Forecasting charging station occupancy using supervised learning algorithms

Adrian Ostermann, Yann Fabel, Kim Ouan

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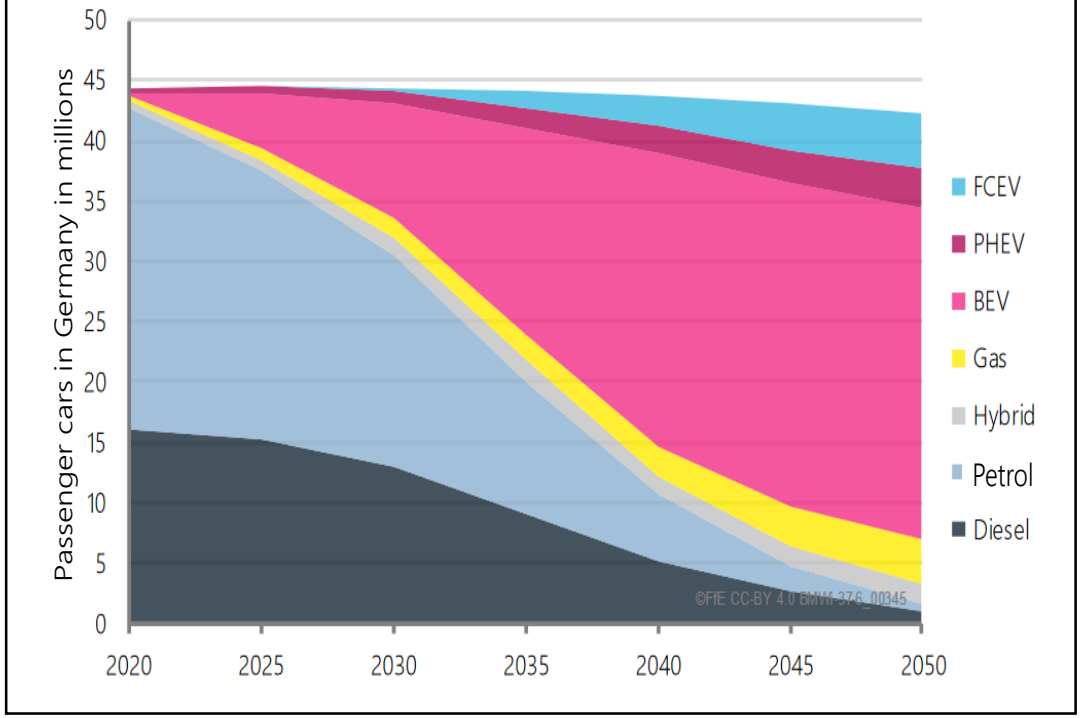
Federal Ministry
for Economic Affairs
and Energy

Agenda

1. Motivation
2. Methodology
3. ACN Data
4. Evaluation
5. Summary & Outlook

Motivation

Development car types in GER [1]



FCEV: fuel cell electric vehicles
PHEV: plugin-in-hybrid
BEV: battery-powered electric vehicles
CP: Charging Point

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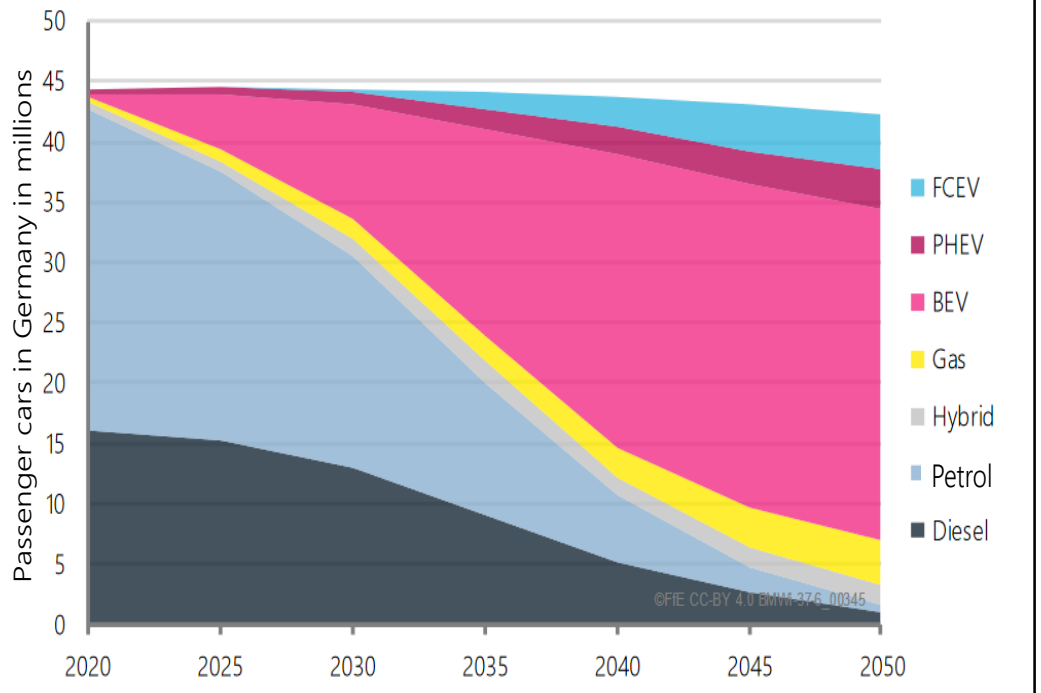

Development charging points in GER [2] [3]

- National Centre for Charging Infrastructure 2030:
  - 440.000 to 843.000 public CP
  - 2.5 Mio to 2.7 Mio. CP at work
- Directive 2014/94/EU:
  - 10:1 ratio of EV to publicly accessible CPs

