# I Know How You Drive!

## Driving Profiling via smartphone

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# Literature study and Motivation

# Auto insurance and UBI products

- Auto insurance is the essential line of business in Property-Casualty (P&C) insurance industry.
    - In 2017, the total volume of the automobile insurance industry was about $267 billion (about 42% of the U.S. P&C industry).
- Usage based Insurance (UBI) first appear in 2004 by Progressive insurance company.
    - Pay As You Drive (PAYD): the driving habits - the average driven distance per year, typical times of day for driving
    - Pay How You Drive (PHYD): the driving style of the driver - hard braking or accelerating, taking steep turns, changing lanes.

# Telematics Research in Actuarial Science

Pay How You Drive

- Nikulin (2016) constructs a driving profile using average speed, average acceleration and deceleration, and average turning speeds
- Weidner et al. (2017, 2016) uses pattern recognition methods and Fourier analysis for constructing a driving profile.
- Wüthrich (2017) suggests using v-a heatmap as a new type of driving profile.
- Gao et al. (2019a,b) examines the predictive power of v-a heatmap in claim frequency models.

# What is our research motivation?

”Similar graphs could be provided for left- and right-turns (using the changes in angles obtained from the GPS data).”

- Wuthrich (2017)

- Literature hasn’t paid attention to the LATERAL acceleration much.
- GPS data is popular in the literature, but it is NOT suitable for the analysis of the lateral movement of vehicle.
- Acceleration data used in the literature including actuarial science has NOT been calibrated for driving profile construction.

# Telematics Research in other field

Research in other fields use other types of data beside GPS data

- Recognize driving events such as turns, swerving, and braking using IMU data format (Johnson & Trivedi, 2011)
- Aljaafreh et al. (2012) clusters the driving style into categories using accelerometer.

The acceleromter is also popular, and it is one of the inertial measurement units (IMUs) of smartphones.

# Smart phone sensors and Data recording

# Global Positioning System

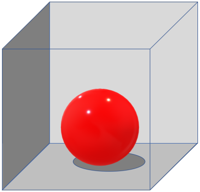
GPS sensor receives the information about the sensor position from multiple satellites.

- Latitude, longitude, altitude, speed, and sensor heading
- GPS position error: approx. 4.9 m (16 ft.) under open sky

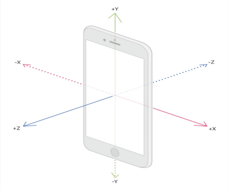
In urban areas accuracy falters due to blocking & reflection; buildings, bridges, and trees

# Accelerometer

- Below is a toy model of the accelerometer
- The accelerometer records the force that applied to the wall of the box in the figure.
  - At rest on a flat, horizontal surface it measures: $g \approx 9.81 m/s^2$.
  - In free fall, it measures zero.



(a) A box model for understanding accelerometer

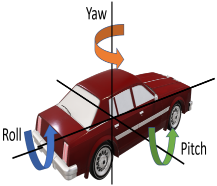



(b) The three directions of accelerometer

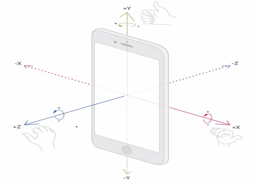
# Gyroscope

A gyroscope is a device used for measuring angular velocity.

- Three measurements comes from each axis of gyroscope: Roll, Pitch, and Yaw
- Absolute orientation of smartphone can be calculated from gyroscope by integrating the angular velocity




(a) The interpretation of roll, pitch and yaw



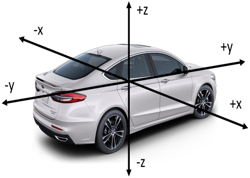
(b) The three directions of gyroscope

# Data recording

IMU data are generated by a smartphone attached to a vehicle as follows;

- Sampling rate: 25 Hz (25 data points per 1 sec.)
- Device: iPhone 6
- Data recording app: Sensor play

(a) Device installation in the vehicle




(b) Three axes of sensors that the vehicle shares with the installed smart phone

# Sample test route

The sample route for the calibration consisted of complicated road components

- Flat road, uphill incline, downhill decline, and turns


Figure: Sample route for the calibration

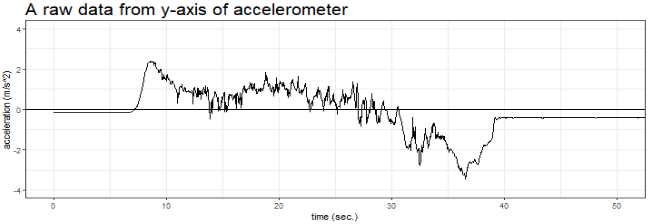
# Data recording result and calibration

# Accelerometer data

The below is the sample plot of accelerometer values for the first 50 seconds of sample route.

