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Driving Events

Driver behavior affects traffic safety, energy consumption and greenhouse gas emissions

Driving style assessment and driving events detection can be fully automated thanks to AI.

Problem definition

- Driver behavior causes the vast majority of motor vehicle accidents.
- The total cost of motor vehicle crashes in the United States is estimated at $1 Trillion / Year.
- Pay-How-You-Drive can make car sharing cheaper by rewarding drivers with good driving scores.
- Good driving behavior increase resource economy, and vehicle lifetime.
- Notifications of unsafe driving events presented to drivers in real-time can help prevent accidents
- Monitoring driver behavior is **profitable**.

How to do it?

- Driver analysis is the process of automatically collecting driving data and applying a computational model to them in order to generate a safety score for the driver and detect dangerous events.
- Driving data may come from several kinds of sensors, like smartphones, monitoring cameras, telematics boxes, and On-Board Diagnostic (OBD) adapters.
- Real time machine learning algorithms analyze data using on-board computers, connected smarphones or servers in the cloud.
- Valuable results are presented to the driver and interested parties.

Data source

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1. The dataset is a collection of smartphone sensor measurements for driving events
2. An Android application is used to record smartphone sensor data, like accelerometer, linear acceleration, magnetometer and gyroscope, while a driver executed particular driving events.
3. The authors provide lables for 7 driving events.
4. The data comes from **https://github.com/jair-jr/driverBehaviorDataset**

Available features

Features collected by the authors are:

Timer with milliseconds precision

Accelerometer

Linear acceleration

Gyroscope

Magnetometer

Available events

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Classes selected for prediction:

Aggressive acceleration

Aggressive breaking

Aggressive right turn

Aggressive left turn

No event

Aggressive left lane change and aggressive right lane change are also available, but they have far fewer examples due to errors during the experiment.

Non-aggressive event is another class present in the dataset, but it was not taken into account because of its ambiguity.

Conclusions

Results

Accuracy **= 93%**

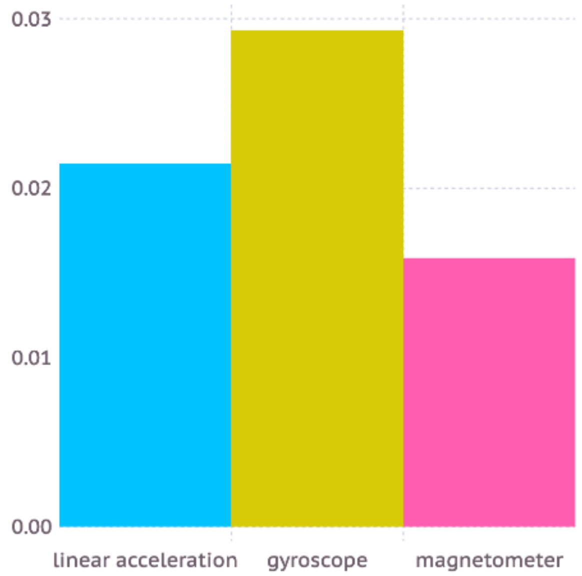
Macro Average F1 **= 93%**

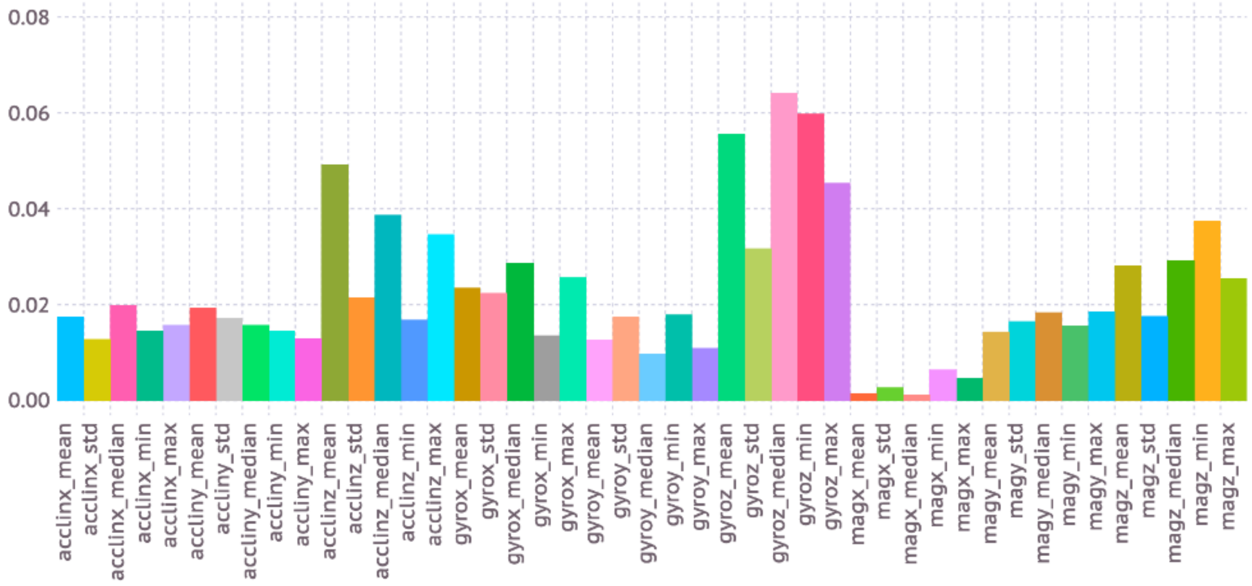
Training and predictions are very fast

The model can make a prediction with 1 - 1.5 s delay

Main features

The sensors usefulness





Possible improvements

1. More labeled events examples may help to achieve results accuracy **around 99%.**

2. This model with relatively small changes can be adapted to various events or driving style detection.

3. The model can be enhanced in several ways.

Thank you

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