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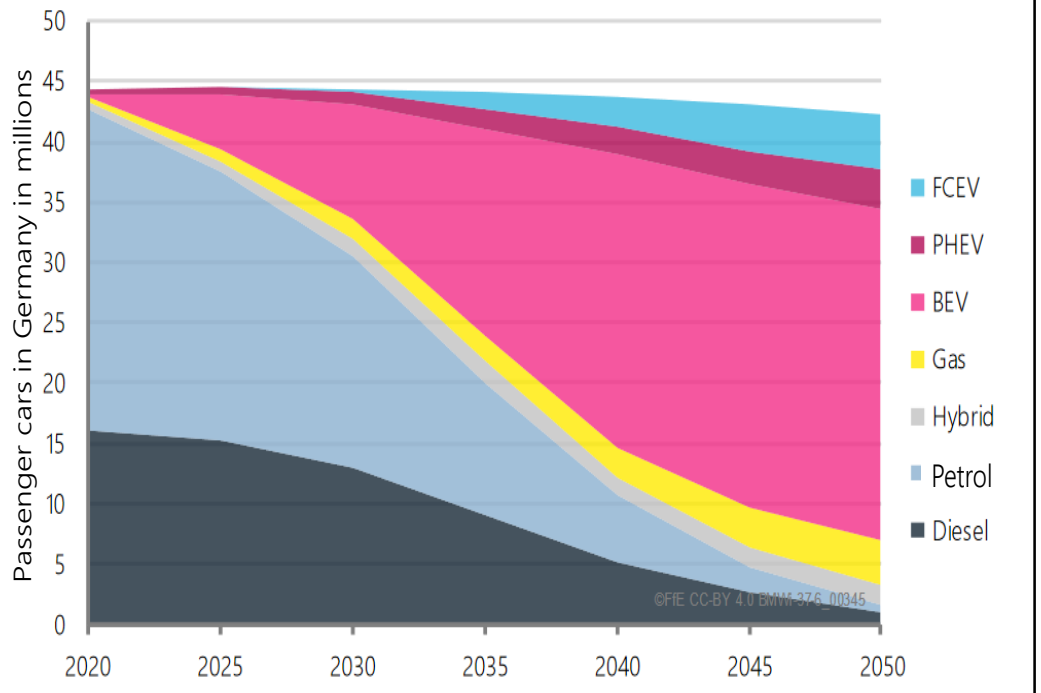

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Charging behaviour in GER [2]

- 20 % of charging done at work
- 12 to 24 % (depending on charging behaviour development) at public CP
- 70 % of EV Users use a public CP at least once per month

->Available infrastructure is one of the main constraints for users

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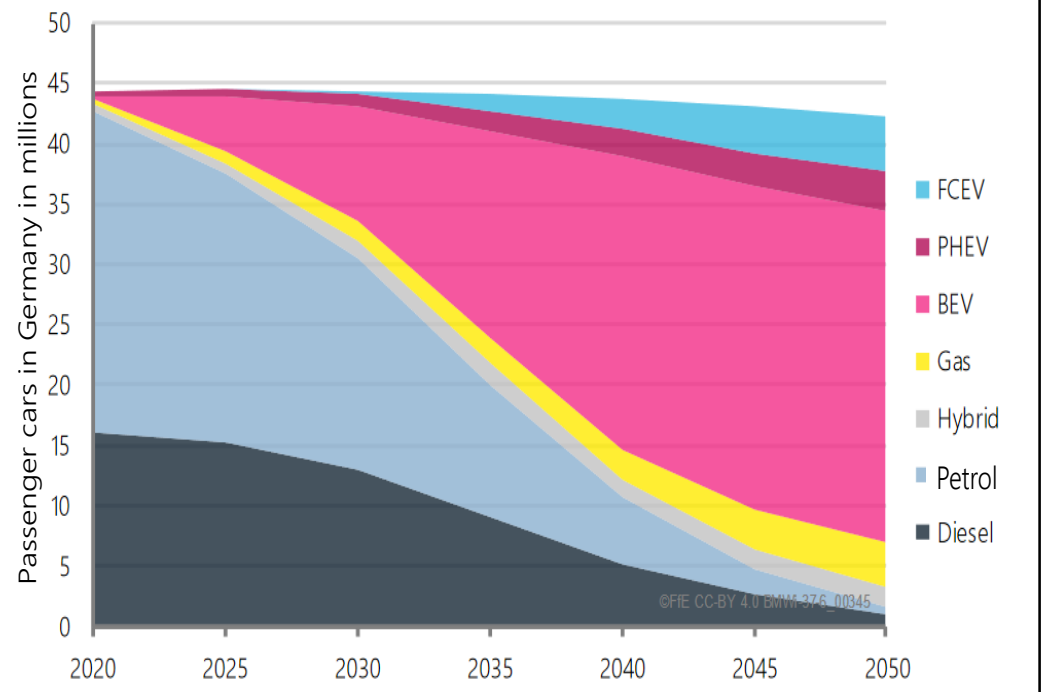

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With the prediction of CP occupancy, we aim to support:

a) EV users to plan their charging progress

b) scheduling CP maintenance

c) energy manager anticipate utilization

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Methodology

ACN Dataset

Caltech	JPL
• 54 EVSE	• 52 EVSE
• Public	• Workplace

Data Exploration

- Describe data
- Per site & station:
  - Occupancy durations
  - Usage patterns

Data Preparation

- Feature Selection
- Target variable: occupation
- Different Feature Sets for comparison
- Train / Test split
- Data preprocessing

