

Continuous behavioral authentication using mouse dynamics based on Artificial Intelligence

Álvaro Sarmiento Borrajo



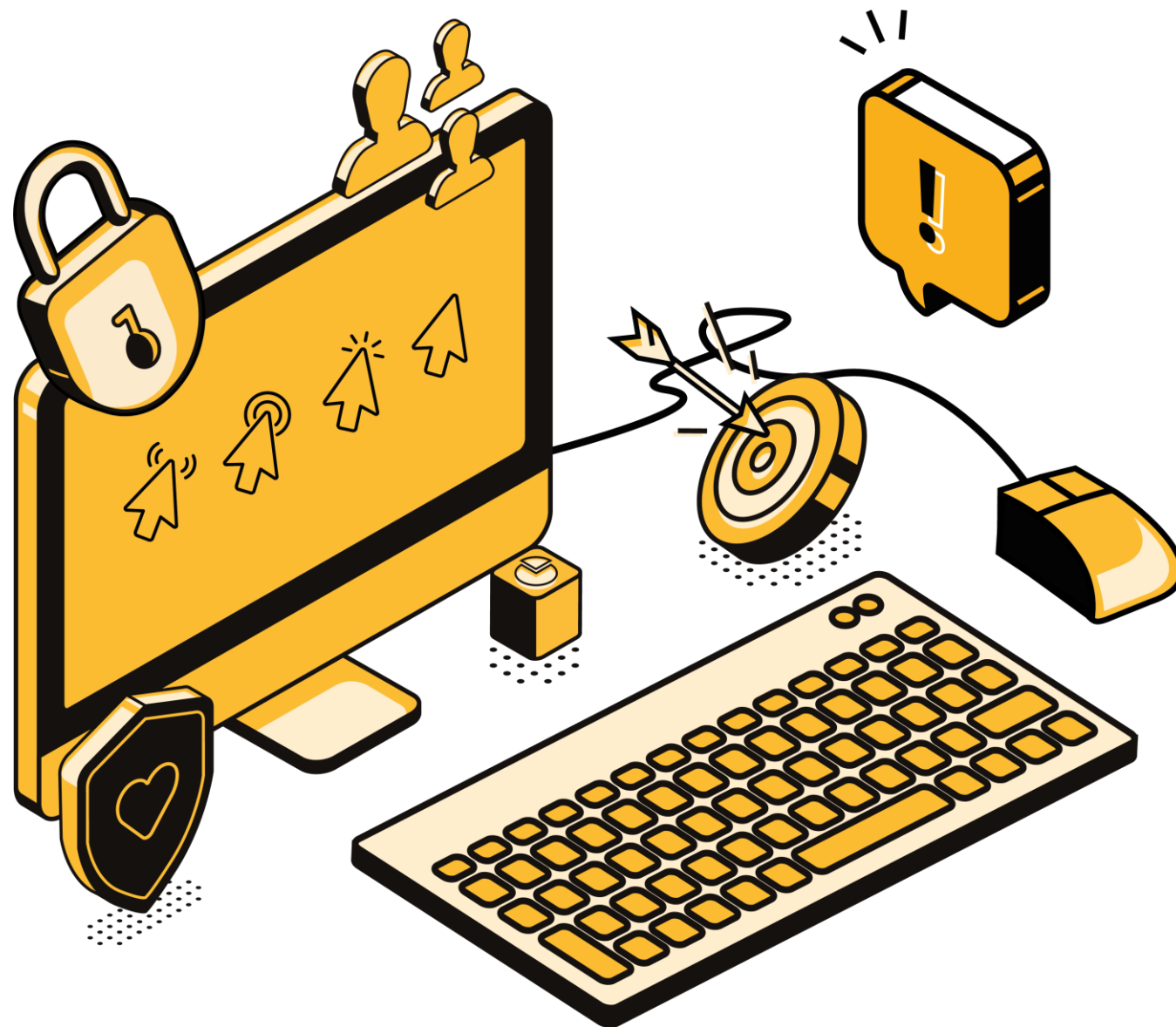
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Introduction I

Authentication systems:

- Classic schemes:
 - Knowledge-based.
 - Possesion-based.
 - Biometric-based.
- Problem:
 - Identity theft.
- Evolution:
 - Multi-factor approach.
- Persistent problem:
 - Identity theft in open sessions.
- **Solution:**
 - Continuous authentication.



