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1 MOTIVATION
ELECTRO-MOBILITY CONTEXT

Electric vehicle acceptance level among customers

Impediments [1,2]:
- range anxiety
- inconvenient charging
- higher price

Ease:
- reliable range assistant
- specific route planning
- proactive driving support

“Impediments: Electric vehicle acceptance level among customers”

[1] Yan, Q.; Qin, G.; Zhang, M.; Xiao, B. Research on Real Purchasing Behavior Analysis of Electric Cars in Beijing Based on Structural Equation Modeling and Multinomial Logit Model. Sustainability 2019, 11, 5870.

[2] Hüben, Y.; Blythe, P.T.; Higgins, G.A.; Hill, G.A.; Neaimeh, M., Eds. Use of its to overcome barriers to the introduction of electric vehicles in the North East of England, 2012.
DRIVING PROFILE

vehicle sensory data | spatio-temporal segmentation | Driving Profile Map Attribute Distributions (DPMADs)

\[ E_{Route, an~Batterieklemme} = \sum_{\text{Start}}^{\text{Ziel}} \frac{1}{\eta \cdot \text{sign}(F_{Rad})} \int_{x_n}^{x_{n+1}} \begin{bmatrix} \alpha(s) \\ v^2(s) \\ \cos(\alpha(s)) \\ \sin(\alpha(s)) \end{bmatrix}^T \begin{bmatrix} m \\ e \\ \rho \cdot c_s \cdot A \\ \frac{2}{f_R \cdot m \cdot g} \end{bmatrix} ds + \frac{\Delta t_n}{\bar{v}_n^2} \cdot P_{NV,n} \]

Integral acceleration \( \frac{m}{s^2} \) | Integral squared velocity \( \frac{km^2}{h^2} \) | Average velocity \( \frac{km}{h} \)
2

PROBLEM STATEMENT & OBJECTIVES
PROBLEM STATEMENT

fleet data set at time $t_n$
PROBLEM STATEMENT

fleet data

time interval 1 of 30 min

06:00 06:30 07:00 \cdots 23:00 23:30 00:00

fleet data set at time $t_n$
Problem scenarios:

- Missing sensory data for spatio-temporal buckets
- Lost connection to the backend
PROBLEM STATEMENT

**Input**

- fleet data

- all weekdays

- every 30 min
PROBLEM STATEMENT

**Input**
- fleet data

**Output**
- 5 DPMADs
- a natural number n of a cluster representative (e.g. cluster #2)

% 
0.00 0.25 0.50 0.75 1.00

ISV_{rec} 
0 50 100 150 200 250

all weekdays
every 30 min

fleet data

50 m 50 m 50 m
PROBLEM STATEMENT

Input

? 

all weekdays 

every 30 min 

50 m 50 m 50 m 

Output

5 DPMADs 

a natural number n of a cluster representative (e.g. cluster #2)
SOLUTION APPROACH

Input

Map features:
- slope
- curvature
- functional road class
- speed limit

Data imputation

supervised Machine Learning (ML) methods:
- Regression
- Classification

Output

- 5 DPMADs
- a natural number n of a cluster representative (e.g. cluster #2)

fleet data / connection

all weekdays

every 30 min

50 m 50 m 50 m
3 METHODOLOGY
EXPERIMENTAL SETUP

**Data Set**

|          | Traces(km) | Traces (count) |
|----------|------------|----------------|
| training | 3.503.958  | 95% of Munich  |
| test (Munich) | 556.135  | 5% of Munich  |
| test (Leipzig) | 554.366   | similar to Munich |

**Comparison based on problem and test scenarios**

- **feature extraction**
  - slope, curvature: {min, max, average}

- **outlier detection**
  - Inter Quartile Range (IQR) method
  - Q1 - 1.5·IQR < filtered output < Q3 + 1.5·IQR
  - reconsider the structure of DPMADs

- **clustering**
  - addressed in previous Master Thesis [3]
  - robustness of the model: DPMADs based on 3 or more measurements

- **regression**
  - Linear Regression algorithm
  - main parameters:
    - fit-intercept = true, normalise = false

- **classification**
  - Decision Tree algorithm
  - main parameters:
    - max-depth = 10, splitter="best"

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[3] Martin Kiener, Master Thesis: Clustering of Fleet Data for Energy Prediction, May 2019
### EVALUATION SCENARIOS

| Test Scenario | Problem Scenario | Lost Backend Connection | Missing Data |
|---------------|------------------|-------------------------|--------------|
| Leipzig area  | regression ↔ classification |                         |              |
| Munich area   | regression ↔ classification | regression ↔ classification |              |
4

RESULTS
Integral Acceleration (IA)
Clsf (-1.5%)
Clsf (-2.3%)
similar (0.0%)
Clsf (-2.1%)

Integral Squared Velocity (ISV)
Clsf (-3.2%)
Regr (-10.7%)
Clsf (-1.3%)
Regr (-12.4%)

Average Velocity (AV)
Regr (-27.2%)
Regr (-28.9%)

- Classification model: perform better in most cases
- Regression model: bigger performance advantages

need problem-specific interpretability
Problem scenarios

- **Lost connection:**
  - the regression model better for both cross validation and application testing sets
  - no relevant overfitting

- **Missing data:**
  - closest to real world situation
  - regression model outcomes within the values in literature (4-8%) [4,5]

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**Table:**

| training region | Munich area | Munich area | Munich area |
|-----------------|-------------|-------------|-------------|
| testing region  | Leipzig area | Munich area | Munich area |
| data imputed    | 100%        | 100%        | 30%         |

[4] Masikos, M.; Demestichas, K.; Adamopoulou, E.; Theologou, M. Mesoscopic forecasting of vehicular consumption using neural networks. Soft Computing 2015, 19, 145–156.
[5] Sarrafan,K.;Mutaqi,K.M.;Sutanto,D.;Town,G.E. AReal-Time Range Indicator for Evs Using Web-Based Environmental Data and Sensorless Estimation of Regenerative Braking Power. IEEE Transactions on Vehicular Technology 2018, 67, 4743–4756.
CONCLUSIONS & OUTLOOK
5 CONCLUSIONS & OUTLOOK

| System Parameter                  | Outlook                                                                 |
|-----------------------------------|-------------------------------------------------------------------------|
| input features                    | - include further available map features                                |
|                                   | - real time features, e.g. weather, traffic                             |
| feature engineering               | - cross correlations                                                     |
|                                   | - higher polynomial degree                                              |
| machine learning algorithms       | - more sophisticated algorithms, e.g. Neural Networks, Support Vector Machines |
|                                   | - further parametric optimization                                       |

Conclusions

- regression model can be deployed in the vehicle given the achieved performances:
  - ✓ lost connection scenario (worst case): 12.6% error
  - ✓ missing data scenario: 7.2% error comparable to related works

- reliable and precise energy prediction

- raise BEVs acceptance level
THANK YOU FOR YOUR ATTENTION!