Road conditions analysis and forecasting in Arctic: multi-source machine learning approach

J. Suutala, M. Malin, H. Tiensuu, S. Tamminen
Biomimetics and Intelligent Systems Group
University of Oulu, Finland

The 28th IUGG General Assembly in Berlin
Symposium on Machine Learning in Geo-, Ocean and Space Sciences
15th Jul 2023

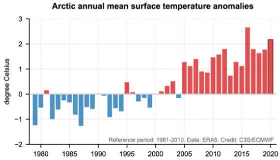
email: jaakko.suutala@oulu.fi

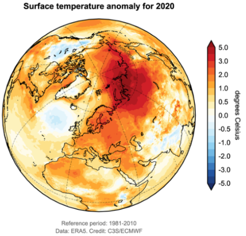
Outline

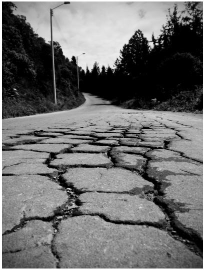
- Background and motivation
- Study sites and measurements
- Road quality forecasting
- Evaluation and analysis
- Future perspectives

Background and Motivation

- Extreme and unusual weather conditions are increasing (especially in sub-Arctic and Arctic regions)
- On-going Academy of Finland multi-disciplinary project studying climate change mitigation of (urban) infrastructure
- Preliminary research on data-driven road quality/damage forecasting and proactive maintenance



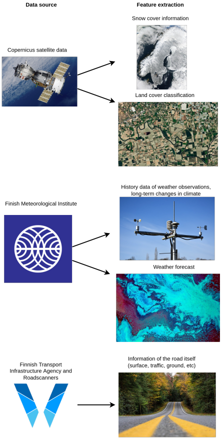




Images: C3S/ECMWF, CC0 Public Domain

Background and Motivation (cont'd)

- Multi-source data-driven approaches for modelling and forecasting
  - Machine learning framework for combining multimodal data
  - Analysis of weather, climate, and geological data, and their effects to road quality and damages
  - Practical forecasting models from sparse time-series measurements



Images: Copernicus, Creative Commons

Study Sites

- Asphalt roads in northern Finland (sub-Arctic, near Arctic region)
- In this study, three different sites where we have:
  - Road surface quality data, 2015-2022
  - Long-term weather and road surface/ground data from road weather stations, 2010-2022
  - Additional data: meas. locations, past road maintenance info, surrounding soil types etc.

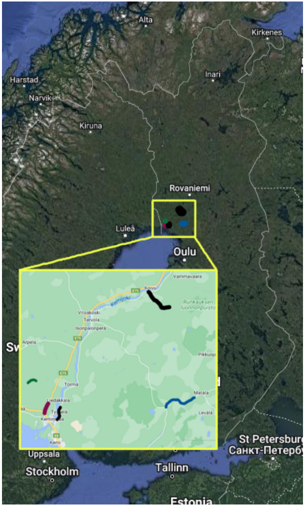
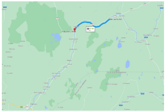
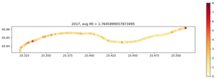


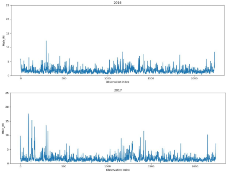
Image: Google maps

Measurements

- Annual road condition and quality data
  - Road surface: International Roughness Index (IRI) (Roadscanners Ltd., IMU-based system)
  - Past maintenance information (open data)
- Static ground data: soil types (open data)
- Daily and sub-hourly observations from the closest road weather stations (open data)
  - Ground temperature
  - Precipitation







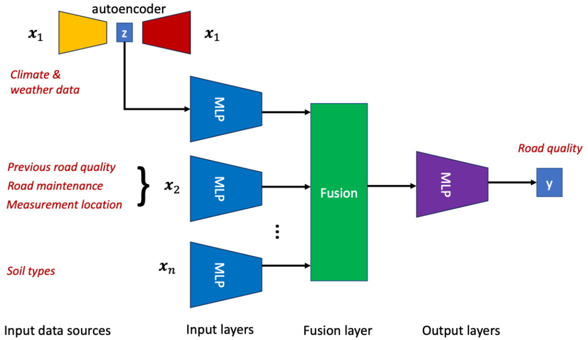
Left image: Roadscanners Ltd.

Dataset Preparation

- Pitch IRI measurements in 100 meter segments (10 meter interval)
  - Input: current year 10 IRI values from each segment
  - Output: next year 10 IRI values from each segment
- 2D Location of each IRI segment
- Past maintenance: days since last repair for each segment, 3+3 repair types from last two maintenance
- Daily road weather / climate data
  - 12 hand-coded features: ground temperature (mean & std) and precipitation (sum & std) for 3 seasons (autumn, winter spring)
  - 64 length latent feature vector: autoencoding of seasonal ground and precipitation observations
- 12 soil types: generic type (such as coarse soil, fine soil, clay etc.) in the road segment

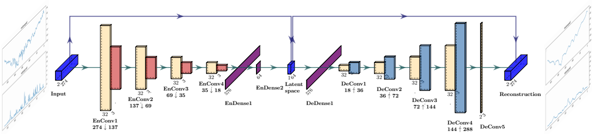
Road Quality Forecasting: Framework

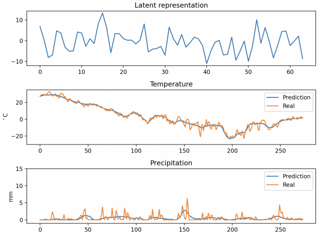
- Deep learning framework for forecasting road quality
  - Autoencoder and feed-forward backbone (input layers), fusion embedding (fusion layer), and regression feed-forward head (output layers)

