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# Analysis of Driving Behaviour Characteristics Based on Smartphone Data

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## Introduction

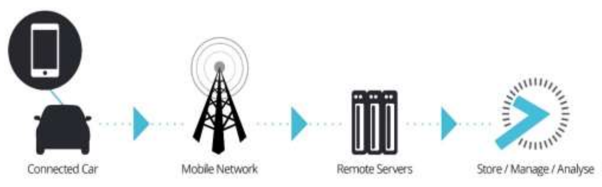
Detect and analyze risky driving behaviour characteristics
Smartphone data
Key driving risk indicators identified in literature:

- mileage
- acceleration (x,y axis)
- harsh driving events
- mobile usage
- speed

## Data collection and processing procedure

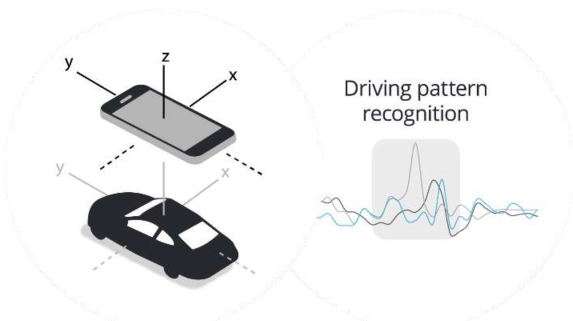
Data flow:

- Mobile app detects the start and stop of driving, with no user involvement
- Data recording from smartphone sensors
- Data transmission to backend (WiFi or 3G/4G)
- Data analyzed using the OSeven algorithms to produce driving metrics




Experiment:

- 4-months naturalistic driving experiment
- 100 participating drivers
- large database of 18,850 trips




Driving behaviour indicators exploited:

- distance travelled
- speed
- rotational speed
- acceleration
- braking
- harsh maneuvers (e.g. harsh acceleration, braking, etc.)
- mobile phone use
- collected from smartphone devices

## Results (1/2)

The number of harsh events change can be predicting using (**Table 1**):

- percentage of mobile usage
- the average speed
- the average exceedance of the speed limit
- the driving period during a day (morning, afternoon rush)
- more frequent use of mobile phone is associated with fewer harsh events

## Results (2/2)

Probability of mobile phone use during the trip is (**Table 2**):

- increased during the morning
- reduced during the afternoon
- not affected by trip duration
- negatively associated average speed per trip, confirming existing studies
- reduced by the average percentage exceedance of speed limits
- decreased as the number of harsh events per km is increased
- decreased as the angular speed (measured in o/s) is increased

"False positives" are a very minor share of the classified cases (**Table 3**)

Table 1. Mixed linear Regression model output for the estimation of Harsh Events per trip

| Parameter estimates | B | p-value |
|---|---|---|
| Constant | .517 | <0.001 |
| Driving during morning rush hour | .018 | .010 |
| Average Speed | -.005 | .007 |
| Average Speed limit exceedance | .294 | <0.001 |
| Mobile Usage % time | $-3.36*10^{-5}$ | .010 |
| Random effect (variance of random intercept) | 0.021 | <0.001 |

Table 2. Parameter estimates of the mixed binary logistic models for all road types

| Parameter estimates (Fixed effects) | B | p-value |
|---|---|---|
| Constant | 1.094 | <0.001 |
| Morning rush | 0.130 | 0.006 |
| Afternoon rush | -0.262 | <0.001 |
| Average percentage of speed over the speed limit | -0.334 | 0.027 |
| Average speed | -0.004 | 0.001 |
| Average angular speed | -0.058 | <0.001 |
| Total Harsh events | -0.064 | <0.001 |
| Random effect (variance of random intercept) | 1.261 | <0.001 |

Table 3. Outcomes Classification Table for all road types

| Mobile Phone use | Predicted (%) | |
|---|---|---|
| Observed | No | Yes |
| No | 71.4 | 28.6 |
| Yes | 29.9 | 70.1 |

## Conclusions

- Mobile usage distraction has a serious impact on the number of harsh events that occur per kilometer and subsequently on the relative crash risk
- Drivers who are speeding more, are less likely to use their mobile phone during the trip
- Drivers reduce speed while distracted, and therefore are less prone to harsh events. This is also in accordance with literature
- Mobile phone use while driving may be accurately "detected" by smartphone sensors data in more than 70% of cases
- Driving metrics can very accurately identify "not talking on mobile phone" conditions, but not so accurately the "talking on mobile phone" conditions


## Acknowledgements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