

# Attention-based Neural Networks for Multi-modal Trajectory Prediction

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## Motivation

Trajectory prediction is of great importance in wireless and intelligent networks. Accurate forecast of users' trajectories can provide efficient handover management, continuous network connection, and generally a better network quality of service.

## Contributions

- A trajectory predictor based on Transformers Neural Networks acquiring the self-attention mechanism [3].
- A social-aware mobility model where agents are not acting in isolation and the interaction between agents is considered [1].
- A reinforcement learning approach to design the highest-performance neural architecture based on the multi-modal trajectory scenario.
- INteractive TRAnsformers ReinFORCED (INTRAFORCE), a framework that achieves high prediction accuracy while reducing training and architecture design time, and computational complexity.

## Transformers Trajectory Prediction

- A trajectory is defined as the sequence of location tags over time as a 2D signal:  $T(Loc, t) = [(Loc_1, t_1), (Loc_2, t_2), \dots, (Loc_n, t_n)]$ .
- A trajectory predictor forecasts mobile user's future location based on his historical data:  $p(Loc_{t+1} | Loc_t, Loc_{t-1}, \dots, Loc_{t-n})$ .
- Transformers consist of attention-based encoder and decoder blocks.
- An attention layer can focus more on some parts of input data based on their measured relevance weights, similar to human brains.

## Reinforcement Learning Optimization

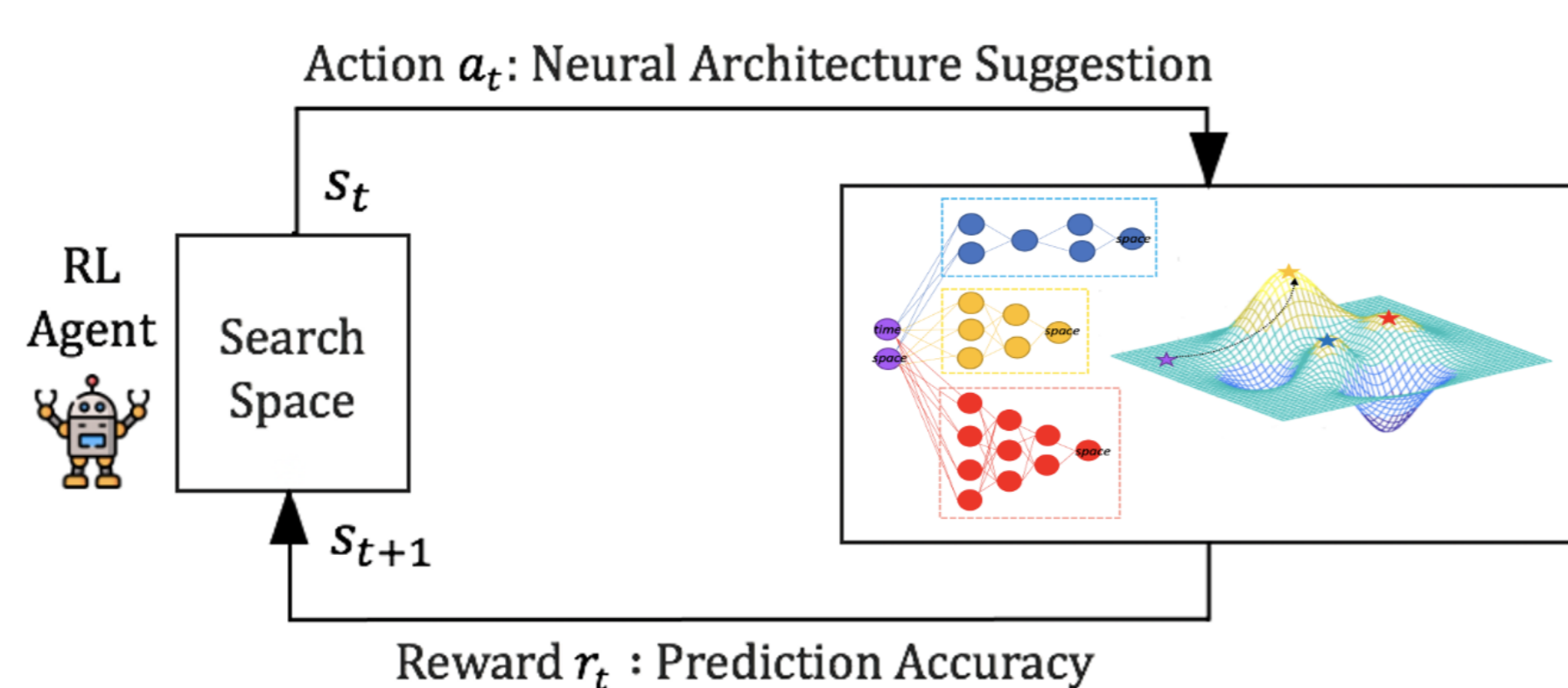


Figure 1: Personalizing transformers neural architecture design through a RL approach.

