Discover User-App Interactions & Solutions to Reducing the Initial User-CPU Latency

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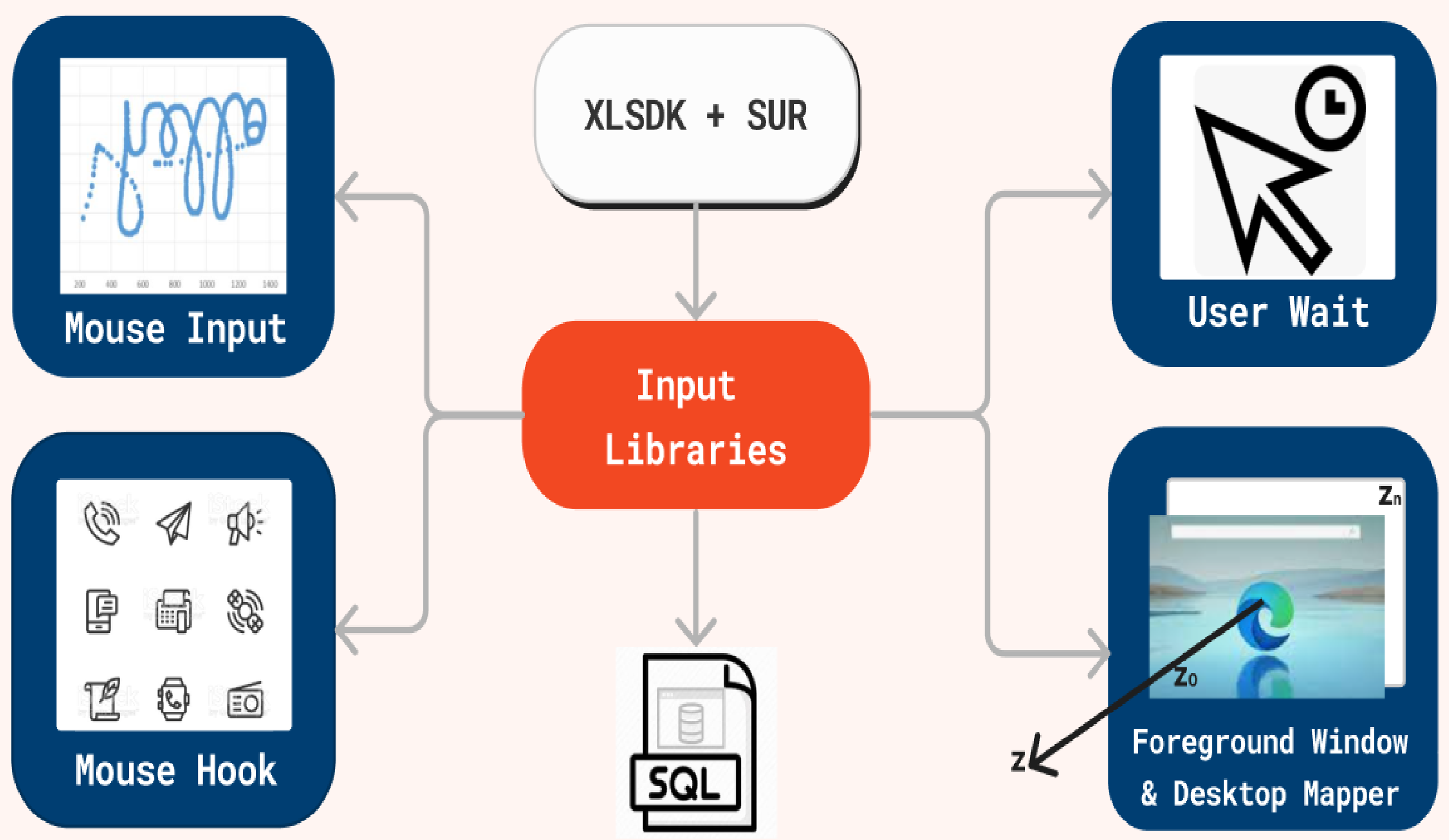
Abstract

- **Data loading** icons signal an unpleasant *user-wait experience*
- To mitigate the initial latency, we analyze user-app interaction data collected by *Intel's Telemetry*, make predictions on said data using *EDA, HMM, & LSTM/RNN*, then propose solutions

