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Understanding Vehicle Reliability and Safety with Multivariate Sensory Data: A Tire Wear Case Study

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Modern automotive vehicles are getting smarter as they are heavily deployed with sensors throughout in order to meet the evolving efficiencies, security and environmental standards, as well as government regulations. Several types of sensors are used in automotive vehicles for monitoring engine operations, external conditions, vehicle dynamics and tire internal states such as Tire Pressure Monitoring Systems (TPMS).

Some of the car sensor functionalities include recording and transmitting the measured signals to some database over period of usage, leading to a collection of complex and large data sets from multiple sensory sources. Such complex data sets usually have multiple highly correlated variables represented in a sequential fashion. Our goal is in two folds: first, to study ways of extracting useful signal patterns from features that better explain tire wear sensitivity to usage over long periods. This realm requires complex data processing approaches, such as ranking features according to their importance, mapping relationships, correlations and possible causalities. Secondly, the information has to be compressed in order to learn a simplified representation of the data-sets. From our core goals, we explore methodologies that can efficiently reduce large multivariate time series data into smaller, manageable and meaningful subsets whilst maintaining the original integrity. We do this with linear methods such as Principal Component Analysis (PCA) and non-linear compression methodologies using deep learning (DL) approaches like auto-encoders (EA) [1], variational auto-encoders (VAE) [2] and auto-encoding generative adversarial networks (AE-GAN) [3] focusing on the latent spaces representation.

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