Supervised Learning

- Binary: available or occupied
- 4 different machine learning algorithms for classification: Logistic Regression, KNN, Random Forest & XGBoost

Hyperparameter Tuning

- Grid search
- Different parameter ranges
- Optimization for AUC-Score

Model Evaluation

- Performance for different metrics
- Comparison:
  - Feature Sets
  - Location: work & public
  - Mode: Individual CP training vs. all

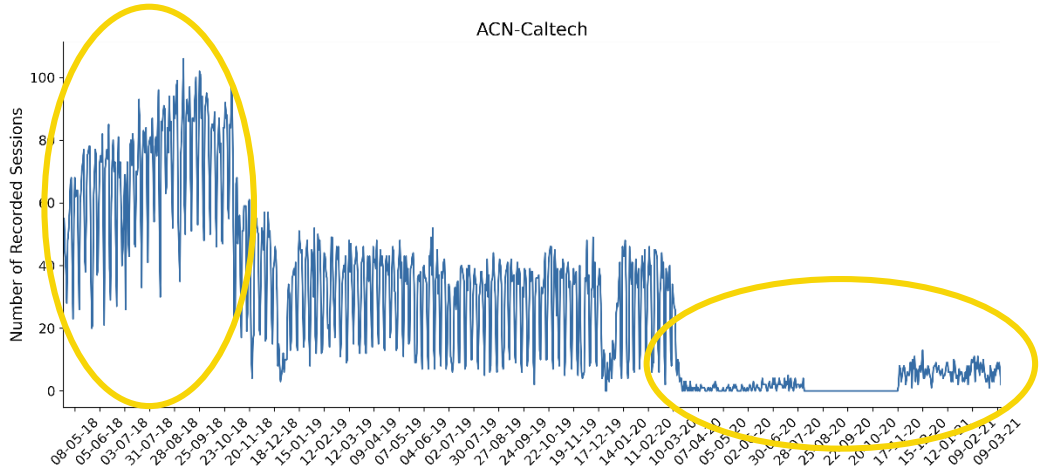
ACN: Adaptive Charging Network
KNN: K-Nearest-Neighbor
AUC: Area under the Curve

How to predict charging station occupancy?

ACN Data

Caltech (public)

- 54 Charging Points
- More than 25.000 charging sessions
- Garage at Caltech campus near campus gym
- Public charging



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- 01.12.2018 - 29.02.2020

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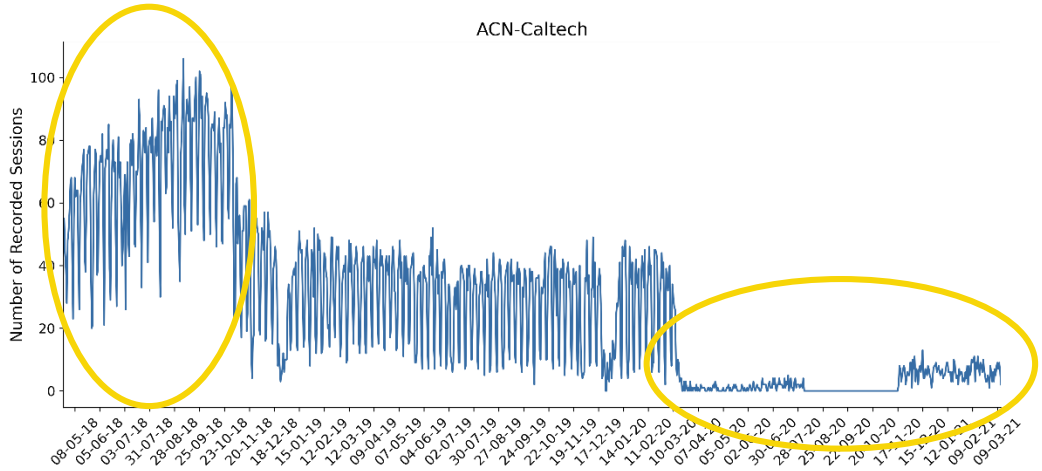

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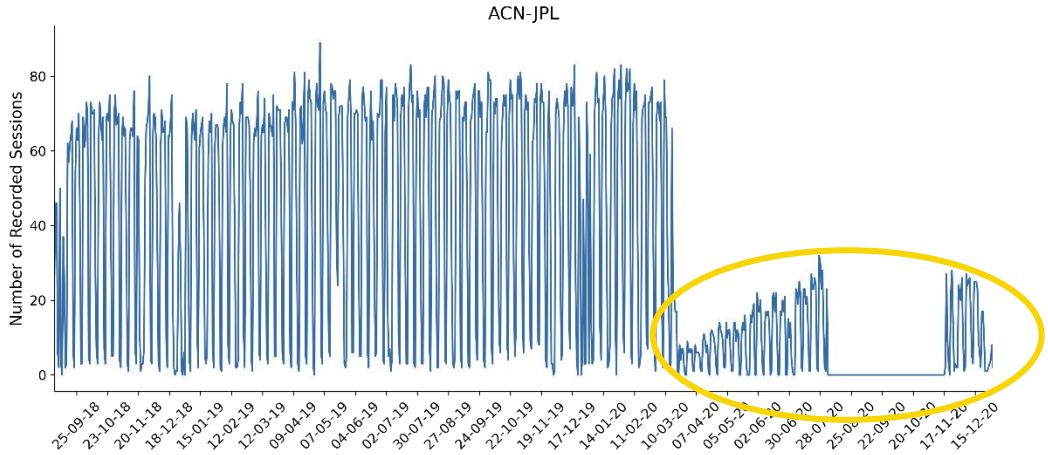
JPL (work)