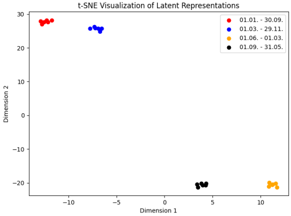


Road Quality Forecasting: Autoencoder

- Stacked convolutional autoencoder for feature extraction
- Latent low-dimensional representation of seasonal weather: daily ground temperature and precipitation

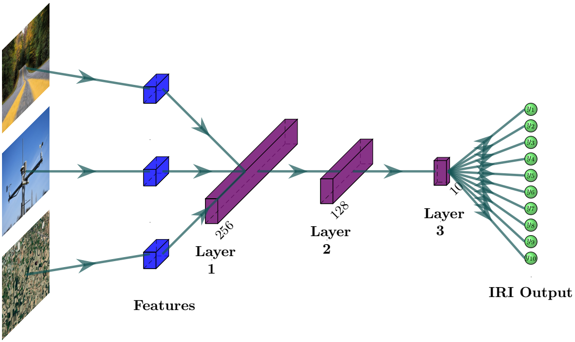






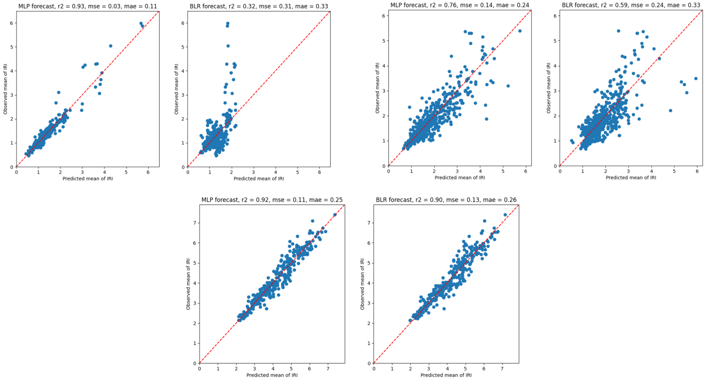
Road Quality Forecasting: MLP

- Feed-forward deep neural networks
  - Multi-layer perceptron (MLP) with multi-source inputs
  - Concatenated fusion, dense ReLU layers



Road Quality Forecasting: Results

- Deep learning approach: MLP + Conv. autoencoder (Early stopping, Adam optimizer with learning rate 1e-4)
- Baseline: Bayesian linear regression (BLR) model (Gaussian priors, HMC sampling with 4 chains and 8000 samples)



Road Quality Forecasting: Results (cont'd)

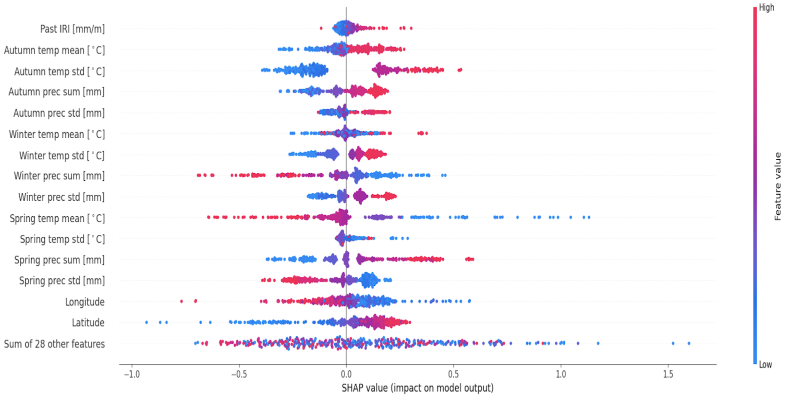
- Comparison of baseline (BLR), MLP, and MLP with convolutional autoencoder

Road	**Baseline (BLR)**			**MLP**			**MLP+Conv-AE**		
	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$
428	0.32	0.31	0.33	0.91	0.04	0.12	**0.93**	**0.03**	**0.11**
924	0.59	0.24	0.33	**0.76**	**0.14**	**0.24**	**0.76**	**0.14**	**0.24**
19541	0.90	0.13	0.26	0.91	0.12	0.26	**0.92**	**0.11**	**0.25**
Avg.	0.60	0.23	0.31	0.86	0.10	0.21	**0.87**	**0.09**	**0.20**

Table: IRI prediction performance.

Road Quality Forecasting: Explainability

- Explainability of MLP predictions (Road 428)
- Shapley Additive Explanations (SHAP)



Road Quality Forecasting: Data Sources

- Influence to prediction performance by adding data sources (Road 428)

Metric	Fusion of data sources				
	IRI	+Weather	+Maint.	+Soil type	+Loc.
$R^2 \uparrow$	0.15	0.41	0.51	0.79	0.93
MSE ↓	0.39	0.28	0.23	0.10	0.03
MAE ↓	0.28	0.24	0.23	0.16	0.11

Table: IRI prediction performance with fusion of data sources.

Future Perspectives

- Extending ML models with different sources: road structural course (e.g., using ground penerating radar), amount of daily traffic, snow water content and soil moisture etc.
- Country (and other (sub-)Arctic regions) level long-term spatio-temporal forecasting
- Studying of more advanced fusion strategies in framework
- Adding more explainability and physics-aware properties to AI/ML framework

Contact Information and Acknowledgement

Data Analysis and Inference Group @ BISG:
https://www.oulu.fi/bisg/data-ai

http://www.cc.oulu.fi/~jsuutala19
e-mail: jaakko.suutala@oulu.fi

The work is supported by Academy of Finland (ADAPTINFA project, decision number: 348811).