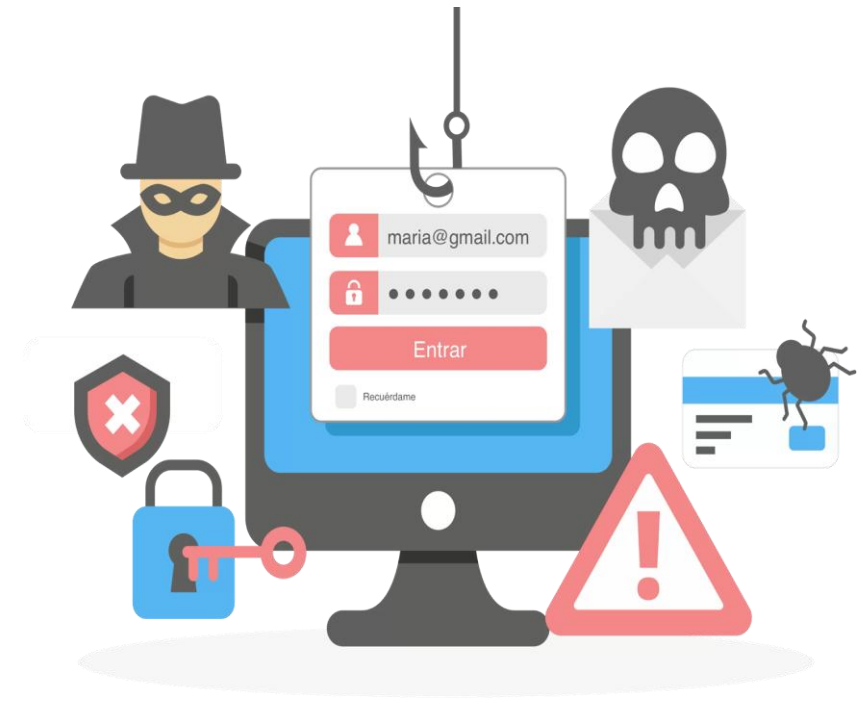


Introduction II

Solution:

Continuous authentication throughout the session.

- Possible approach:
 - Activate the authentication mechanism periodically.
- Problem:
 - Usability: constant interruptions.
- Proposed solution:
 - Use the behaviour of the users themselves.
 - User interactions with input/output devices:
 - Keyboard keystrokes: Too sensitive information!
 - Mouse movement dynamics.





Main objective

Analysis, design, implementation, and deployment of a continuous authentication platform based on user interaction with the mouse.