- 52 Charging Points
- More than 25.000 charging sessions
- Garage at JPL campus with restricted access
- Workplace charging



- Exclude corona period
- 05.09.2018 - 29.02.2020

Two datasets: public & work place charging sessions for more than one year

ACN Data

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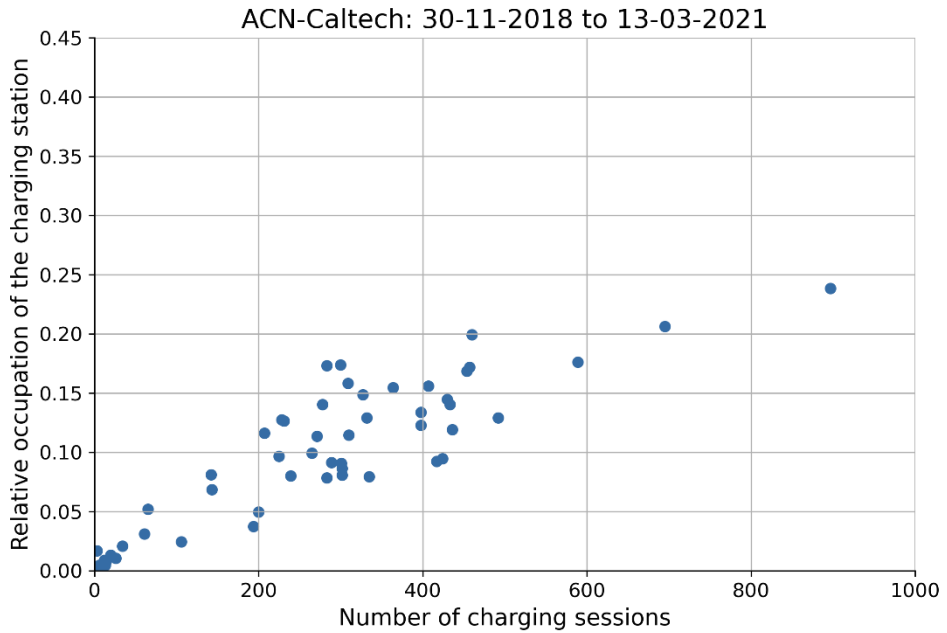

- More heterogeneous
- Relative occupation low, some stations less than 200 charging sessions
- Occupied - 14 %, Not Occupied - 86 %

JPL (work)

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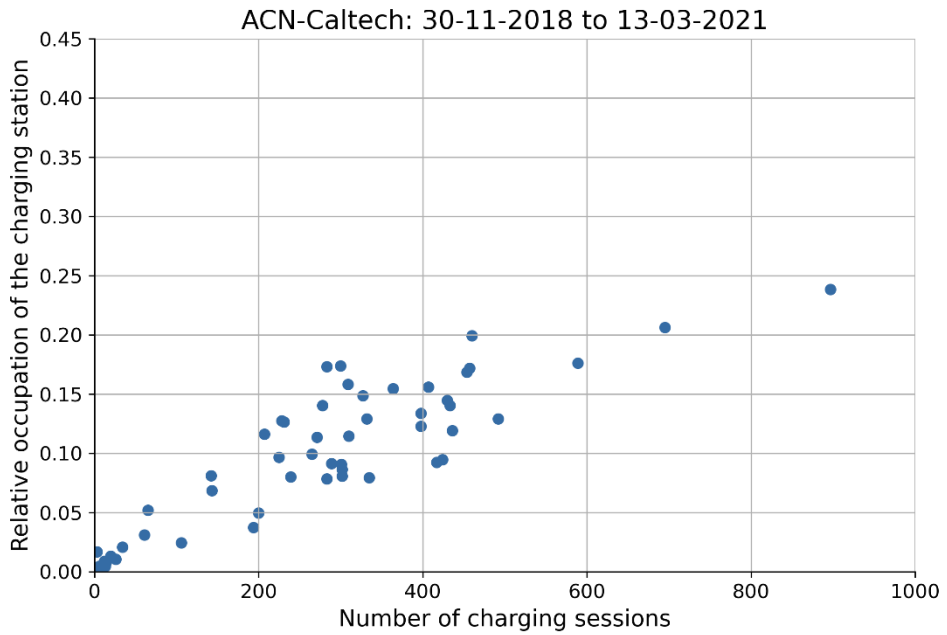

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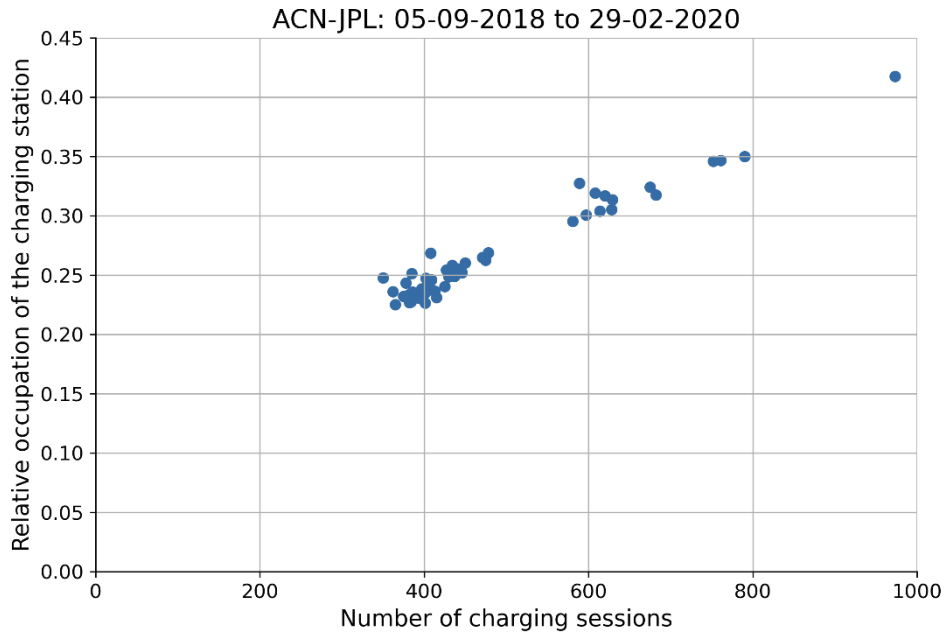

