Enabling Delayed-Full Charging Through Transformer-Based Real-Time-to-Departure Modeling for EV Battery Longevity

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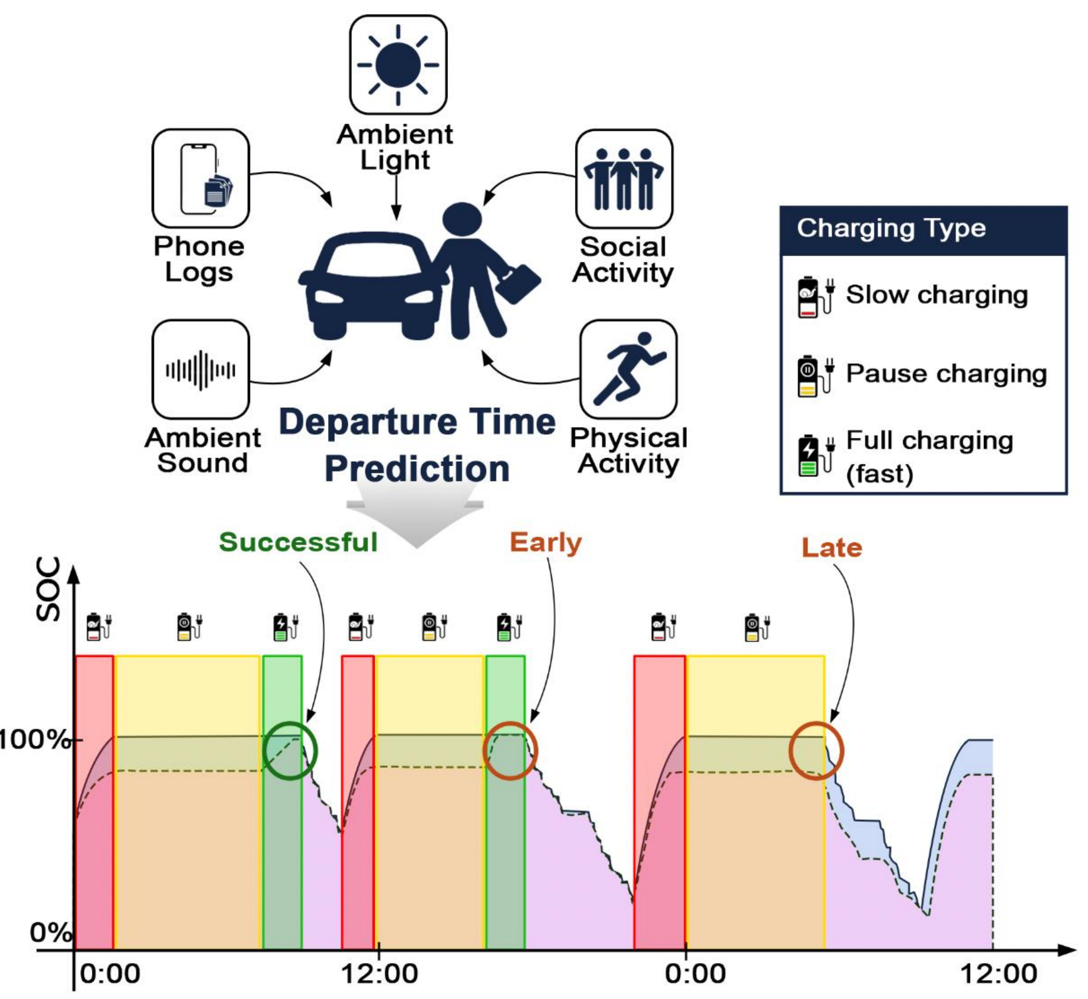
1. Introduction

Accurate Prediction: The Key to DFC Success



Early Prediction:
Reduces the benefits of the strategy by **prolonging high SOC exposure**, which accelerates battery degradation

Late Prediction:
Risks leaving **insufficient energy at departure**, thereby causing **range anxiety** for the user