Sub-objectives



Data extraction and validation



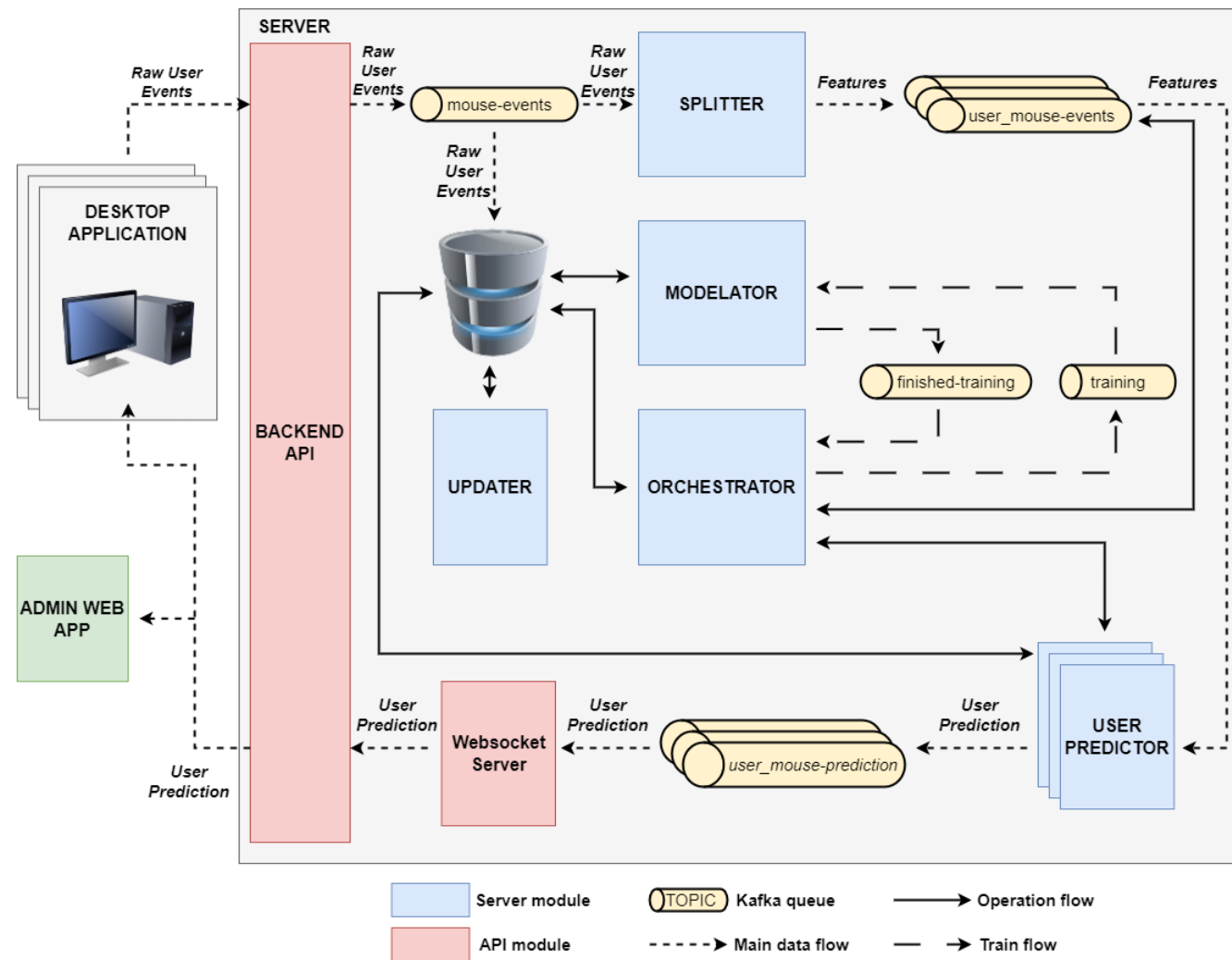
Scalable infrastructure



Study of AI models



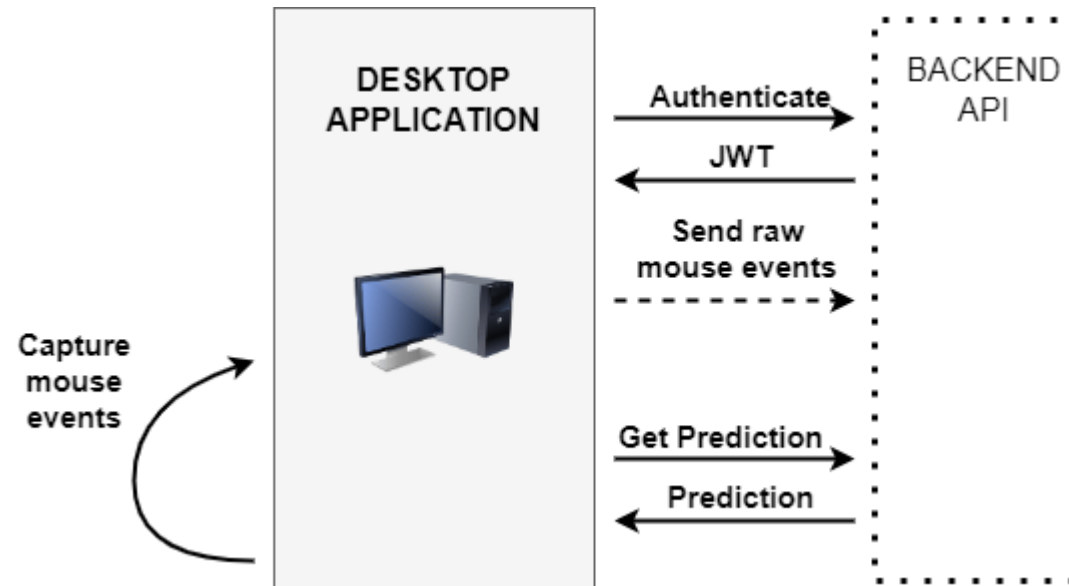
Global architecture





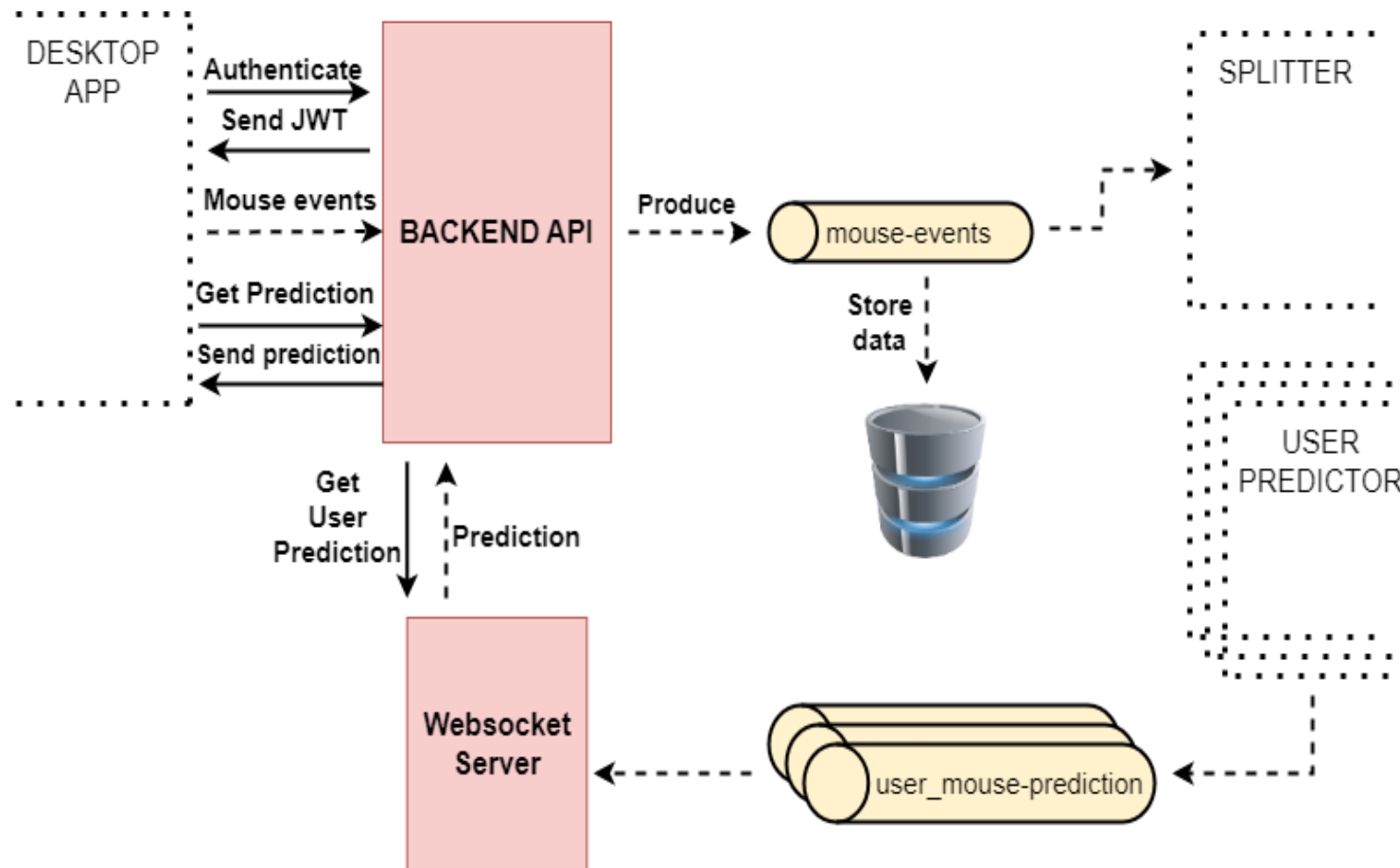
Component-based design I

- Java implementation.
- Blocks of 1,000 events.
- Prediction: value between 0 and 1.