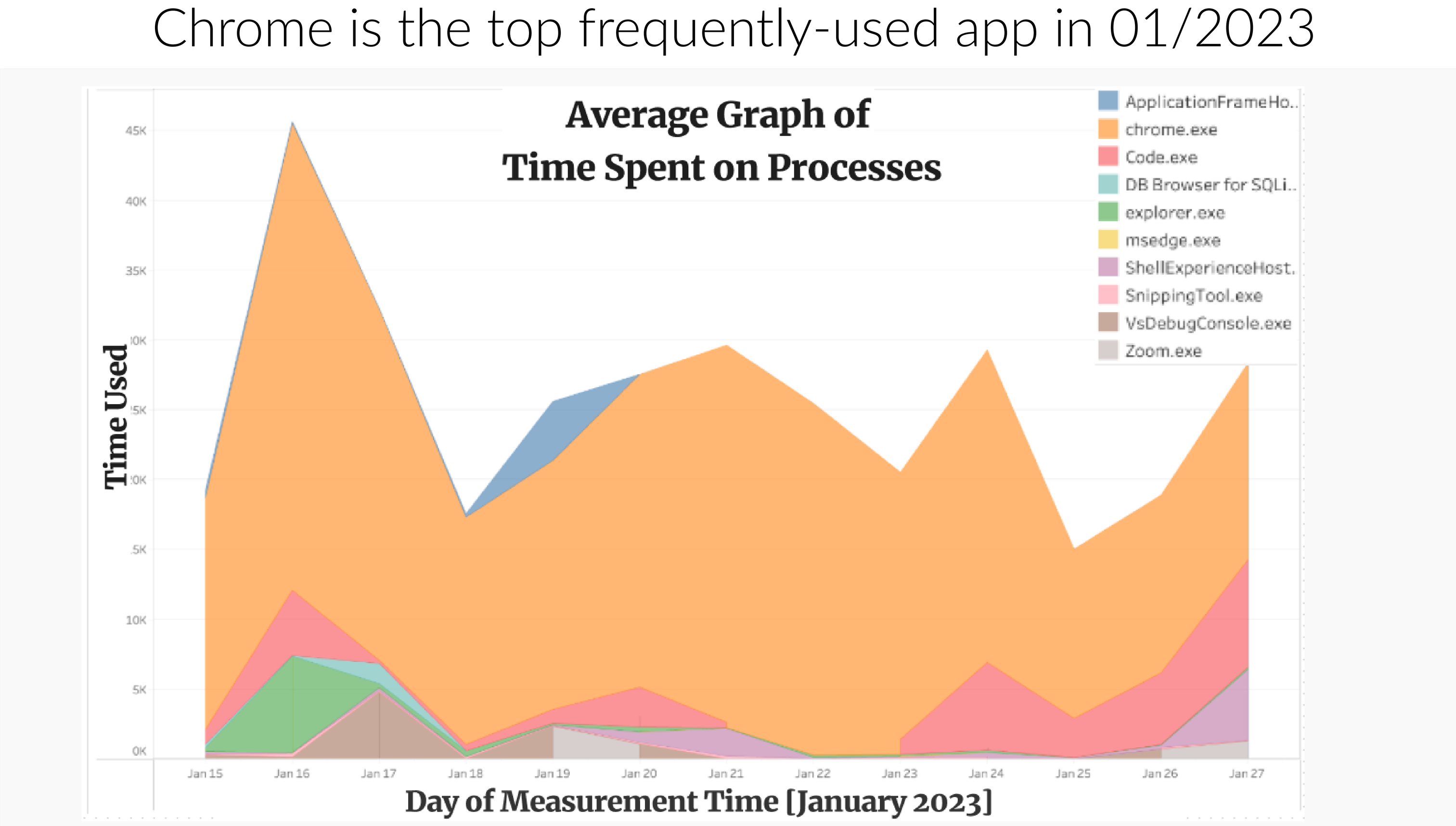
Methodology of Data Collection

- We apply *Intel® Software Development Kit* and *System Usage Report* framework to anonymously gather data usage from multiple devices
- We develop 4 input libraries, esp. *Foreground Window IL*, using *C* and *Event-Driven* programming knowledge



