

Claims Frequency Modeling using Telematics Car Driving Data

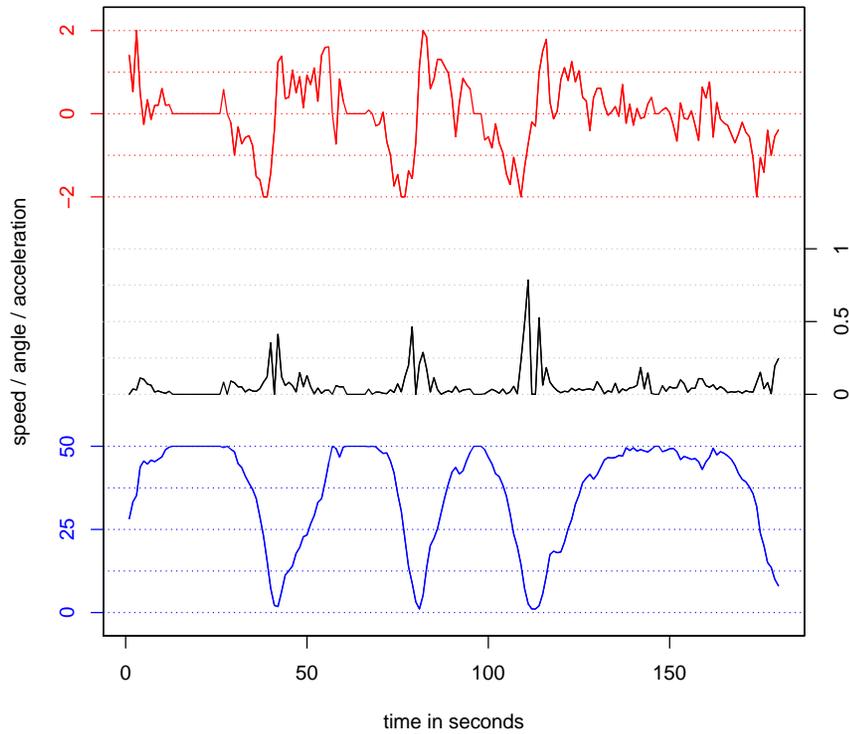
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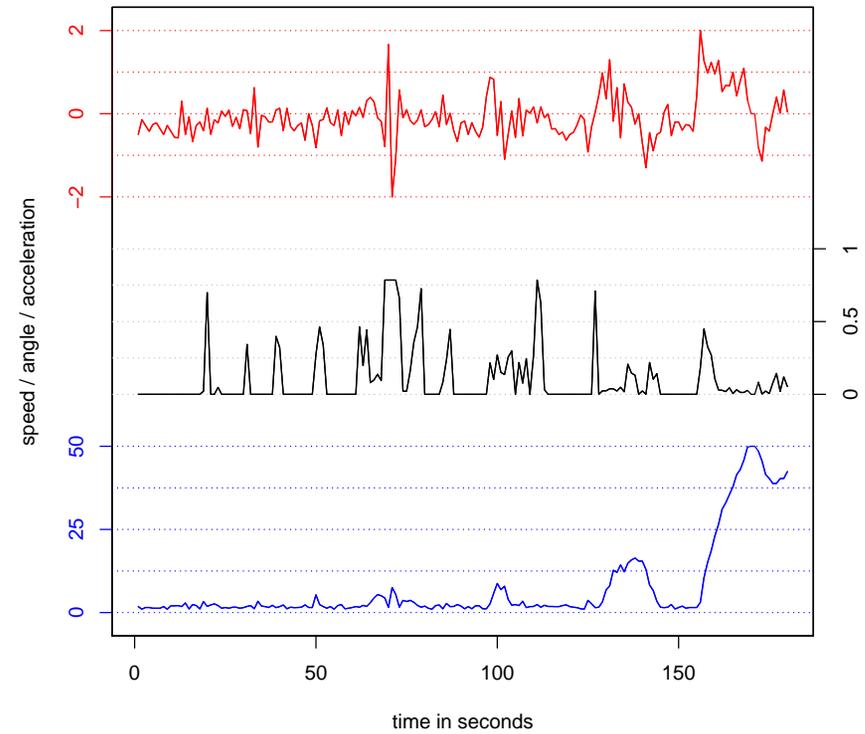
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Telematics Car Driving Data

driver 21, trip number 1



driver 20, trip number 7



acceleration / change in direction / speed

Available Car Driving Data

- ▷ Find **structure** (**driving styles**) in features

$$\{\mathbf{x}_1, \dots, \mathbf{x}_n\} \subset \mathcal{X},$$

of n insurance policies in a given feature space \mathcal{X} .