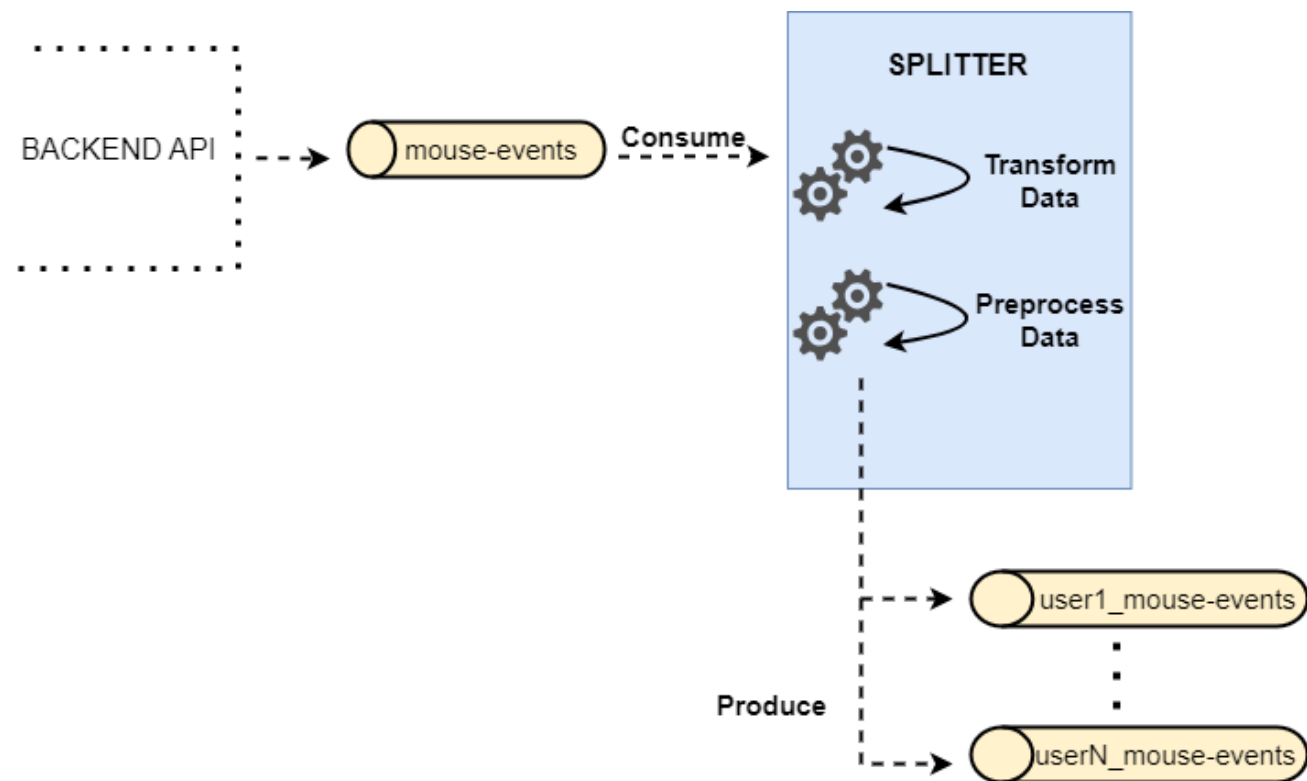
Component-based design II





Component-based design III

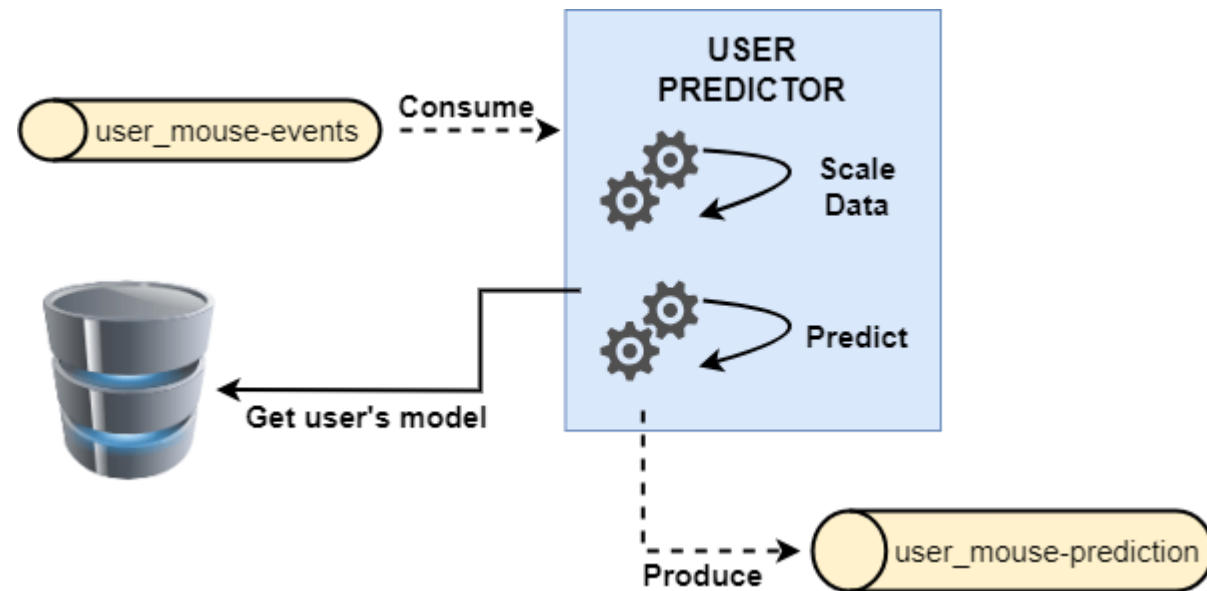
- Data preprocessing:
 - Outliers removal.
 - Data clustering.