Exploratory Data Analysis

Chrome is the top frequently-used app in 01/2023



Methodology of Predictive Tasks

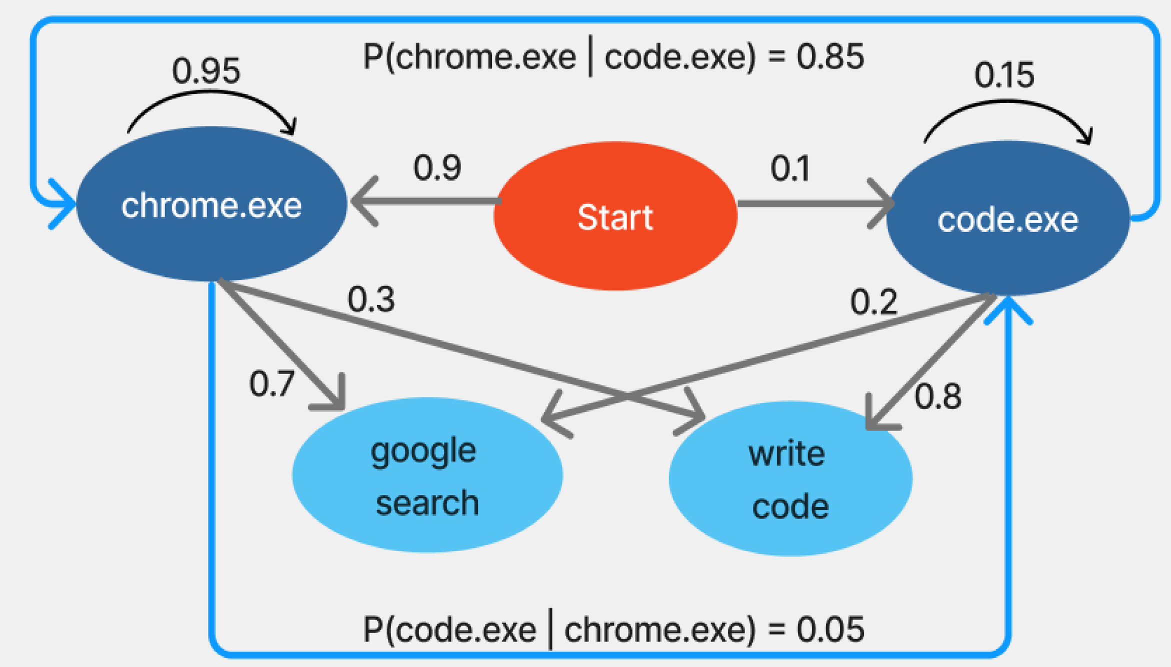
Hidden Markov Model (HMM)

- **Problem Statement**: Predict the likelihood of using an app *given* the former sequence of application usage
- **Basic Idea**: Utilize conditional probability $P(A|B) = \frac{P(A \cap B)}{P(B)}$
- **A1 Markov Chain**: Only the <u>*current*</u> state q_{i-1} plays the most crucial role in predicting the future in the sequence

$$P(q_i = a | q_1 q_2 ... q_{i-1}) = P(q_i = a | q_{i-1})$$

- **A2 Output Independence**: The probability of observing an event o_i only relies on the state q_i that <u>*directly*</u> produced o_i