- The agent after taking an action and receiving the reward, updates state-action value  $Q(s, a)$  on each iteration through Bellman's Equation:

$$Q_{t+1}(s, a) = (1 - \alpha)Q_t(s, a) + \alpha \left( r_t + \gamma \max_{a' \in \mathcal{R}(s')} Q_t(s', a') \right).$$

- The  $Q$  values helps the agent to narrow down the search space toward high-performance neural architectures.

## Social Awareness

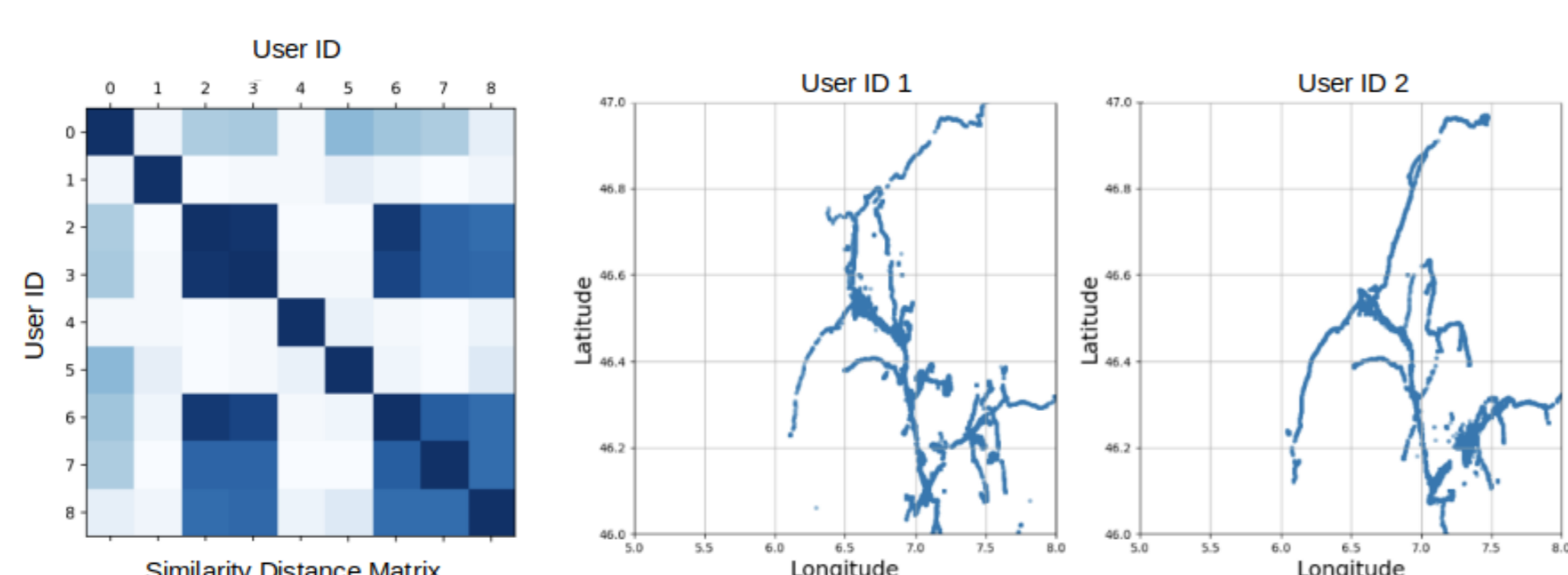


Figure 2: Measuring similarity and clustering adjacent trajectories.

