENANCE**







#### A CLOUD IOT EDGE FRAMEWORK FOR EFFICIENT DATA-DRIVEN AUTOMOTIVE DIAGNOSTICS ALVIN CHIN<sup>1</sup>, PETER WP WOLF<sup>2</sup> AND JILEI TIAN<sup>1</sup> <sup>1</sup>BMW TECHNOLOGY CORPORATION (CHICAGO), <sup>2</sup>BMW GROUP (MUNICH)

BARCELONA, PASSEIG TAULAT

Add as intermediate destination

tart route guidance



Alvin Chin







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#### **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 <sup>[1]</sup>:

- 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).

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

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DADN for pre-ignition detection through classification.



#### **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:

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- 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



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#### **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

|               | F1-score and network parameters for model |                            |  |  |  |
|---------------|---|----------------------------|--|--|--|
| Model         | F1-score                                  | # of network<br>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%)**

|                  | Performance results (prediction time, memory used) and<br>F1-score ranked by prediction time  |  |  |   |  |  |
|------------------|---|--|--|---|--|--|
| Model            | F1-<br>score  | Mean<br>predicted<br>time<br>(ms)  | Standard<br>deviation<br>for<br>predicted<br>time  | Memory<br>overhead<br>for setup<br>(MB)   | Memory for<br>second<br>prediction<br>(MB)   | A102   |
| LDA-LR           | 0.692   | 12.4   | 5.08   | 71.4  | 0  | i i i  |
| 1 CNN,<br>0 LSTM | 0.872   | 22.7   | 8.84   | 160   | 2.4  |  |
| 2 CNN,<br>0 LSTM | 0.886   | 28.4   | 13.6   | 161   | 1.9  |  |
| 6 CNN,<br>0 LSTM | 0.892   | 37.7   | 14.9   | 166   | 1.8  |  |
| 0 CNN,<br>1 LSTM | 0.876   | 75.4   | 115  | 176   | 8.2  | 1  |
| 4 CNN,<br>2 LSTM | 0.893   | 104  | <mark>43.7</mark>  | 196   | 14.7   |  |
| 0 CNN,<br>2 LSTM | 0.882   | 126  | 50   | 191   | 11.6   |  |
| 2 CNN,<br>2 LSTM | 0.888   | 128  | 51.1   | 193   | 4.7  |  |
|                  | Model<br>LDA-LR<br>1 CNN,<br>0 LSTM<br>2 CNN,<br>0 LSTM<br>6 CNN,<br>0 LSTM<br>6 CNN,<br>1 LSTM<br>4 CNN,<br>1 LSTM<br>4 CNN,<br>2 LSTM<br>0 CNN,<br>2 LSTM<br>2 CNN,<br>2 LSTM | ModelPerform<br>F1-sconModelF1-<br>scoreLDA-LR0.6921CNN,<br>0.8722CNN,<br>0.LSTM0LSTM6CNN,<br>0.8920CNN,<br>1.LSTM0CNN,<br>0.8930CNN,<br>0.8930CNN,<br>0.8930CNN,<br>0.8822CNN,<br>0.8822CNN,<br>0.888 | ModelPerformance result<br>F1-score<br>ranked byModelF1-<br>score<br>predicted<br>time<br>(ms)LDA-LR0.69212.41CNN,<br>0.87222.72CNN,<br>0LSTM0.88628.46CNN,<br>0.89237.70CNN,<br>1LSTM0.87675.44CNN,<br>2LSTM0.8931040CNN,<br>2LSTM0.8821262CNN,<br>0.888128 | ModelPerformance results (prediction<br>F1-score ranked by prediction t<br>scoreModelF1-<br>scoreMean<br>predicted<br>(ms)Standard<br>deviation<br>for<br>predicted<br>time<br>(ms)LDA-LR0.69212.45.081CNN,<br>0.87222.78.842CNN,<br>0 LSTM0.87222.78.842CNN,<br>0 LSTM0.88628.413.66CNN,<br>0 LSTM0.89237.714.90CNN,<br>1 LSTM0.87675.41154CNN,<br>2 LSTM0.88310443.70CNN,<br>2 LSTM0.88812851.1 | Performance results (prediction time, memor           Model $F1$ -score ranked by prediction time         Standard deviation for predicted time (ms)         Memory overhead for setup (MB)           LDA-LR         0.692         12.4         5.08         71.4           1         CNN, 0.872         22.7         8.84         160           2         CNN, 0.886         28.4         13.6         161           6         CNN, 0.892         37.7         14.9         166           0         LSTM         0.876         75.4         115         176           4         CNN, 0.893         104         43.7         196         0           0         CNN, 0.888         128         51.1         193 | Performance results (prediction time, memory used) and<br>F1-score ranked by prediction timeModelF1-<br>scoreMean<br>predicted<br>time<br>(ms)Standard<br>deviation<br>for<br>predicted<br>time<br>(MB)Memory<br>overhead<br>for setup<br>(MB)LDA-LR0.69212.45.0871.401CNN,<br>0 LSTM0.87222.78.841602.42CNN,<br>0 LSTM0.88628.413.61611.96CNN,<br>0 LSTM0.89237.714.91661.80CNN,<br>1 LSTM0.87675.41151768.24CNN,<br>2 LSTM0.8821265019111.62CNN,<br>0.88812851.11934.7 |







#### **ACCURACY OF PREDICTED PRE-IGNITION FROM DADN**









# **PERSONAL PREFERENCES**





Machine Learning for the Connected Car



#### TOWARD CONTEXTUAL AND PERSONALIZED INTERIOR EXPERIENCE IN A VEHICLE: PREDICTIVE PRECONDITIONING ALVIN CHIN<sup>1</sup>, JILEI TIAN<sup>1</sup> AND JOHANN PRENNINGER<sup>2</sup> <sup>1</sup>BMW TECHNOLOGY CORPORATION (CHICAGO), <sup>2</sup>BMW GROUP (MUNICH)

BARCELONA, PASSEIG TAULAT

Start route guidance Add as intermediate destination

Nov 18-Dec 16, 2020

Alvin Chin







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#### **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**

| Collect all the histo | ory driving data | about the user |
|-----------------------|------------------|----------------|
|-----------------------|------------------|----------------|

| <ul> <li>Location data</li> </ul> | а |
|-----------------------------------|---|
|-----------------------------------|---|

- Exterior temperature: *T*<sub>out</sub>
- Interior temperature: *T<sub>in</sub>*
- Weather temperature: W





Global users'

driving data



#### **PREDICTIVE PRECONDITIONING MODEL:** 2. CREATE GLOBAL MODEL (i) Feature e



# (iii) Global comfortable temperature model



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#### (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 $(abs(T_{out_i}, T_{in_i}))$ , 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

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

#### (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



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#### (i) Bi-logistic regression

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

(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



Machine Learning for the Connected Car

#### **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





Machine Learning for the Connected Car





- 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

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