- More homogeneous
- Relative occupation high, all stations more than 350 charging sessions
- Occupied - 27 %, Not Occupied - 73 %

Caltech more imbalanced than JPL

Evaluation – Individual vs. All

Individual

- Use grid search for each charging station to determine hyperparameters where model performs best on charging station specific data set
- One model per algorithm for each charging station per site

All

- Use grid search to determine hyperparameters where model performs best on whole data set
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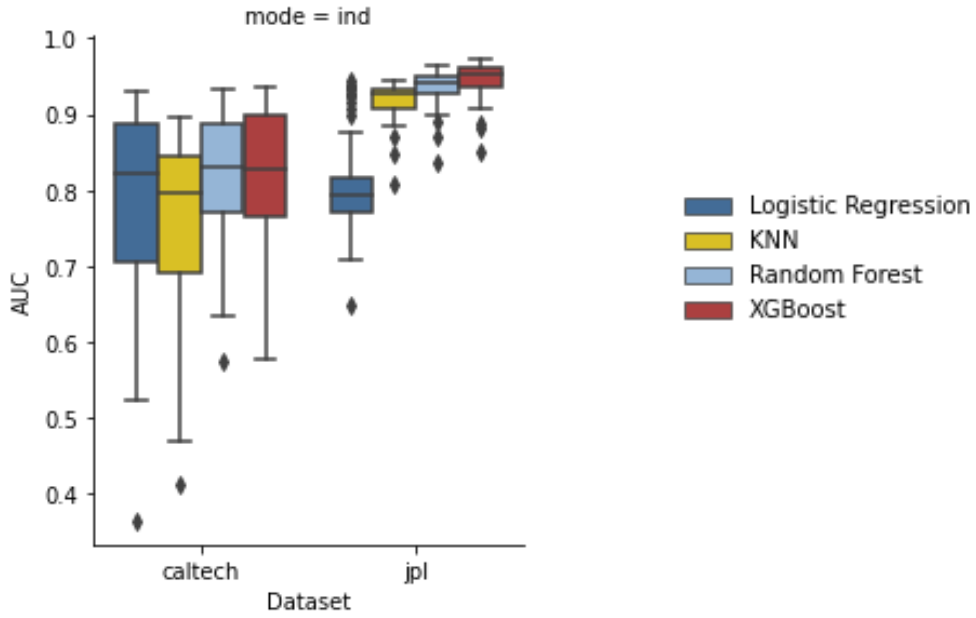

