ZENUITY

Make it real.
Machine Learning for Autonomous Driving

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Stockholm (KTH), 2017-04-03
Zenuity!

- Develop software for autonomous driving and driver assistance systems
- Autoliv and Volvo Cars will own Zenuity 50/50
- Starting with 200 employees from Autoliv and Volvo Cars
- Volvo Cars and Autoliv will license and transfer the intellectual property for their ADAS systems to Zenuity
- Headquartered in Gothenburg with additional operations in Munich, Germany, and Detroit, USA

CEO: Dennis Nobelius
AD AND AI AMONG HOTTEST TRENDS

Gartner's 2016 Hype Cycle for Emerging Technologies
Autonomous Driving (AD)

ML in the era of AD
  - Interest in ML in the IV/ITS community
  - Applications
  - Some examples
GLOBAL TRENDS

- Urbanisation
- Growing mega cities
- Air quality major health problem
- Traffic accident global health issue
- Time for commuting
- Desire for time efficiency
- Desire for constant connectivity
SHAPING THE FUTURE MOBILITY

AD will be important for a sustainable mobility
- Improved traffic safety
- Improved environmental outcomes
- Regain time
No one should be killed or seriously injured in a new Volvo car by 2020.
IT WAS ALWAYS ABOUT FREEDOM
AND IT'S STILL ABOUT FREEDOM
JOINT EFFORT AND PROPER RESEARCH

Global challenges – Demand a joint effort
Drive Me – Nordic model of collaboration
Research platform – How autonomous cars can contribute to a sustainable development
Pilots with real customers in real traffic
The Pilots – All About Learning

- Traffic environments
- Customer preferences
- Exporting the Nordic model of collaboration

Gothenburg – proof of concept
China and London – verify our technology
WELL-DEFINED COMMUTE HIGHWAYS

- Customer focus
- Simplification
- Risk Management

A

Neighborhood

Your neighborhood, children, no lane markings, roundabouts, ...

Frustrating commute

Well defined use case on city highways

Close to work

Traffic lights, pedestrians, bicyclists, ...

B
PILOT ASSIST VERSUS AUTOPILOT

PILOT ASSIST / SUPERVISED

- Driver is responsible, should monitor and supervise
- Driver responsible to intervene whenever needed
- Limitations: Lane markings, road design, oncoming objects, pedestrians, animals, restrictions in steering/braking/acceleration force that can be applied

AUTOPilot / UNSUPERVISED

- Manufacturer responsible
- Tested on and expects extreme situations
- Takes precautions, takes decisions
- Driver free to do something else
SAFETY IMPACT

Safety Benefits

Precautionary Safety
- Low-risk driving
- Risky driving behaviours & situations

Crash Avoidance
- Conflict/Net-Crash

Injury Reduction
- Crash
- After crash

Unsupervised AD (Level 4)
Supervised AD (Level 1&2)
Manual (Level 0)

AD Car

Unsupervised AD (Level 4)
Supervised AD (Level 1&2)
Manual (Level 0)
“Volvo will assume liability for its autonomous technology, when used properly.”
TECHNOLOGY

- Camera
- Radar
- Laser
- Ultrasonic
- Map data
- Cloud connection
- Traffic Control Centre

“Machine learning for sensor signal processing is in the core!”
REDUNDANCY

Perception

Sensor Fusion 1

Sensor Fusion 2

Decision

Decision & Control 1

Decision & Control 2

Vehicle Dynamics Management 1

Vehicle Dynamics Management 1

Action

Brake Control 1

Brake Control 2

Brake Control 2

Steering Control 1

Steering Control 2

Power steering

Power steering

Vision

Radar

Lidar

Ultrasonic

Cloud
INTEREST IN ML, RELATED TO AD AND ITS

Records in Google Scholar

ITSC 2016 (out of 430 papers)
IMPROVING THE RESULTS OVER THE YEARS

- Object detection rate in KITTI
- Moderate: Min. bounding box height: 25 Px, Max. occlusion level: Partly occluded, Max. truncation: 30 %
## GROUPING THE ML METHODS

<table>
<thead>
<tr>
<th>Training</th>
<th>Deployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Where is it trained?</td>
<td>Where is it executed?</td>
</tr>
<tr>
<td>• Locally</td>
<td>• On-board</td>
</tr>
<tr>
<td>• In the cloud</td>
<td>• Off-board (e.g., in the cloud)</td>
</tr>
<tr>
<td>When is it trained?</td>
<td>When is it executed?</td>
</tr>
<tr>
<td>• Offline</td>
<td>• Real-time</td>
</tr>
<tr>
<td>• Online</td>
<td>• Offline (or batch processing)</td>
</tr>
<tr>
<td>How is it trained?</td>
<td>Continuous learning?</td>
</tr>
<tr>
<td>• Supervised</td>
<td>• Yes</td>
</tr>
<tr>
<td>• Un-supervised (semi-supervised)</td>
<td>• No</td>
</tr>
</tbody>
</table>

**Application**
- System design
- Verification
MODULAR SYSTEMS VS HOLISTIC DESIGN

- Modular systems and ML to design individual components
- Holistic and end to end learning for driving
MODULAR SYSTEMS

(1) Well-defined task-specific modules (2) Could have parallel modules

Examples:
• Semantic segmentation and free space and drivable area detection
• Object detection and tracking and information (speed, heading, type, ...)
• Road information and geometry of the routes
• Sensor fusion
• Scene Semantics such as traffic and signs, turn indicators, on-road markings etc
• Maps and updating them over time
• Positioning and localization
• Path planning
• Driving policy learning and decision making
• Other road user behavior analysis such as intention prediction
• Driver monitoring
HOLISTIC AND END TO END LEARNING