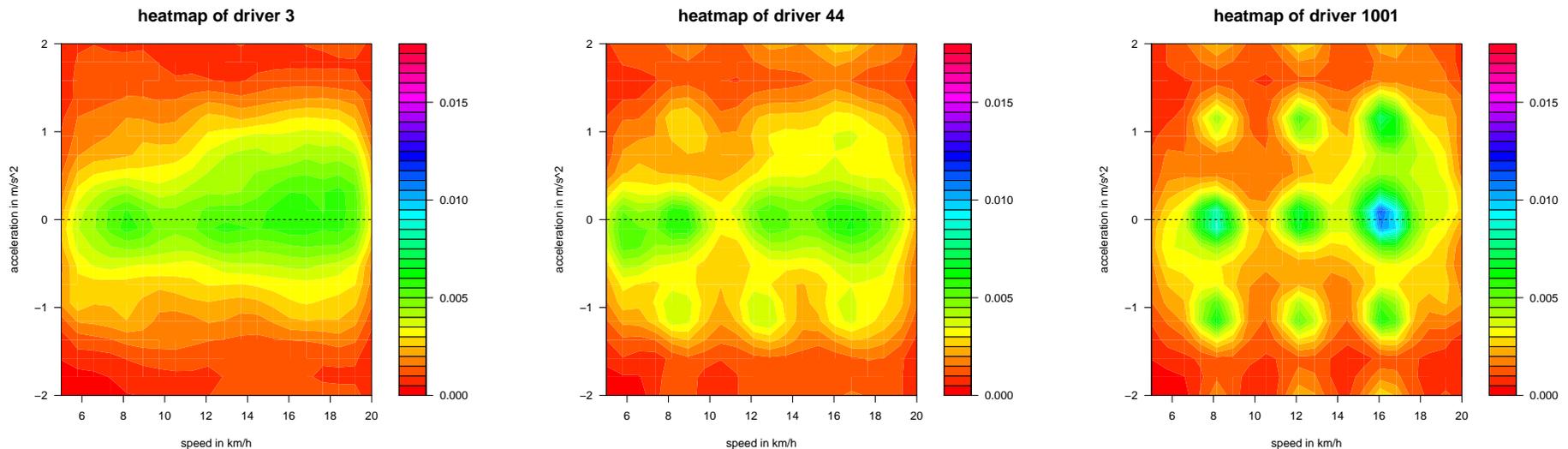
- **Data:** 12'076 drivers with
 - ★ classical features like age, gender, type of car, prize of car, etc.,
 - ★ telematics data of all trips including GPS location (sec by sec), time stamp, speed, acceleration (in all directions), engine revolutions per minute,
 - ★ claims data,
- from 2014-2017 (1GB per day, 1.5TB in total).

Two Different Approaches for Driving Styles

- Score individual trips.
- Build summary statistics per driver (law of large numbers) and score those.

Normalized v - a Heatmaps

- Calculate v - a heatmap of all trips in speed bucket $[5, 20)$ km/h for all n drivers.
- These heatmaps measure the amount of time spent in a (v, a) location.
- Normalization gives (discrete) probability distributions x_i for drivers $i = 1, \dots, n$.



v - a heatmaps of drivers $i = 3, 44, 1001$ in speed bucket $[5, 20)$ km/h.

Autoencoders for Data Compression

- **Encoder:**

$$\varphi : \mathcal{X} \rightarrow \mathcal{Z},$$

where \mathcal{Z} is low-dimensional.

