Federated Learning for Autonomous Driving

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A bit of background for AD

- According to National Highway Traffic Safety Administration (NHTSA)
  - **3,142 fatalities** in 2019 involved distracted drivers
  - **10,142 fatalities** in 2019 involved alcohol-impaired drivers
**Why is this important?**

**Pros & Cons of Self-Driving Cars**

**Pros**
- Self-driving vehicles can remove human error from the equation when it comes to car accidents.
- Self-driving vehicles can reduce traffic jams and save driving time.
- Self-driving vehicles can provide transportation for individuals who are driving impaired.

**Fast Facts**
- Each year about 2 million people have permanent injuries as a result of car accidents.
- 94% of serious crashes are due to human error.
- About 1/3 of all motor vehicle fatalities for the past two decades, speeding has been the main factor.

**Cons**
- Self-driving vehicles can be prone to hacking but developments are underway for cybersecurity protection.
- Liability when it comes to car accidents with self-driving vehicles are still being discussed. Is the car company or car owner liable?
- Self-driving vehicles require traffic lights, lines and signs in order to operate safely. This would lead to financial stress on keeping roadways up to par.

Sources:
https://driving-tests.org/driving-statistics/
http://dx.doi.org/10.5772/intechopen.99020
What is Federated Autonomous Driving Network (FADNet)?

- Focuses on a **Peer-to-Peer** Deep Federated Learning approach to train **deep architectures** in a **fully decentralized manner** and removing the need for central orchestration.
- Respects **privacy concerns** by **not collecting user data** to a central server.
- Improves **model stability**, ensures **convergence**, and handles **imbalance data distribution problems**.
- Based on Residual Neural Network 8 (ResNet8)
**How does it work? (Datasets)**

Fig. 4. Visualization of sample images in three datasets: Udacity (first row), Gazebo (second row), and Carla (third row).

Fig. 5. Spatial support regions for predicting steering angle in three datasets. In most cases, we can observe that our FADNet focuses on “line-like” patterns to predict the driving direction.
### Results

| Architecture  | Learning Method | Dataset       | #Params  
|---------------|-----------------|---------------|----------
| Random [14]   | -               | Udacity: 0.301, Gazebo: 0.117, Carla: 0.464 | -        
| Constant [14] | -               | Udacity: 0.209, Gazebo: 0.092, Carla: 0.348 | -        
| Inception [57]| CLL             | Udacity: 0.154, Gazebo: 0.085, Carla: 0.297 | 21,787,617 |
| MobileNet [58]| CLL             | Udacity: 0.142, Gazebo: 0.083, Carla: 0.286 | 2,225,153 |
| VGG-16 [59]   | CLL             | Udacity: 0.121, Gazebo: 0.083, Carla: 0.316 | 7,501,587 |
| DroNet [14]   | CLL             | Udacity: 0.110, Gazebo: 0.082, Carla: 0.333 | 314,657  |
| FADNet (ours) | DFL             | Udacity: 0.107, Gazebo: 0.069, Carla: 0.203 | 317,729  |

**TABLE II**

Performance comparison between different methods. The Gaia network topology is used in our DFL learning method.

Table II summarises the performance of our method and recent state-of-the-art approaches.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}
\]

Fig. 6. The convergence ability of our FADNet and DFL under Gaia and NWS topology. Wall-clock time or elapsed real-time is the actual time taken from the start of the whole training process to the end, including the synchronization time of the weight aggregation process. All experiments are conducted with 3,000 communication rounds.
Conclusion

- In conclusion, we introduced a peer-to-peer to deep federated learning method that effectively utilizes the user data in a fully distributed manner. Our FADNet architecture has proven to have better accuracy performance than existing works.
- Currently, our deployment experiment is limited to a mobile robot in an indoor environment.
- In the future, we would like to test our approach with more silos and deploy the trained model using an autonomous car on man-made roads.
References