- From the longitudinal accelerometer data, the vehicle speed can be estimated by using the following integration formula;

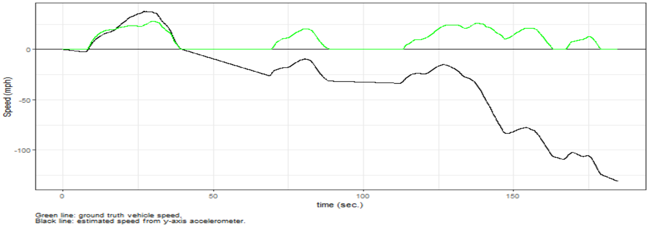
$$speed_t = speed_{t-1} + \Delta t \times acc_t$$



# Speed from accelerometer data

There is a difference between the estimated speed from the accelerometer values and vehicle speed.

- Uphill (25 sec.) and downhill (125 sec.), stopped at the tilted road (50 sec.)

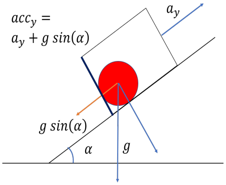


# Road grade effect

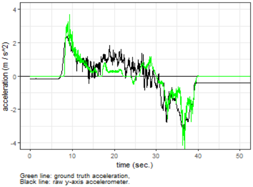
The integration method does not work, because of the road grade effect.

- Accelerometer measures the acceleration applied to the sensor body, which includes the gravity force accused by the road grade $\alpha$.

$$a_t = acc_t - g \times sin(\alpha_t)$$




(a)

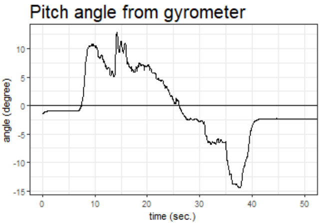


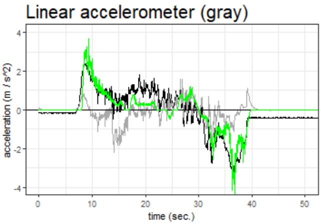

(b) Green line is the approximation of ground truth acceleration from OBD using spline

# Road grade estimation

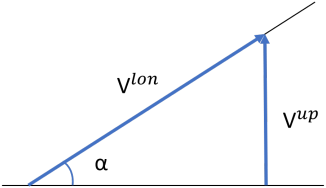
Gyroscope measures pitch angle which is an angle between the horizontal plane and the plane that the smartphone attached to.

- Pitch angle is NOT the same as the road grade, $\alpha$, because of the acceleration and deceleration of vehicle.
- Linear accelerometer values are the gravity adjusted accelerometer value using the pitch angle from gyroscope.



# Speed estimation with road grade and Kalman filter



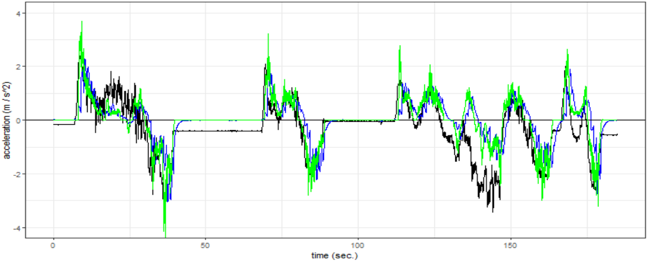

Kalman filter can be used for combining the information from multiple sources;

- Source 1:
  - Speed: y-axis accelerometer
  - Road grade: gyroscope pitch angle
- Source 2:
  - Speed: GPS
  - Road grade: $v^{long}$ and $v^{up}$ (GPS)