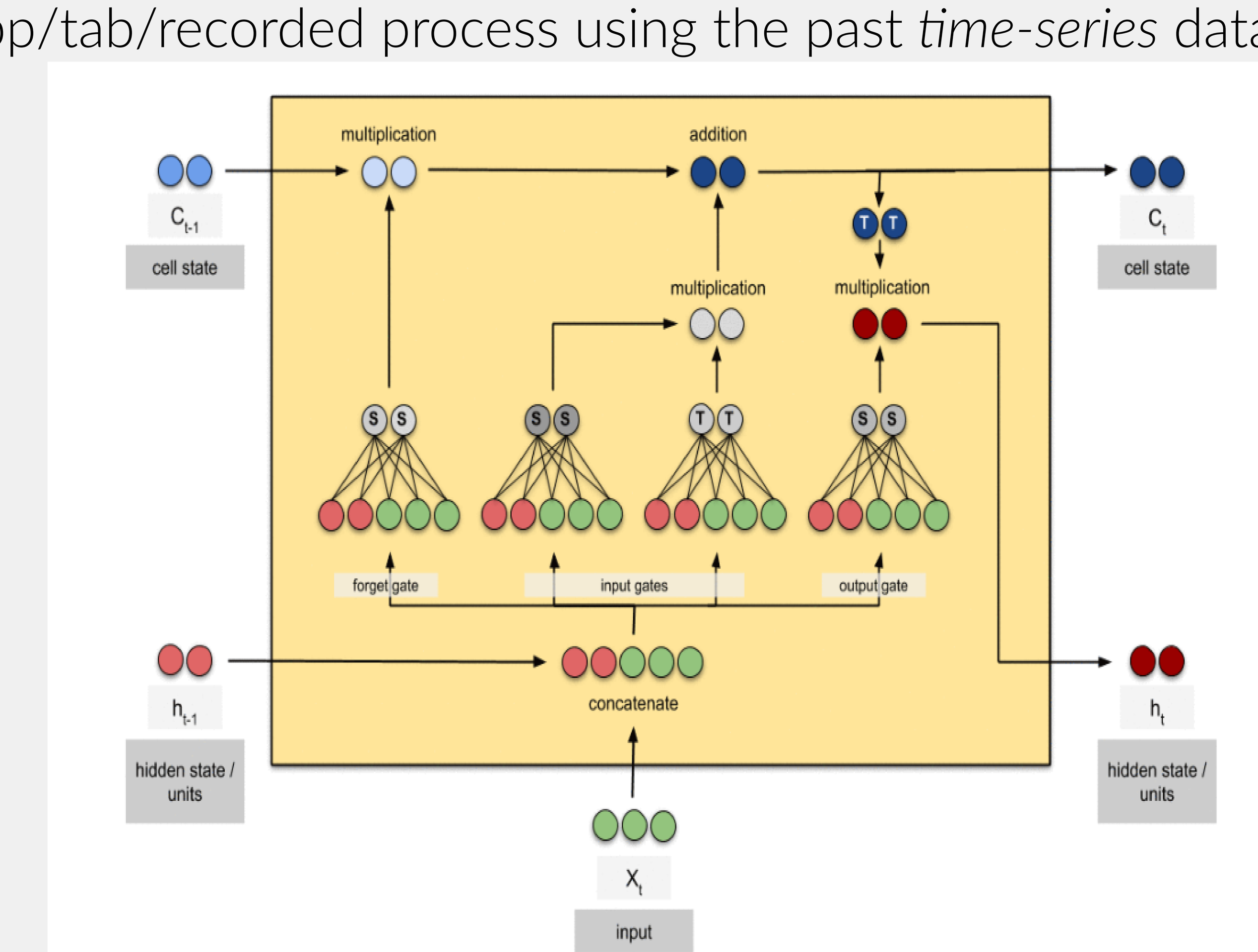
$$P(o_i | q_1, ... q_i, ..., q_T, o_1, ..., o_i, ..., o_T) = P(o_i | q_i)$$



- **Metrics**: Preds==True if within top n probabilities of the app

Recurrent Neural Network (LSTM/RNN)