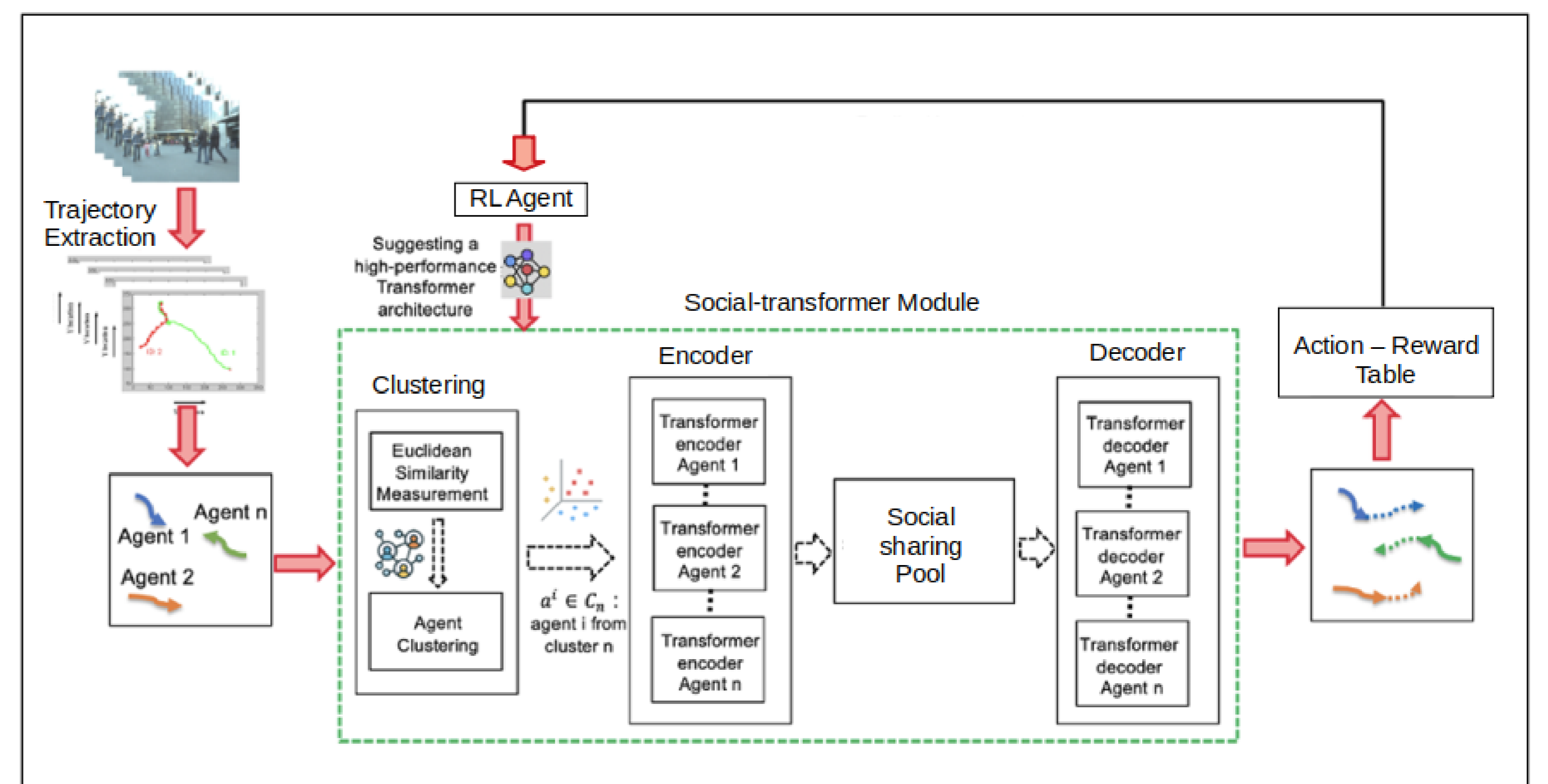


Figure 3: INTRAFORCE architecture.

- Clustering neighbor trajectory users to extract spatio-temporal dependencies of neighbor trajectories.
- Feeding co-cluster users to Intraforce.
- Pooling knowledge of adjacent users to capture the interactions.
- Feeding back the model's output to RL for a better decision making.
- Objective function:  $\min \sum_i \frac{1}{m_i} \|y_i - x_i W_i\| + \lambda \sum_{i,j} A_{i,j} \|w_i - w_j\|$ .