- First implemented around 28 years ago in the ALVINN system
  - Number of parameters < 50,000
- Dave-2
  - 9 layers (5 convolutional and 3 fully connected)
  - 250,000 parameters

AD VERIFICATION

- Requirements: setting safety scope for function and AD test scenarios
- Test methods
  - Test track
  - Test in real traffic and expeditions
  - Virtual testing and simulations

- Analyzing logged data
  - Need to have tools such as reference system
  - Need to have advanced analysis methods

Some Examples
Object Detection

(1) Accuracy  (2) Speed

• Florian Janda et al., "A road edge detection approach for marked and unmarked lanes based on video and radar", FUSION, 2013.
• Bei He et al., “Accurate and Robust Lane Detection based on Dual-View Convolutional Neural Network”, IV, 2016.
• Gabriel L. Oliveira et al., "Efficient deep models for monocular road segmentation", IROS, 2016.
# TRAFFIC SIGN RECOGNITION

<table>
<thead>
<tr>
<th>CCR (%)</th>
<th>Team</th>
<th>Method</th>
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</thead>
<tbody>
<tr>
<td>99.46</td>
<td>IDSIA</td>
<td>Committee of CNNs</td>
</tr>
<tr>
<td>99.22</td>
<td>INI-RTCV</td>
<td>Human (best individual)</td>
</tr>
<tr>
<td>98.84</td>
<td>INI-RTCV</td>
<td>Human (average)</td>
</tr>
<tr>
<td>98.31</td>
<td>Sermanet</td>
<td>Multi-Scale CNN</td>
</tr>
<tr>
<td>96.14</td>
<td>CAOR</td>
<td>Random Forests</td>
</tr>
<tr>
<td>95.68</td>
<td>INI-RTCV</td>
<td>LDA (HOG 2)</td>
</tr>
<tr>
<td>93.18</td>
<td>INI-RTCV</td>
<td>LDA (HOG 1)</td>
</tr>
<tr>
<td>92.34</td>
<td>INI-RTCV</td>
<td>LDA (HOG 3)</td>
</tr>
</tbody>
</table>

German Traffic Sign Recognition Benchmark (GTSRB) [Stallkamp 2012]

ROAD FRICTION ESTIMATION FROM CONNECTED VEHICLES DATA

- Prediction using both historical friction data from the connected cars and data from weather stations
- Busy roads
- Missing data

<table>
<thead>
<tr>
<th></th>
<th>Error rate</th>
<th>Sensitivity</th>
<th>Specificity</th>
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<tr>
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<td>0.9609</td>
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<tr>
<td></td>
<td>60</td>
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<td>0.9668</td>
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<td></td>
<td>90</td>
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<tr>
<td></td>
<td>120</td>
<td>0.2612</td>
<td>0.9283</td>
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<tr>
<td>SVM</td>
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<td>ANN</td>
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<td></td>
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<tr>
<td></td>
<td>120</td>
<td>0.2303</td>
<td>0.8632</td>
</tr>
</tbody>
</table>

Driver Route and Destination Prediction

- History of driving for individuals
- Use of metadata such as driver id, the number of passengers, time-of-day, day-of-week
- Destination clustering

Ghazaleh Panahandeh, “Driver Route and Destination Prediction”, IV 2017
**COMPRESSED NETWORKS**

- Pruning or quantizing weights
- Devising new and smaller architectures

- Forrest N. Iandola et al. "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size", *arXiv*, Nov. 2016
• Deep network understanding and interpretation
• Secure and privacy-preserving deep learning
• Transfer learning
• Pedestrian intention estimation
• Applications of generative adversarial networks
• Learning to attend
• Instance segmentation
• Object tracking
• Harsh weather conditions
• Traffic understanding such as brake light detection

**Classification of 3D Point Clouds**


**Table:**

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean accuracy</th>
<th>Total accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D-CNN</td>
<td>95.06%</td>
<td>96.35%</td>
</tr>
<tr>
<td>SVM</td>
<td>73.36%</td>
<td>96.08%</td>
</tr>
<tr>
<td>KNN</td>
<td>66.82%</td>
<td>93.99%</td>
</tr>
<tr>
<td>FFNN</td>
<td>77.83%</td>
<td>95.87%</td>
</tr>
<tr>
<td>RFC</td>
<td>74.85%</td>
<td>95.14%</td>
</tr>
</tbody>
</table>

**Classification accuracies for feature set A**

- SVM
- KNN
- FFNN
- RF

- Pedestrian
- Car
- Van
- Bicycle
- Truck
- Pole
- Unknown

- Accuracy %
GROUND TRUTH FOR POSITIONING

- High-accuracy positioning in GPS-denied environments
- Scalability to new locations

WRAP-UP

- High expectations from ML to overcome some of the biggest challenges in autonomous driving
- Successful applications of ML especially for perception already being used in the industry
- New challenges arise in designing complete ML systems (integration, updating, safety, interpretation...)
- Wide range of applications for ML from raw sensor data processing to developing offline methods for verification purposes
OPPORTUNITIES

• **Industrial PhD** position on “Reinforcement Learning for Autonomous Driving” at Zenuity/Chalmers
• **Postdoc** position on “Big Sensor Data Analysis for Verification of Autonomous Driving” at Zenuity/Chalmers
• **Research Engineer** position on “Big Sensor Data Analysis for Verification of Autonomous Driving” at Zenuity/Chalmers

Contact me: nasser.mohammadiha@volvocars.com

More positions on:
• [http://career.zenuity.com/](http://career.zenity.com/)