2. Motivation

Deep Survival Analysis

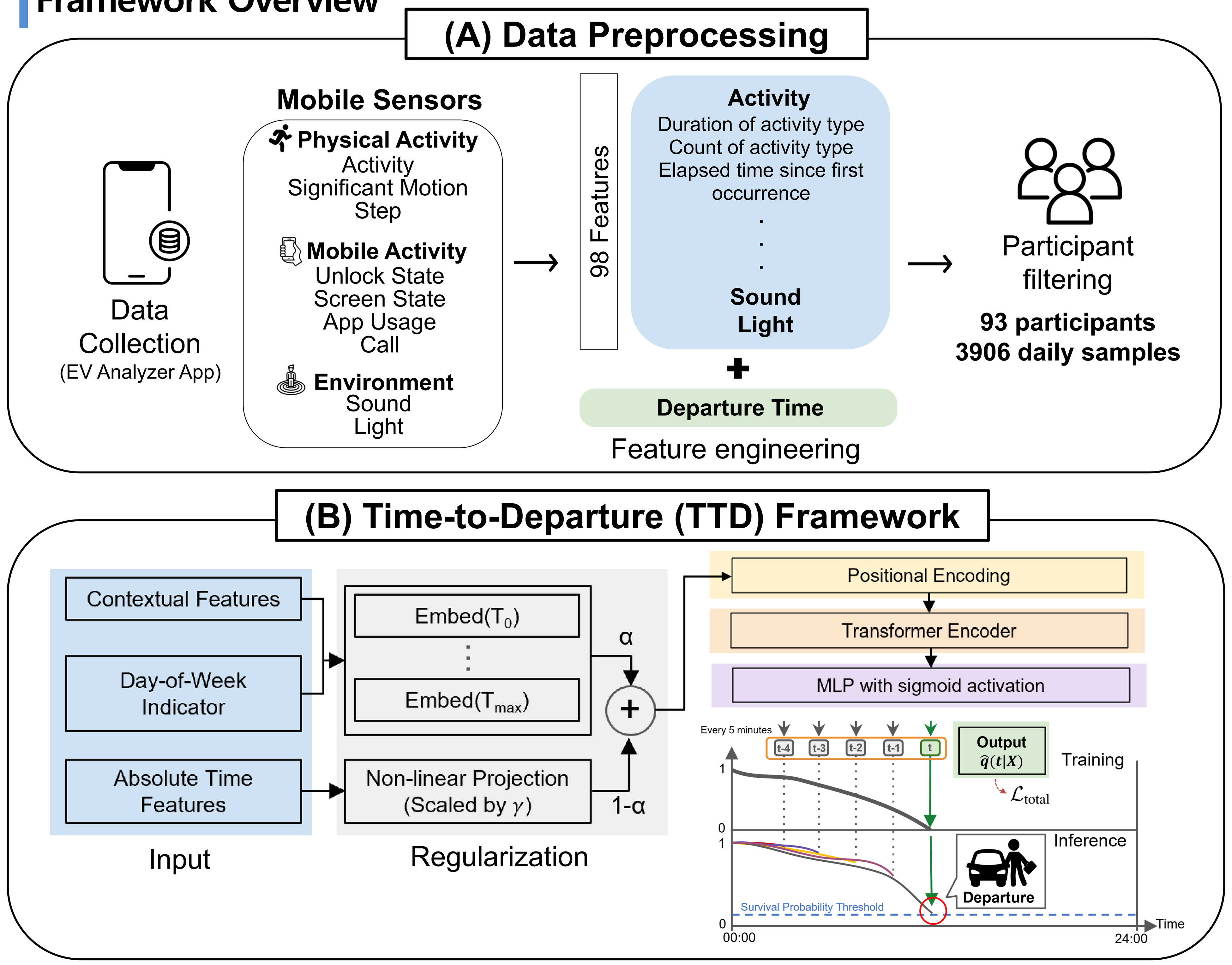
Mitigation of Label Imbalance: Overcomes the severe class imbalance inherent in classification models by reformulating the problem to treat each day as a single observation rather than multiple binary windows.

Real-Time Probabilistic Inference: Utilizes survival functions $S(t|X)$ to provide rich temporal modeling, enabling continuous updates of departure probabilities as streaming observations arrive

Leveraging **contextual feature embeddings** and **time token-level survival updates** to enable streaming inference for timely, accurate departure detection

3. Methodology

Framework Overview



Regularization Strategies

- Implementing **dropout time** and **time scaler γ** to reduce reliance on deterministic schedules by regulating the influence of absolute time features.
- Employing **alpha-fusion** α to adaptively balance contextual versus temporal signals, enhancing generalization across diverse behavioral patterns.