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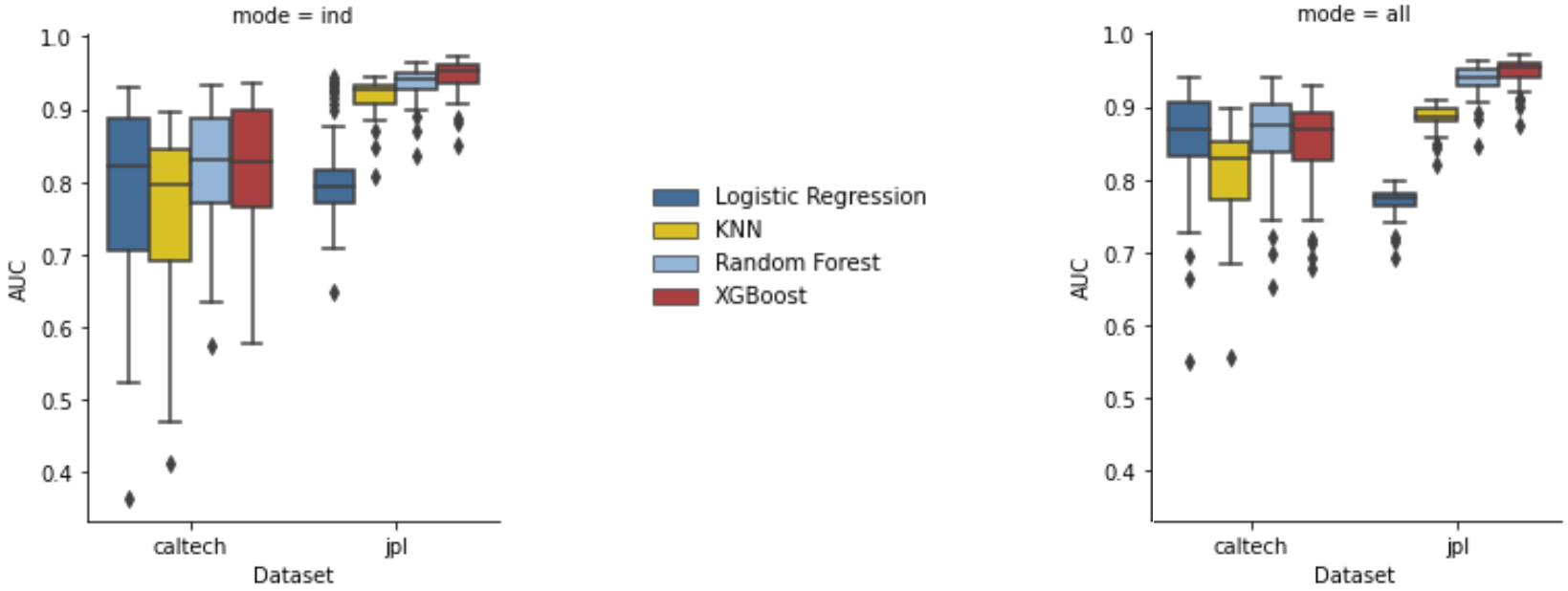
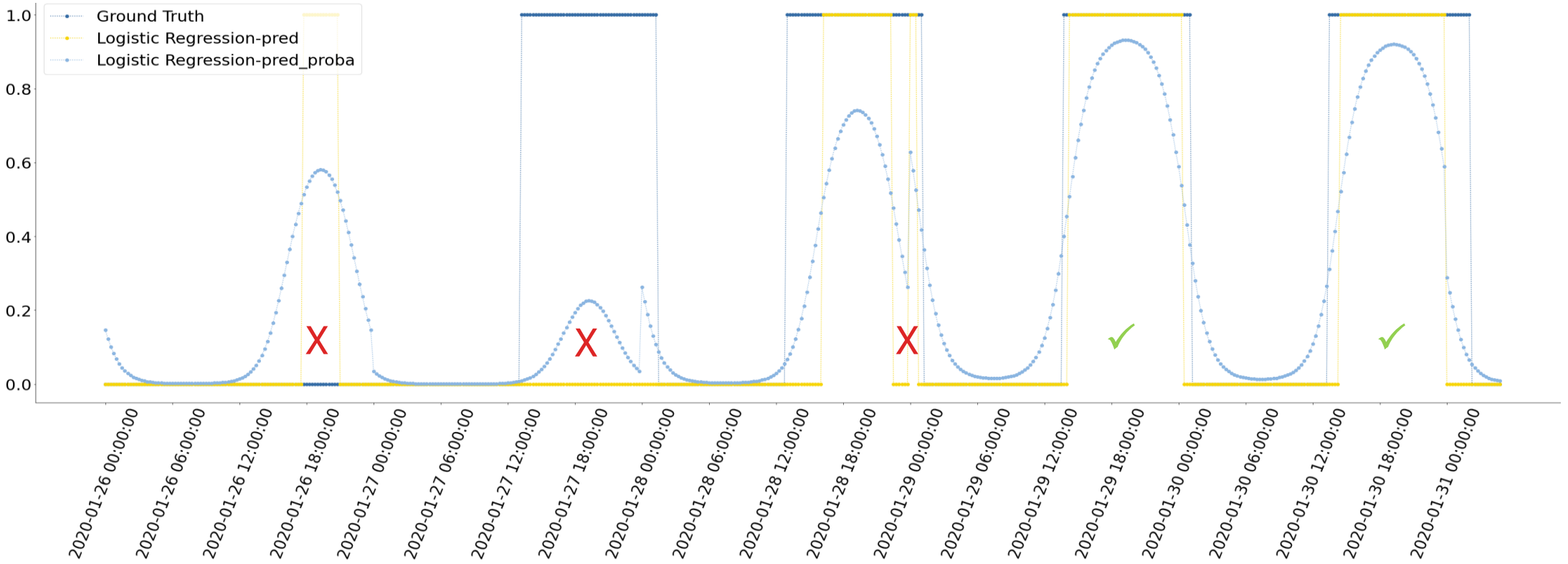


XGBoost performs best on JPL-data, Random Forest on Caltech-data
Individual mode has higher variation
All mode performs better on Caltech-data

Evaluation – Logistic Regression (LR)
JPL Sample Week 26.01.2020 (Sun) – 31.01.2020 (Fri)