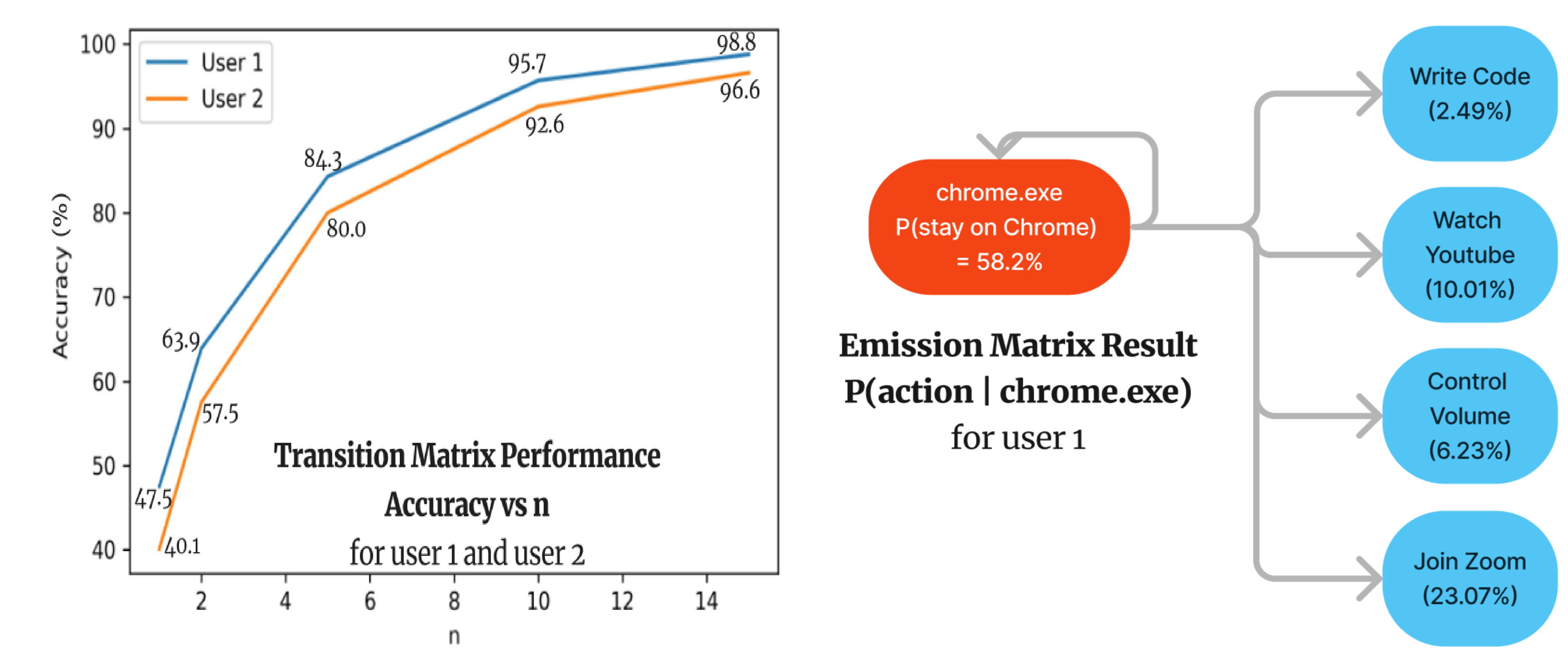
- **Problem Statement**: Predict the (total) time usage of an app/tab/recorded process using the past *time-series* data