- **Decoder:**

$$\psi : \mathcal{Z} \rightarrow \mathcal{X}.$$

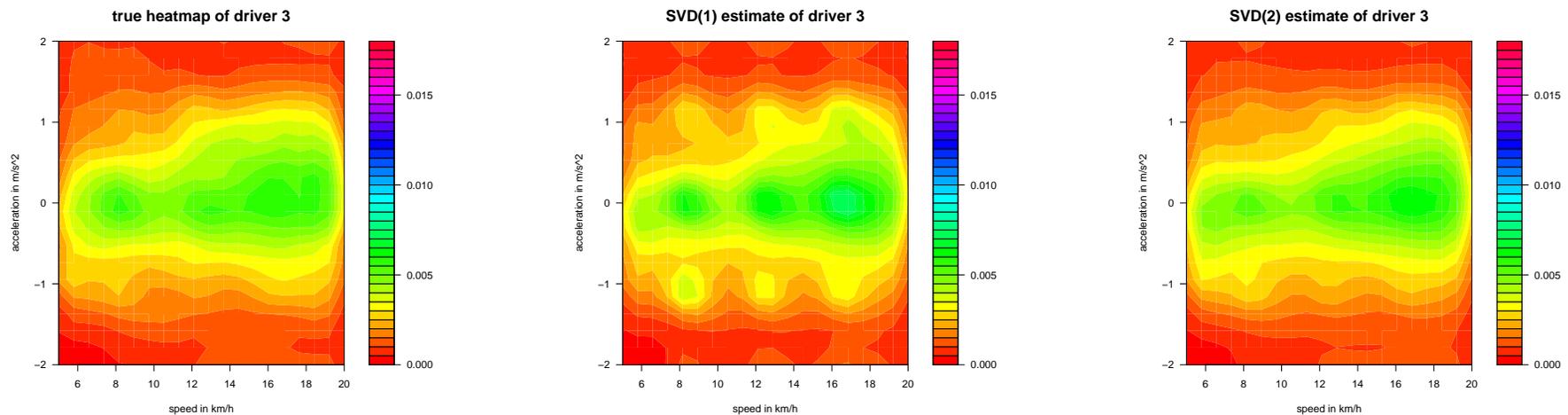
- **Goal:** Choose functions φ and ψ such that

output $\pi(\mathbf{x}) = \psi \circ \varphi(\mathbf{x})$ is close to input \mathbf{x} .

▷ $\varphi(\mathbf{x}) \in \mathcal{Z}$ is used as low-dimensional representation for $\mathbf{x} \in \mathcal{X}$.

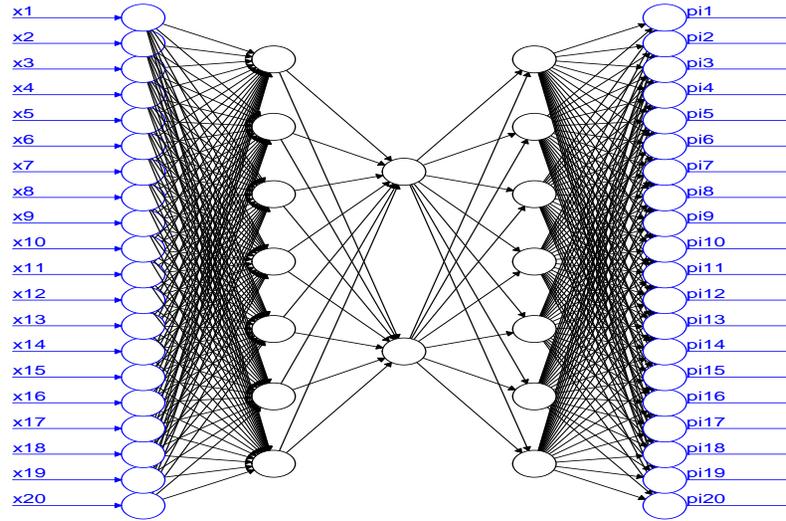
Principal Component Analysis (PCA)

- Consider the design matrix $\mathbf{X} = (\mathbf{x}'_1, \dots, \mathbf{x}'_n)' \in \mathbb{R}^{n \times d}$ of rank $d \leq n$.
- Singular value decomposition (SVD) provides (an) optimal approximation \mathbf{X}_q of design matrix \mathbf{X} of (smaller) rank $q \leq d$ (in Frobenius norm).



SVD result of driver $i = 3$ for ranks $q = 1, 2$ (true heatmap on the left).