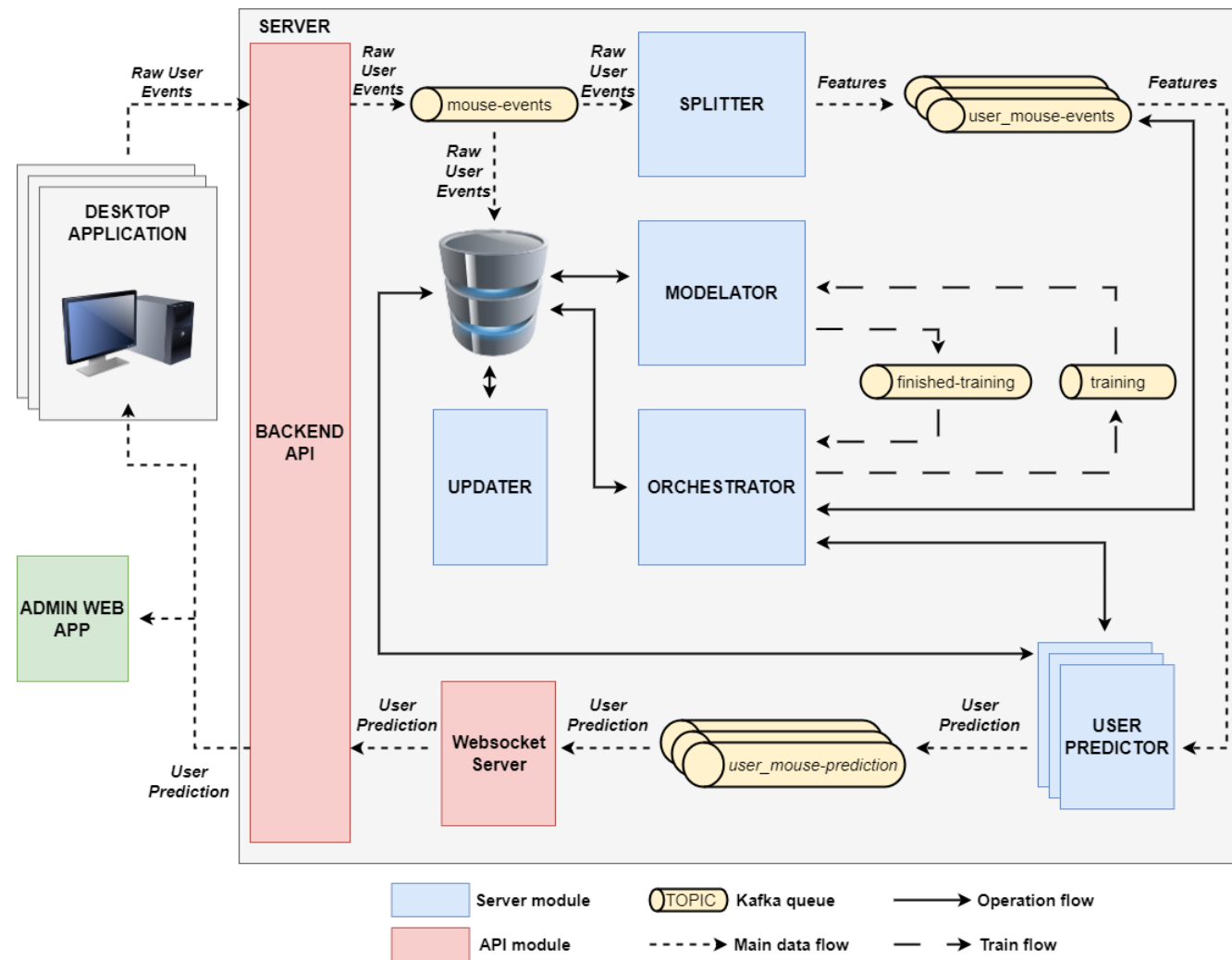
Component-based design IV

- Data preprocessing:
 - Data scaling.
- Prediction generation.