## Evaluations and Conclusions

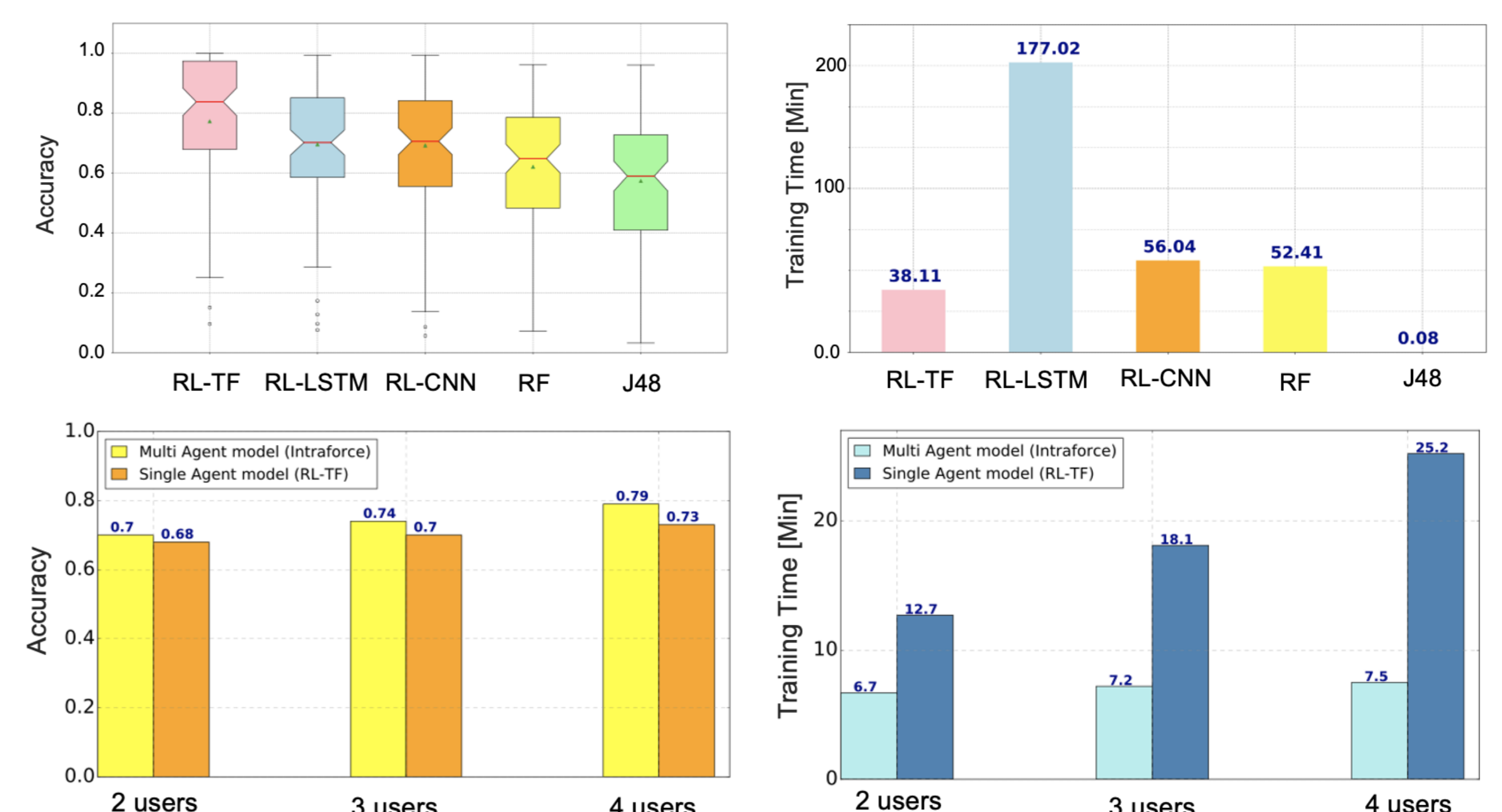


Figure 4: Accuracy and training time comparison of different mobility predictors.

- We evaluate our proposed model on Orange dataset [4].
- We observe that RL-TF remarkably outperforms the state-of-the-art trajectory predictors in terms of prediction accuracy and training time [2].
- We observe that the social-aware INTRAFORCE predictor brings a noticeable efficiency into the trade-off between accuracy, training time, and computational complexity.

## References

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- [2] N. Emami, L. de Sousa Pacheco, A. Di Maio, and T. Braun. Rc-tl: Reinforcement convolutional transfer learning for large-scale trajectory prediction. 2022.
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- [4] Z. Zhao, N. Emami, H. Santos, L. Pacheco, M. Karimzadeh, T. Braun, A. Braud, B. Radier, and P. Tammann. Reinforced-lstm trajectory prediction-driven dynamic service migration: A case study. *IEEE Transactions on Network Science and Engineering*, 2022.