1 = Occupied
0 = Available

Evaluation – KNN
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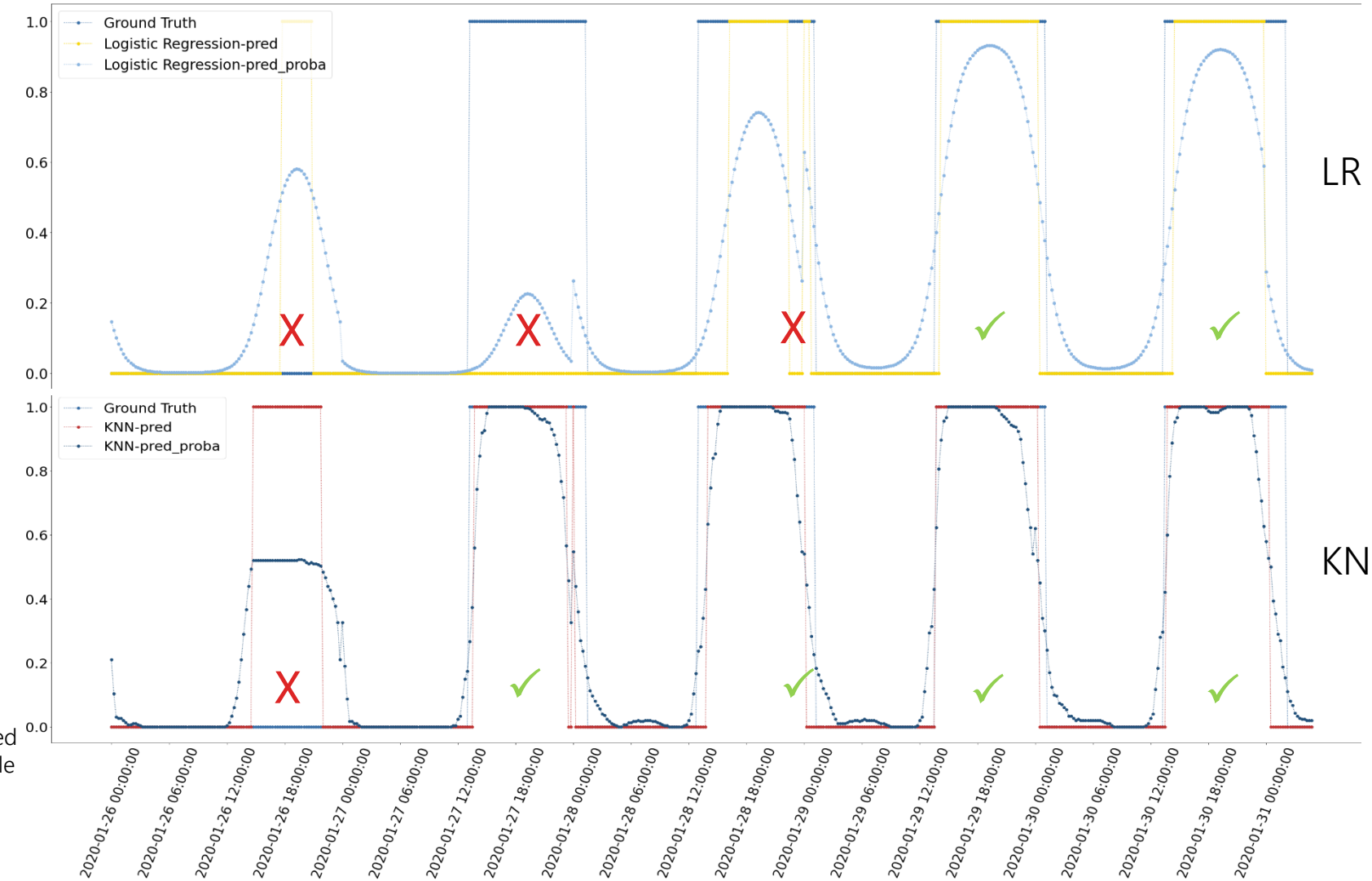

LR

KNN

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Evaluation – Random Forest
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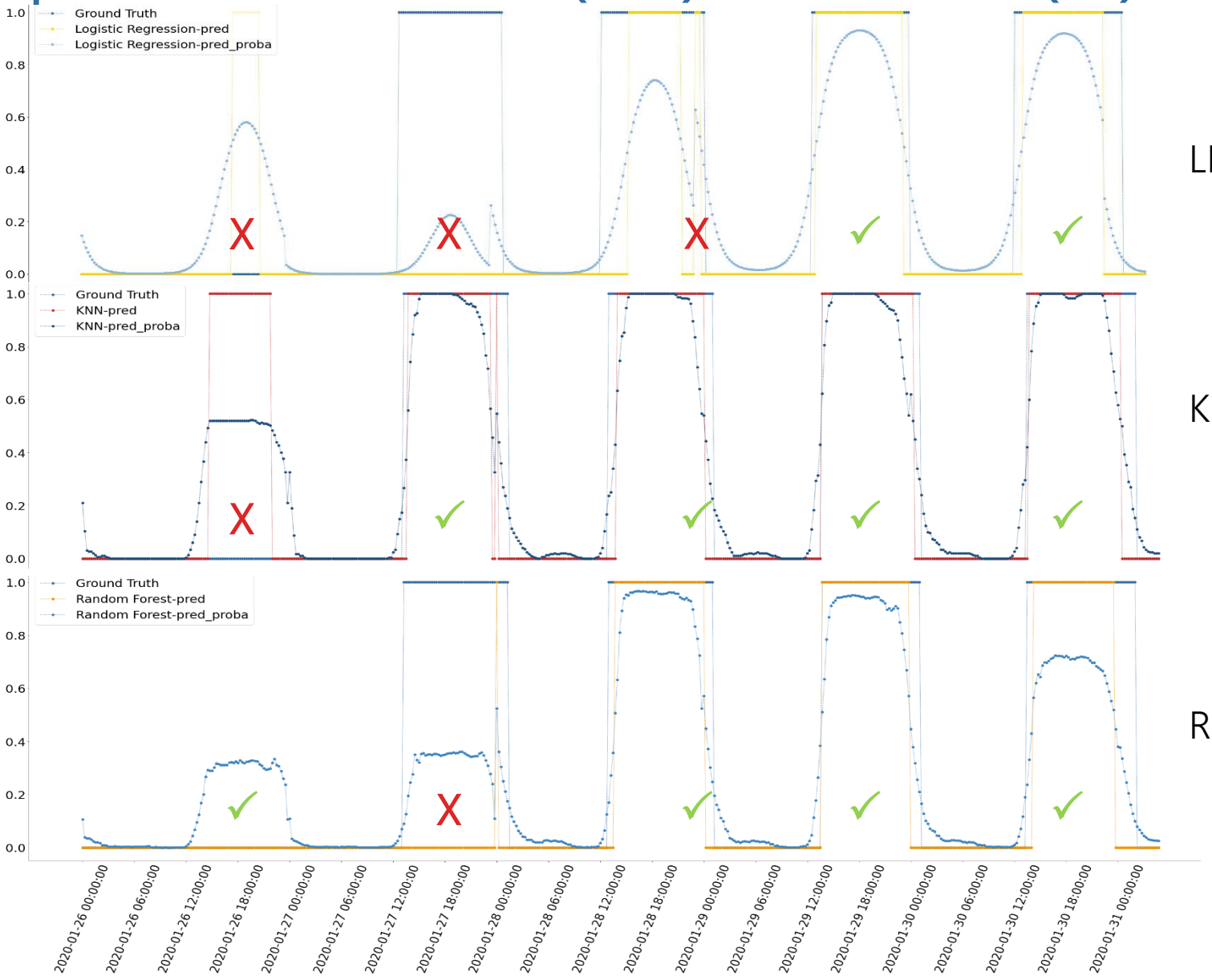