# Calibration result - Longitudinal acceleration

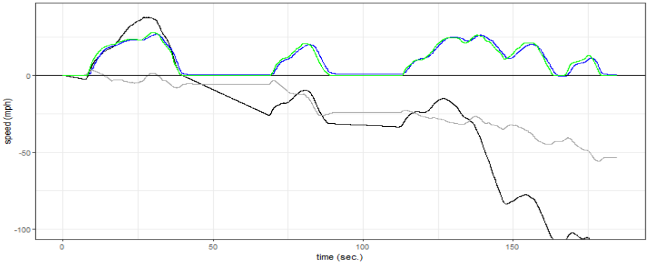
Kalman filtered (blue) vs. raw accelerometer (black)

- Kalman filtered accelerometer (blue) synchronized with the longitudinal acceleration estimated from OBD (green)



# Calibration result - Speed graph

- Kalman filtered speed (blue) synchronized with the speed from OBD (green)
- the estimated speed from the raw accelerometer (black)
- the estimated speed from the linear accelerometer (grey)




The University of Iowa

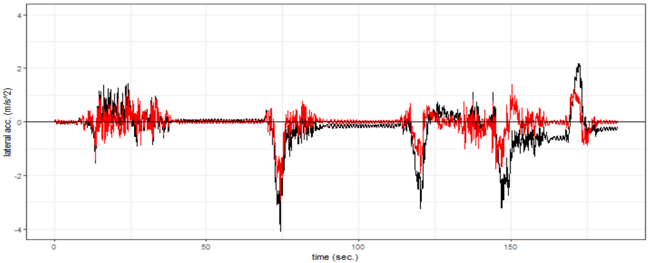
# Calibration result - Lateral acceleration

Lateral acceleration can be obtained as follows;

$$a_x = acc_t^x - g \times sin(\phi_t)$$

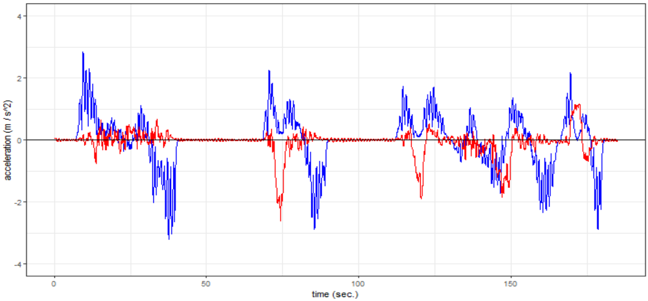
where $\phi_t$ is roll angle from gyroscope.

- The roll angle can capture the road grade effect for the lateral movements of the vehicle since it is relatively stable than pitch angle.



# R package for lon. and lat. acc calibration

R package *ikhyd* [1] *can do this for you;*

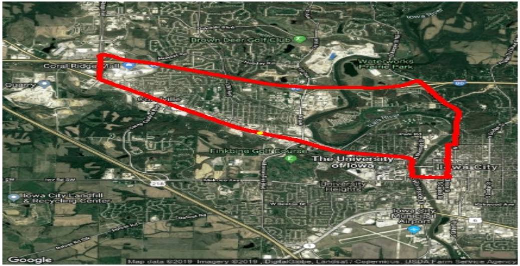



[1] https://github.com/issactoast/ikhyd

# The driving style analysis

# Test route for the analysis

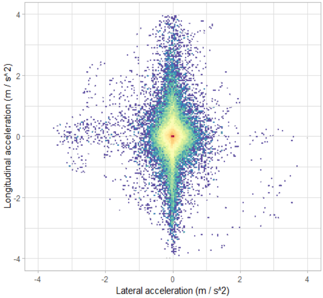
- The test route for the driving style analysis for four drivers.
- We control time (5pm - 6pm) and vehicle (Ford fusion 2015)
- Route takes about 25 min. per each driver.



# Lon-Lat Plot

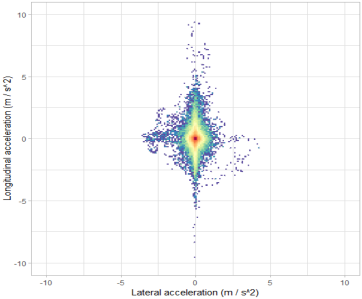
One way of constructing a driving profile using the calibrated telematics data is to draw a Lon-Lat plot.