Loss Function

$$\mathcal{L}_{\text{total}} = \sum_{i=1}^{N} \omega_w^{(i)} \left(\sum_{t=0}^{T_{\max}} w_i(t) \cdot \ell_{i,t} \right) \qquad w_i(t) = \exp\left[-\frac{(t-t_i^*)^2}{2\sigma^2} \right], \quad t \le t_i^*,$$

$$\text{where } \ell_{i,t} = \begin{cases} \log \hat{q}(t \mid \mathbf{X}_i), & t < t_i^*, \\ \omega_e \cdot \log\big(1 - \hat{q}(t \mid \mathbf{X}_i)\big), & t = t_i^*, \\ 0, & t > t_i^*, \end{cases} \quad \text{and } \omega_w^{(i)} = \begin{cases} \omega_w, & \text{if weekend/holiday}, \\ 1, & \text{otherwise}. \end{cases}$$

- Applying **Gaussian-smoothed soft supervision** to mitigate sensitivity to minor timing shifts, thereby enhancing robustness against label uncertainties and contextual noise near the departure event
- Enhancing predictive accuracy by introducing $\boldsymbol{\omega_e}$ to prioritize critical departure moments ($\frac{\partial \mathcal{L}}{\partial \theta} \propto \omega_e$) and $\boldsymbol{\omega_w}$ to adapt to irregular weekend patterns

4. Evaluation

Experimental Results

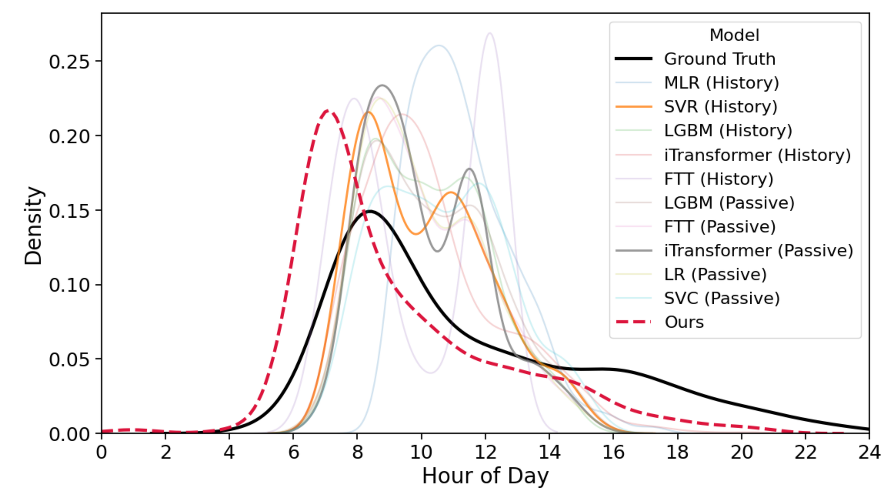
Data	Models	All days	Weekdays	Weekends
History	MLR	2.90	2.93	2.82
	SVR	2.57	2.52	2.63
	LGBM	2.58	2.54	2.59
	FTT	2.74	2.72	2.76
	iTransformer	2.61	2.59	2.65
Passive	LR	2.67	2.61	2.79
	SVC	2.66	2.64	2.70
	LGBM	2.72	2.81	2.65
	FTT	2.70	2.63	2.84
	iTransformer	2.59	2.56	2.65
Passive	**Ours**	**2.20**	**2.26**	**2.07**

Ablation Study

Variants	All days	Weekdays	Weekends
w/o Context	4.47 ± 0.18	4.88 ± 0.18	3.55 ± 0.16
w/o PE	4.25 ± 1.74	4.19 ± 1.54	4.40 ± 2.23
w/o Time	3.01 ± 0.67	2.96 ± 0.60	3.10 ± 0.85
w/o DoW	2.64 ± 0.60	2.63 ± 0.45	2.66 ± 0.94
w/o α	2.55 ± 0.42	2.58 ± 0.32	2.49 ± 0.66
w/o γ scale & GSS	2.36 ± 0.04	2.42 ± 0.03	2.24 ± 0.09
Full Model	**2.20 ± 0.13**	**2.26 ± 0.13**	**2.07 ± 0.17**

- **Contextual Features and Positional Encoding** are the most influential factors, underscoring the importance of digital phenotyping features and temporal sequence modeling.
- Contrary to expectations, **weekdays exhibited higher errors than weekends**, likely due to the increased variability of routines driven by pandemic-era (2021–2022) hybrid work trends.

Distribution Analysis



- Driven by **real-time contextual signals**, our model shows high temporal adaptability, accurately capturing **dynamic departure routines**.