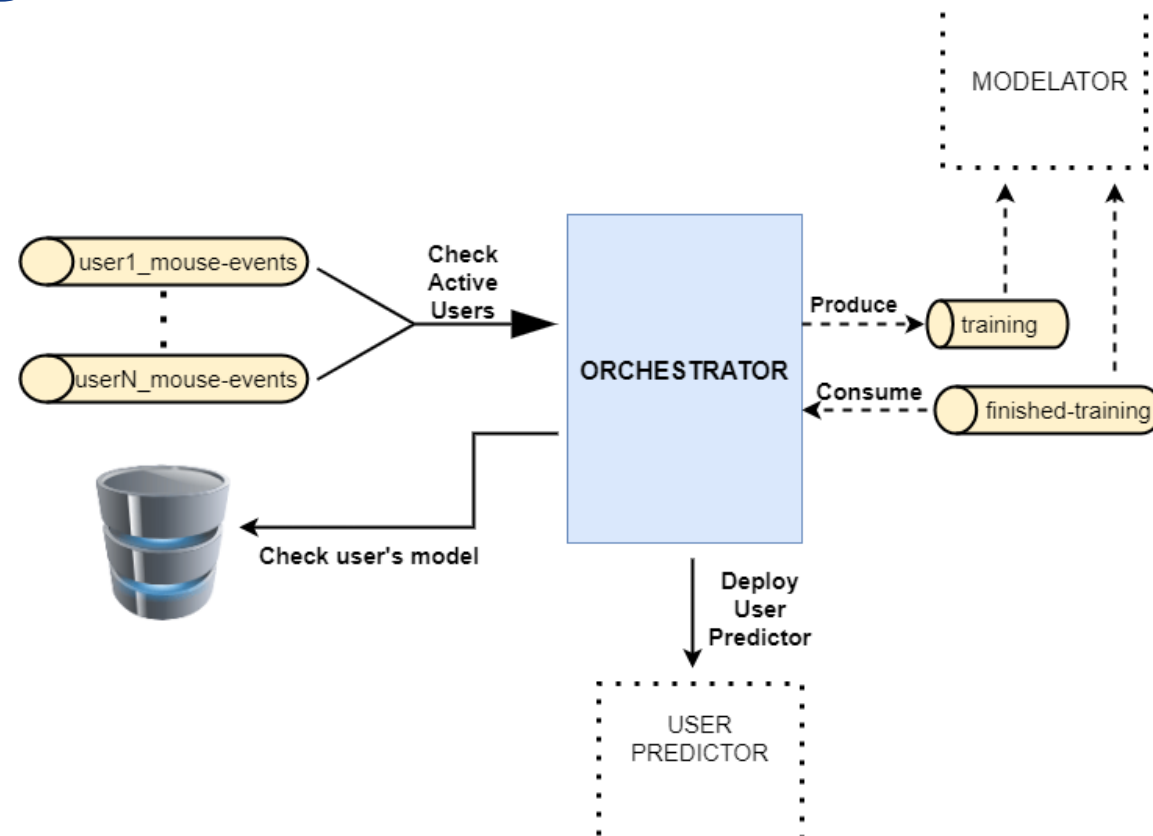
Global architecture





Component-based design V

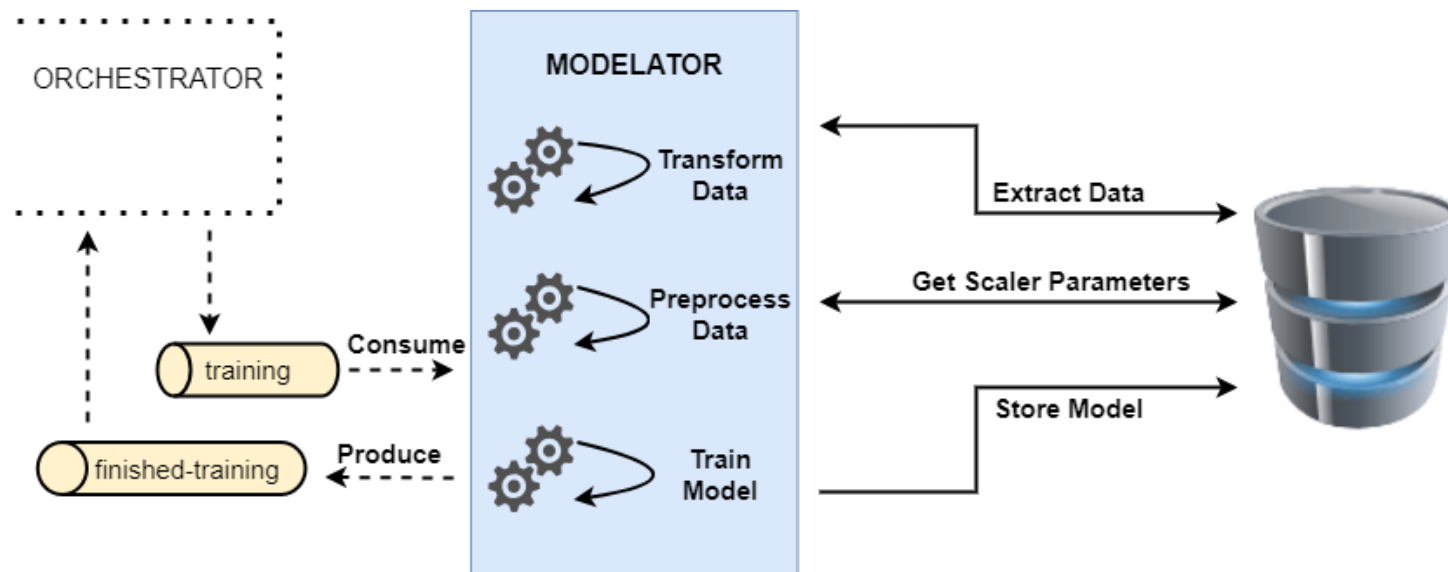
- Cases:
 - No model and insufficient data.
 - No model, sufficient data.
 - Model available, but no predictor.