Bottleneck Neural Network Autoencoder

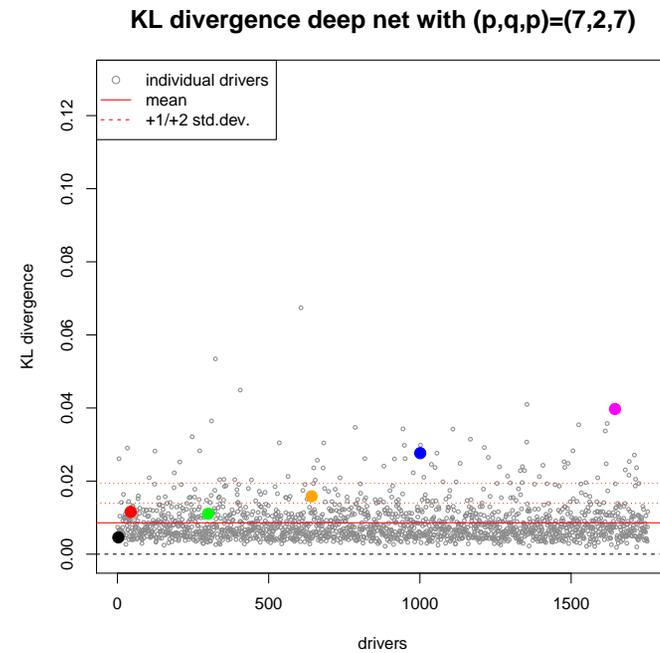
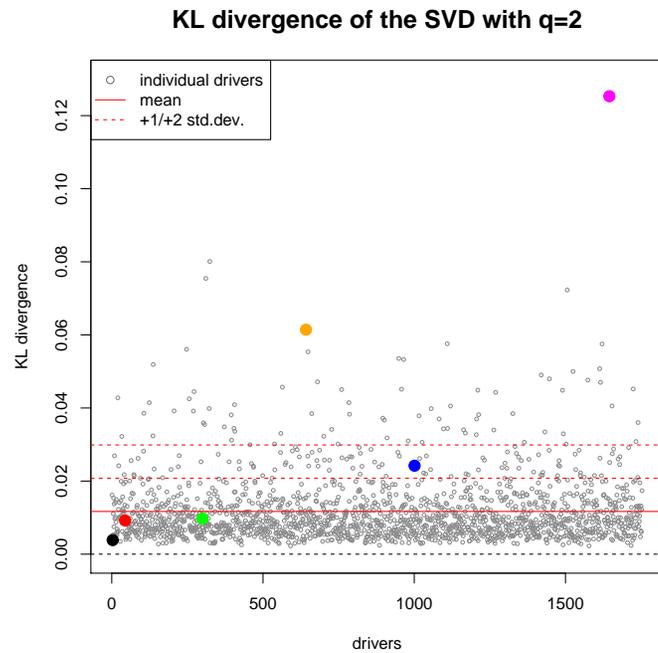


- Calibrate **bottleneck neural network** such that inputs x_i and outputs $\pi_i = \pi(x_i)$ are **close** in Kullback-Leibler (KL) divergence

$$\mathcal{L}_{\text{KL}}((x_i)_i, (\pi_i)_i) = \frac{1}{n} \sum_{i=1}^n d_{\text{KL}}(x_i \parallel \pi_i).$$

- **Signals** at the **bottleneck** are the \mathcal{Z} -representations of drivers $i = 1, \dots, n$.

SVD vs. Bottleneck Network for $q = 2$



KL divergences of SVD and the bottleneck neural network

(drivers $i = 3, 44, 300, 1001; 642, 1645$).

- **Predictive Power of v - a Heatmaps?**

Poisson GAM Regression Models

Assume for $i = 1, \dots, n$

$$Y_i \stackrel{\text{ind.}}{\sim} \text{Poi}(\lambda(\mathbf{x}_i)v_i),$$

with exposures $v_i > 0$ and regression function $\lambda : \mathcal{X} \rightarrow \mathbb{R}_+$ given by

Model 0: $\log \lambda(\mathbf{x}) = \beta_0 + s_1(\text{age driver}) + \beta_2 \cdot \text{age car},$

Model 1: $\log \lambda(\mathbf{x}) = \beta_0 + s_1(\text{age driver}) + \beta_2 \cdot \text{age car} + \beta_3 \cdot \text{PCA}(\text{heatmap}),$

Model 2: $\log \lambda(\mathbf{x}) = \beta_0 + s_1(\text{age driver}) + \beta_2 \cdot \text{age car} + \beta_3 \cdot \text{BN}(\text{heatmap}).$

	cross-validation out-of-sample loss	std. dev. error
Model 0 (GAM classic)	1.4806	0.0240
Model 1 (PCA)	1.4573	0.0266
Model 2 (bottleneck net)	1.4579	0.0232

Conclusions

- v - a heatmaps allow for low-dimensional representations and approximations.
- Do these heatmaps have predictive power? Preliminary analysis shows “yes”!
- We have central limit theorems and rate of convergence for v - a heatmaps.
- Other speed buckets and claim sizes?