- Discrete density plot of the calibrated telematics data
  - Interpretable
  - Suitable for lateral acceleration analysis

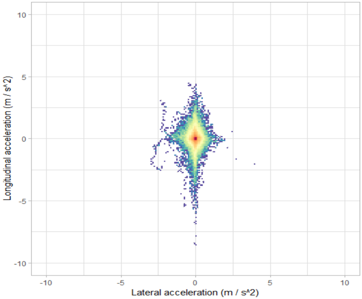


# Comparison of the calibrated Lon-Lat plot

The comparison between driver 1 and 3. Which one is riskier?



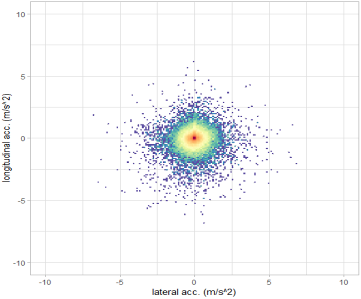

(a) Driver 1



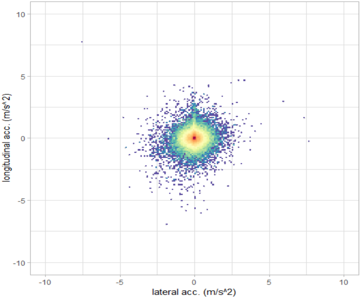

(b) Driver 3

# Comparison of the linear acc. based Lon-Lat plot

The comparison between driver 1 and 3.



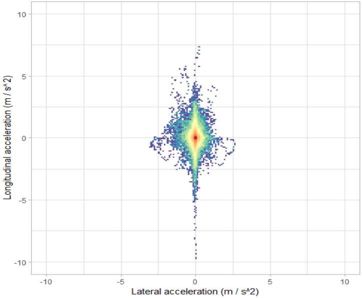

(a) Driver 1



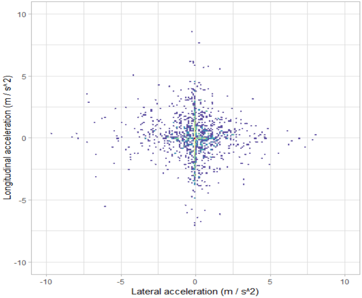

(b) Driver 3

# Calibrated vs. GPS Lon-Lat

The calibrated Lon-Lat is more suitable for the lateral acceleration analysis than the GPS data.




(a) Calibrated based Lon-Lat (Driver 2)




(b) GPS based Lon-Lat (Driver 2)

# Conclusion

- The telematics data from smartphone sensors need a careful calibration process.
- Traditional telematics data used in actuarial science could lead to a miss interpretation of lateral movement of driving behavior.
    - GPS data could have an erroneous interpretation about the lateral vehicle movement.
    - Linear accelerometer data lose the information about driver's driving style.
- Since the calibrated telematics data contains the longitudinal and lateral movement behavior of the driver, it could become a fundamental building block for more realistic telematics analysis.


Thank you!

# Selected References


Aljaafreh, A., Alshabatat, N., and Al-Din, M. S. N. (2012). Driving style recognition using fuzzy logic. In *2012 IEEE International Conference on Vehicular Electronics and Safety (ICVES 2012)*, pages 460–463. IEEE.

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Weidner, W., Transchel, F. W., and Weidner, R. (2016). Classification of scale-sensitive telematic observables for riskindividual pricing. *European Actuarial Journal*, 6(1):3–24.

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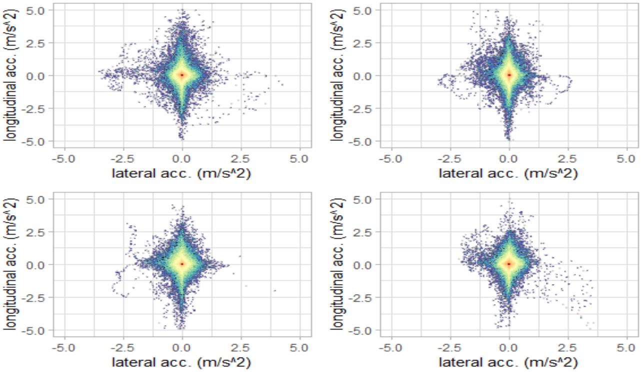
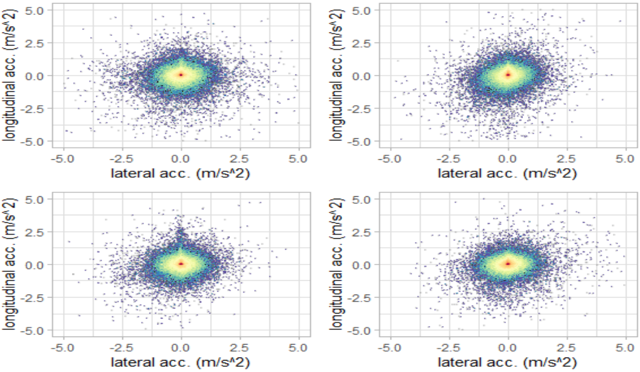
Wüthrich, M. V. (2017). Covariate selection from telematics car driving data. *European Actuarial Journal*, 7(1):89–108.