LR

KNN

RF

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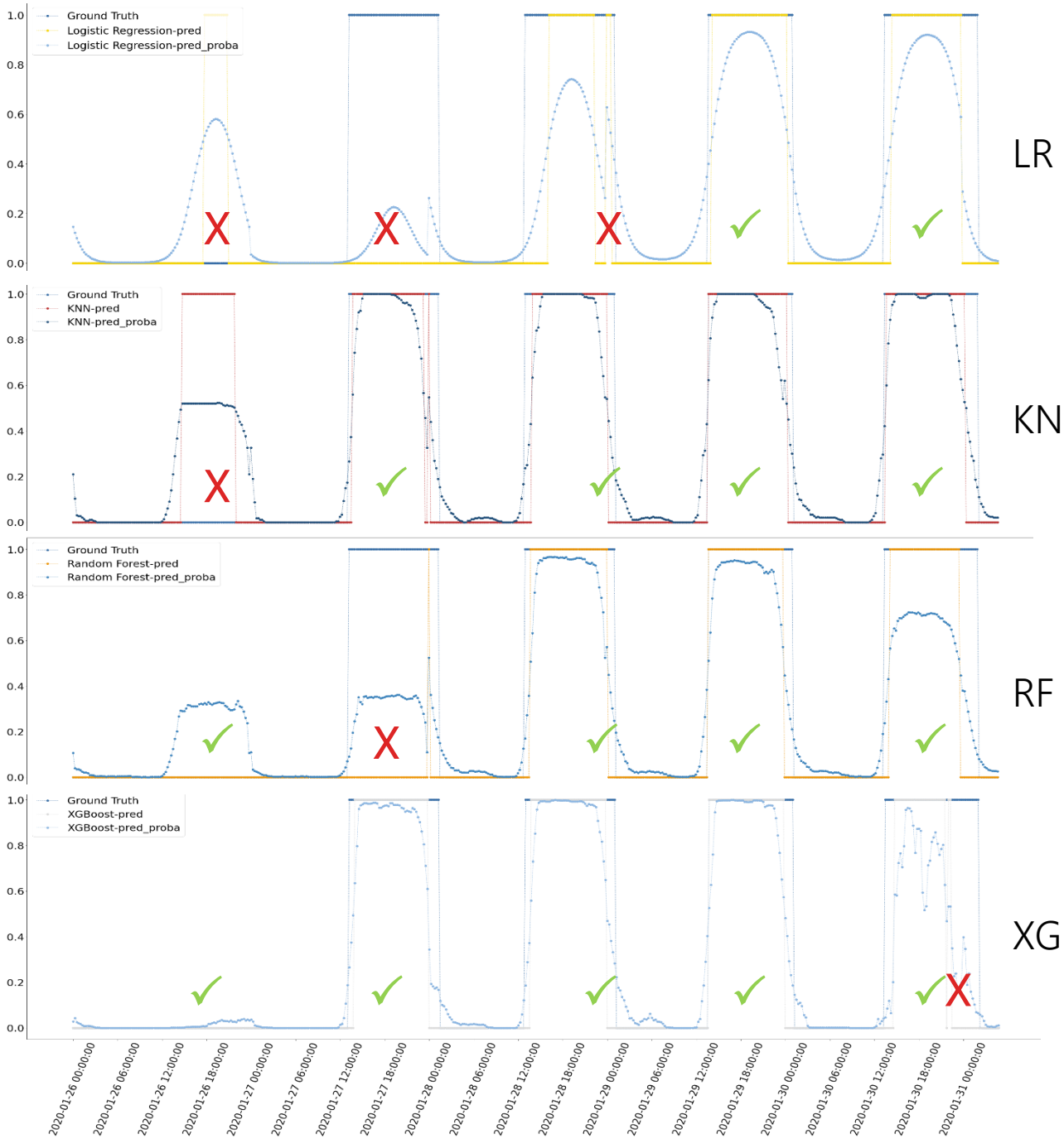
Evaluation
JPL XGBoost



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Summary & Outlook

Summary

- Random Forest and XGBoost perform best on our data
- Higher relative occupancy rate leads to better prediction
- Considering all data from one site can lead to better prediction for a single charging station

Outlook

- Comparison of different input feature sets
- Optimization and comparison for different metrics

Adrian Ostermann, M. Sc.

Research Center for Energy Economics (FfE)

Phone: +49(0)89 15 81 21 – 50

Email: aostermann@ffe.de

Forschungsstelle für Energiewirtschaft

Am Blütenanger 71 – 80995 München

Tel.: +49(0)89 15 81 21 – 0

Email: info@ffe.de

Internet: www.ffe.de

Twitter: @FfE_Muenchen

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[1] Fattler, Steffen; Conrad, Jochen; Regett, Anika et al.: Dynamis Hauptbericht - Dynamis - Dynamische und intersektorale Maßnahmenbewertung zur kosteneffizienten Dekarbonisierung des Energiesystems - Online: https://www.ffe.de/dynamis. München: Forschungsstelle für Energiewirtschaft e.V., 2019. DOI: 10.34805/ffe-144-19

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