Component-based design VI

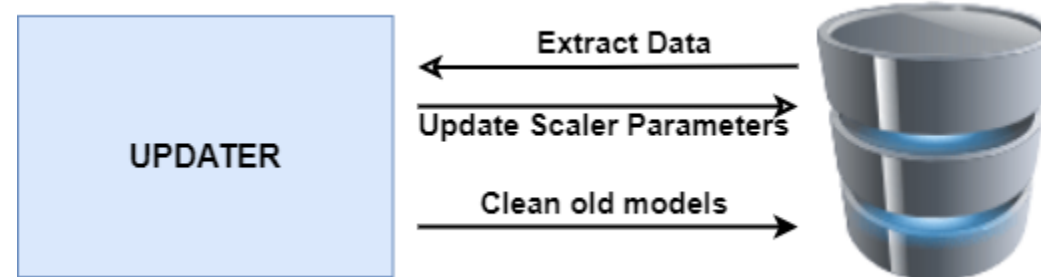
- Resilience to system crashes.





Component-based design VII

- Update scaling values in short periods.
- Constant but reduced consumption.





Data I

Event compilation

```
{
  "events": [
    {
      "x": 2256,
      "y": 896,
      "timestamp": 1739910791642
    },
    ...
    {
      "x": 3148,
      "y": 659,
      "timestamp": 1739910821268
    }
  ],
  "metadata": {
    "user": "Ejemplo",
    "mac": "00-00-00-00-00-00",
    "os": "Windows",
    "osVersion": "11",
    "appVersion": "4.0.0.1",
    "timestamp": 1739910821269,
    "UID": "00000000-0000-0000-0000-000000000000"
  }
}
```



Data II

- Feature extraction.
- Feature processing:
 1. Outliers removal.
 2. Data clustering.
 3. Data scaling.

Feature	Definition
Horizontal velocity	$hv_i = \frac{x_i - x_{i-1}}{t_i - t_{i-1}}$
Vertical velocity	$vv_i = \frac{y_i - y_{i-1}}{t_i - t_{i-1}}$
Tangencial velocity	$tv_i = \sqrt{hv_i^2 + vv_i^2}$
Tangencial acceleration	$ta_i = \frac{tv_i - tv_{i-1}}{t_i - t_{i-1}}$
Tangencial jerk	$tj_i = \frac{ta_i - ta_{i-1}}{t_i - t_{i-1}}$
Distance from the origin	$l_i^0 = \sqrt{x_i^2 + y_i^2}$
Distance from the chunk reference	$l_i^{cr} = \sqrt{(x_{cr} - x_i)^2 + (y_{cr} - y_i)^2}$
Slope angle of the tangent from the origin	$\theta_i^0 = \arctan\left(\frac{y_i}{x_i}\right)$
Slope angle of the tangent from the chunk reference	$\theta_i^{cr} = \arctan\left(\frac{y_i - y_{cr}}{x_i - x_{cr}}\right)$
Curvature	$c_i = \frac{\theta_i^0 - \theta_{i-1}^0}{l_i^0 - l_{i-1}^0}$
Curvature rate of change	$\delta c_i = \frac{c_i - c_{i-1}}{l_i^0 - l_{i-1}^0}$
Curvature within the chunk	$c_i^{cr} = \frac{\theta_i^{cr} - \theta_{i-1}^{cr}}{l_i^{cr} - l_{i-1}^{cr}}$
Curvature rate of change within the chunk	$\delta c_i^{cr} = \frac{c_i^{cr} - c_{i-1}^{cr}}{l_i^{cr} - l_{i-1}^{cr}}$
Curvature from the origin	$c_i^0 = \frac{\theta_i^0 - \theta_{i-1}^0}{l_i^0}$
Curvature rate of change from the origin	$\delta c_i^0 = \frac{c_i^0 - c_{i-1}^0}{l_i^0}$

where x_i and y_i are the mouse positions and t_i is the *timestamp* for a given record.



Results

Analysis of Artificial Intelligence models



CatBoost



Decision trees



Neural Networks



Random Forest



Support Vector
Machines (SVM)