# Appendix

# Calibrated acc. based Lon-Lat plots for four drivers

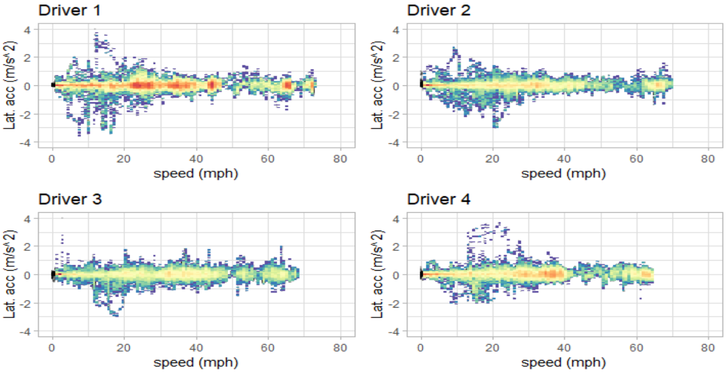


# Linear acc. based Lon-Lat plots for four drivers



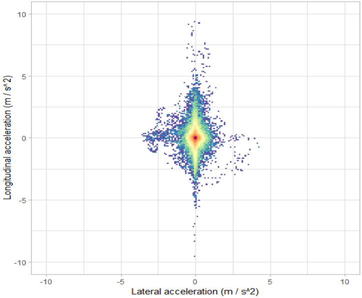
# Information in lateral acceleration

Using the lateral acceleration, we can draw v-a heatmap instead of using the longitudinal acceleration.

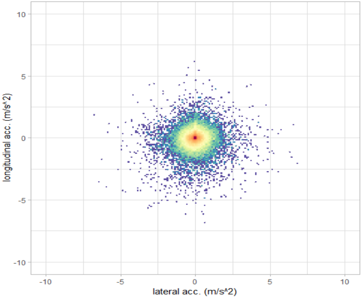


# Calibrated vs. Linear Lon-Lat

The calibrated Lon-Lat is more interpretable than the linear accelerometer-based Lon-Lat plot.



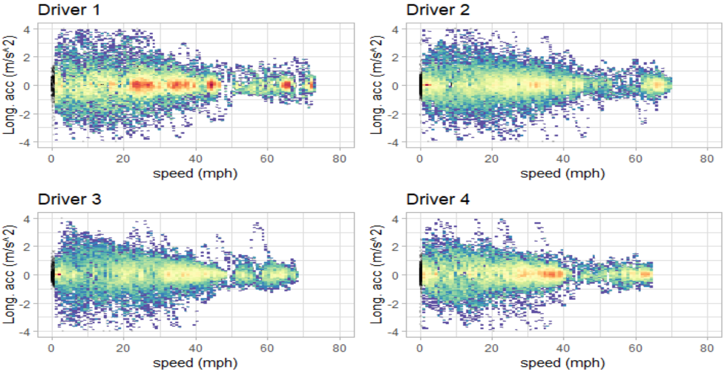

(a) Calibrated acc. data based Lon-Lat (Driver 1)




(b) Linear acc. data based Lon-Lat (Driver 1)

# Transform to a v-a heatmap using IMU data

The calibrated 3-tuples of long. and lat. acceleration and speed also can be used to draw v-a heatmap.



# GPS driving profiling (Driver 1 vs. Driver 2)

The lateral acceleration information from GPS data could lead to an erroneous decision.

- Driver 1 has sharper and harder turns than Driver 2 in the comparison of the calibrated Lon-Lat plots, but not in the GPS based Lon-Lat.