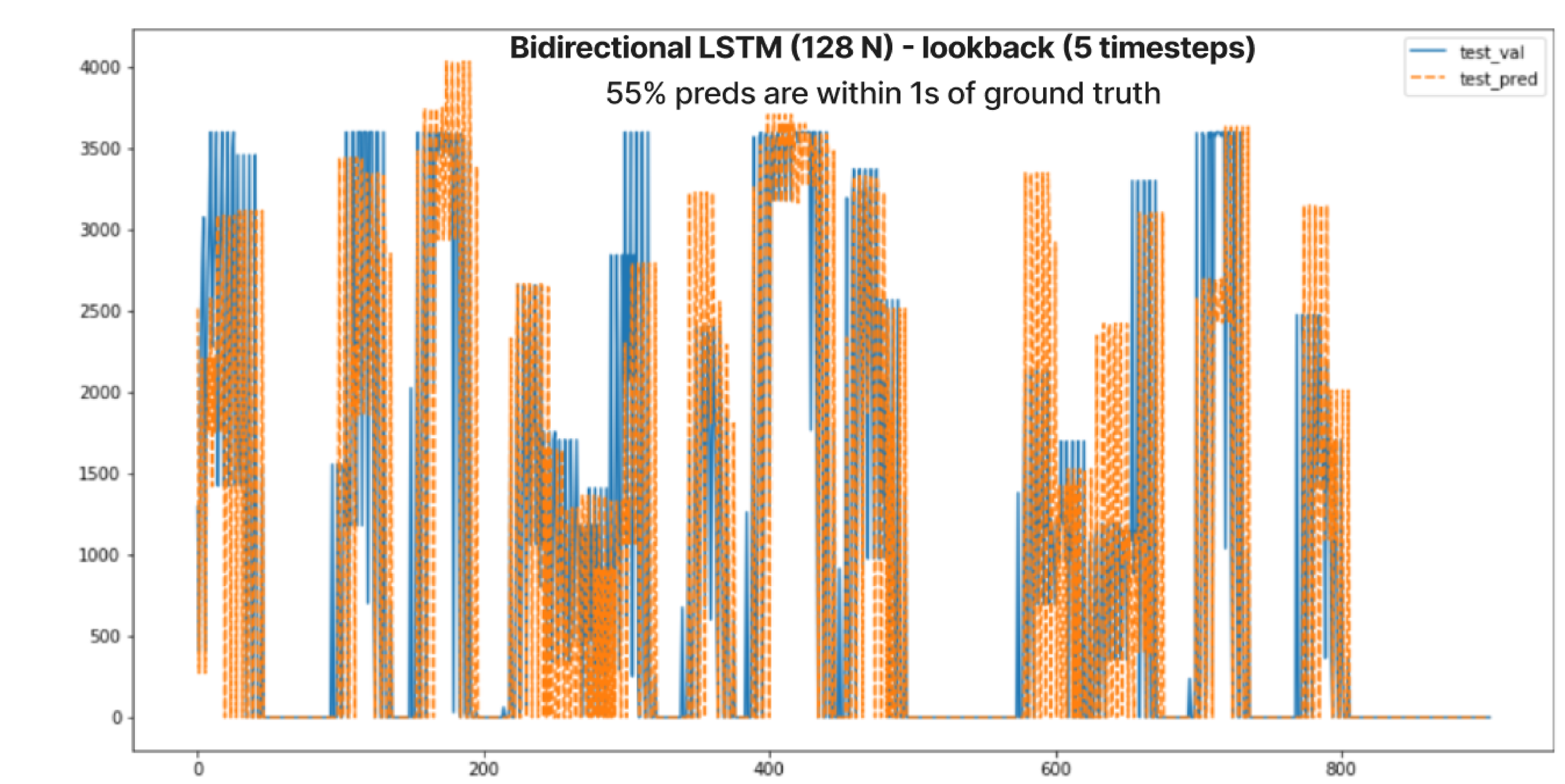
- **Feature Engineering**:
  1. Hourly split daily usage into 24 cols (labeled 0 - 23)
  2. Lookback 3-5 time steps from the current timestamp
  3. One-hot-encoding (process names); Min-Max scaler
- **Experiments**: Train/Test: 80/20, no shuffle; Keras
- **Metrics**: TP/TN/FP/FN; Preds==True if w/in 1 sec of real vals

Predictive Results

HMM Performance on Chrome



LSTM Performance on Chrome



Other Models	Design (N=nodes)	Eval Bins	Performance
Vanilla LSTM > Split Hourly > OH(Process Names)	Input RNN (64N) Hidden Dense (4N) Output Dense (1N)	[0, 0.01] (0.01, 0.02] (0.02, 0.2] (0.2, max]	TP = 691, TN = 0 FP = 65, FN = 0 ACC ≈ 91.4%
Stacked LSTM > Split Hourly > OH(Process Names)	Input LSTM (16N) Hidden LSTM (32N) Hidden Dense (64N) Output Dense (1N)	[0, 0.01] (0.01, 0.02] (0.02, 0.2] (0.2, max]	TP = 467, TN = 52 FP = 13, FN = 224 ACC ≈ 68.65%

Conclusions

- We should collect data <u>*continuously*</u> and <u>*consistently*</u> to achieve high accuracies in detecting patterns of user behaviors
- We wish to incorporate data collected using ***Desktop Mapper IL*** and check if it helps improve our predictions
- The analysis/predictive results allow the inference of daily app sequence and time usage
- We can develop a script to process background tasks and utilize ***Scheduler*** to open the next app 2-3 mins beforehand