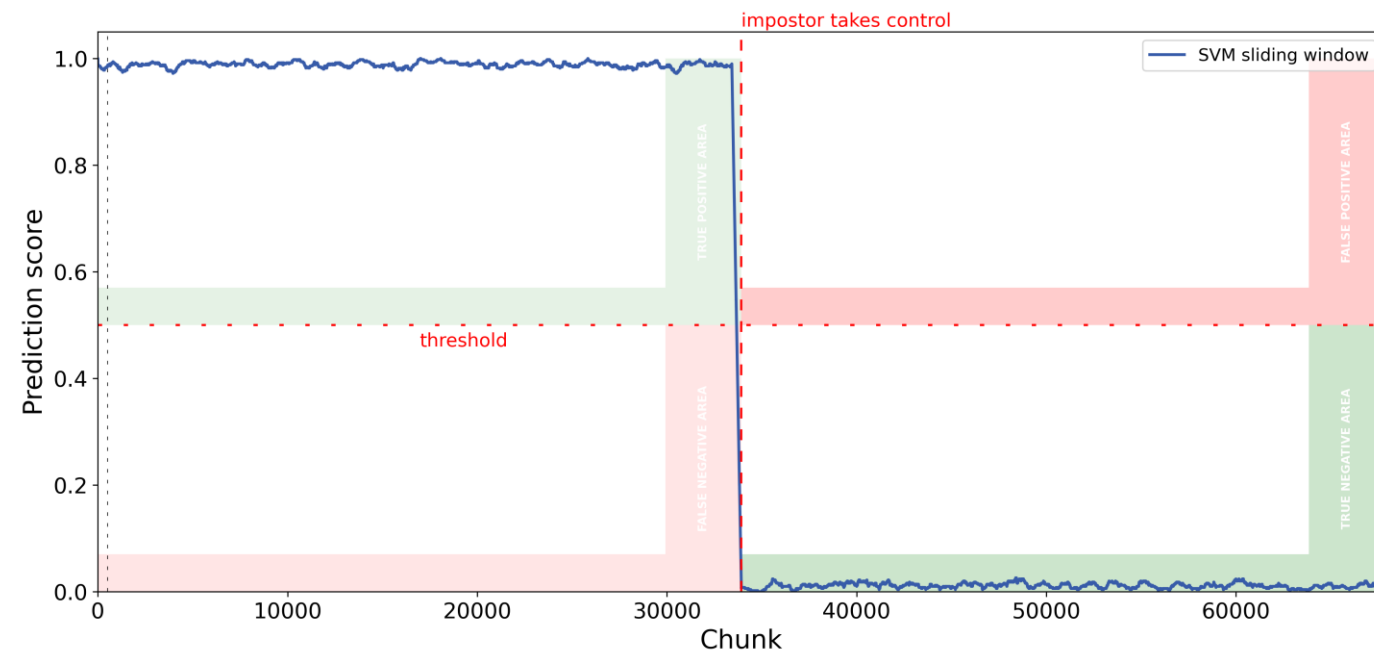
Results

	Accuracy	Precision	Recall	F1	CV Precision (Std Dev)
CatBoost	0.9856	0.9824	0.9894	0.9859	0.9789 (± 0.0022)
Decision Tree	0.9571	0.9618	0.9529	0.9573	0.9562 (± 0.0069)
Neural Network	0.9596	0.9524	0.9692	0.9607	0.9488 (± 0.0082)
Random Forest	0.9744	0.9703	0.9799	0.9750	0.9644 (± 0.0039)
SVM	0.9790	0.9766	0.9821	0.9794	0.9729 (± 0.0033)



Results

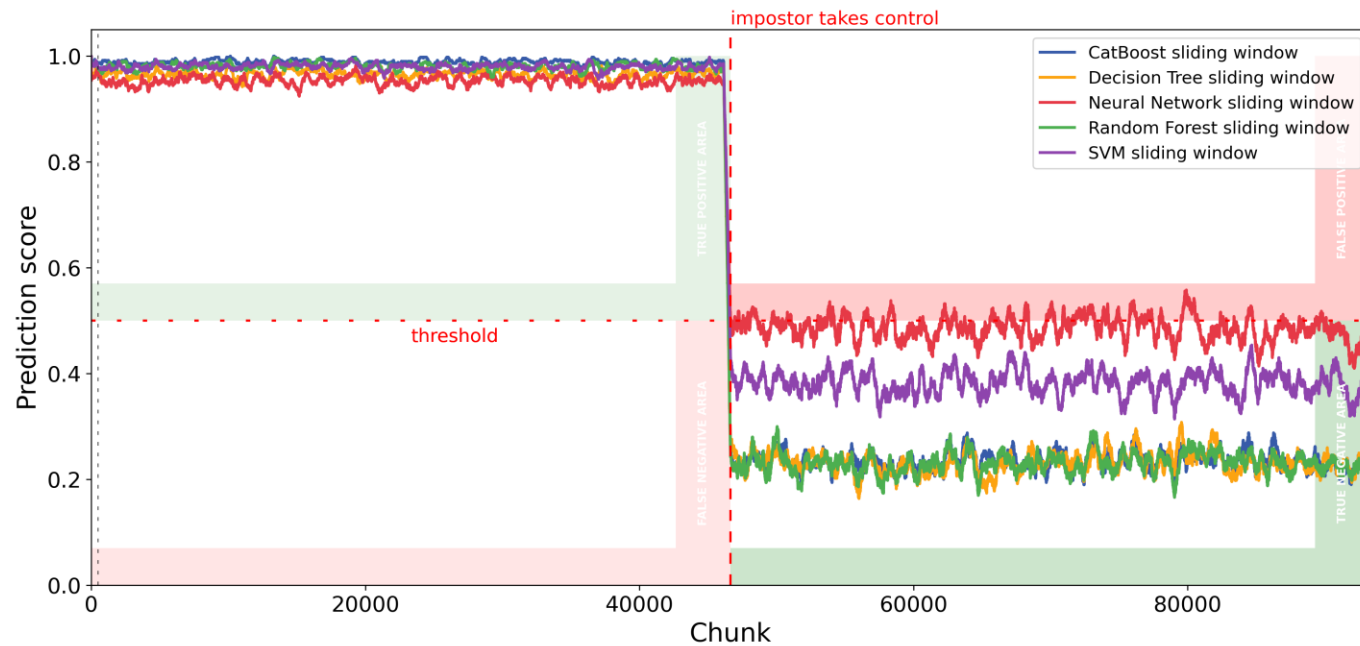
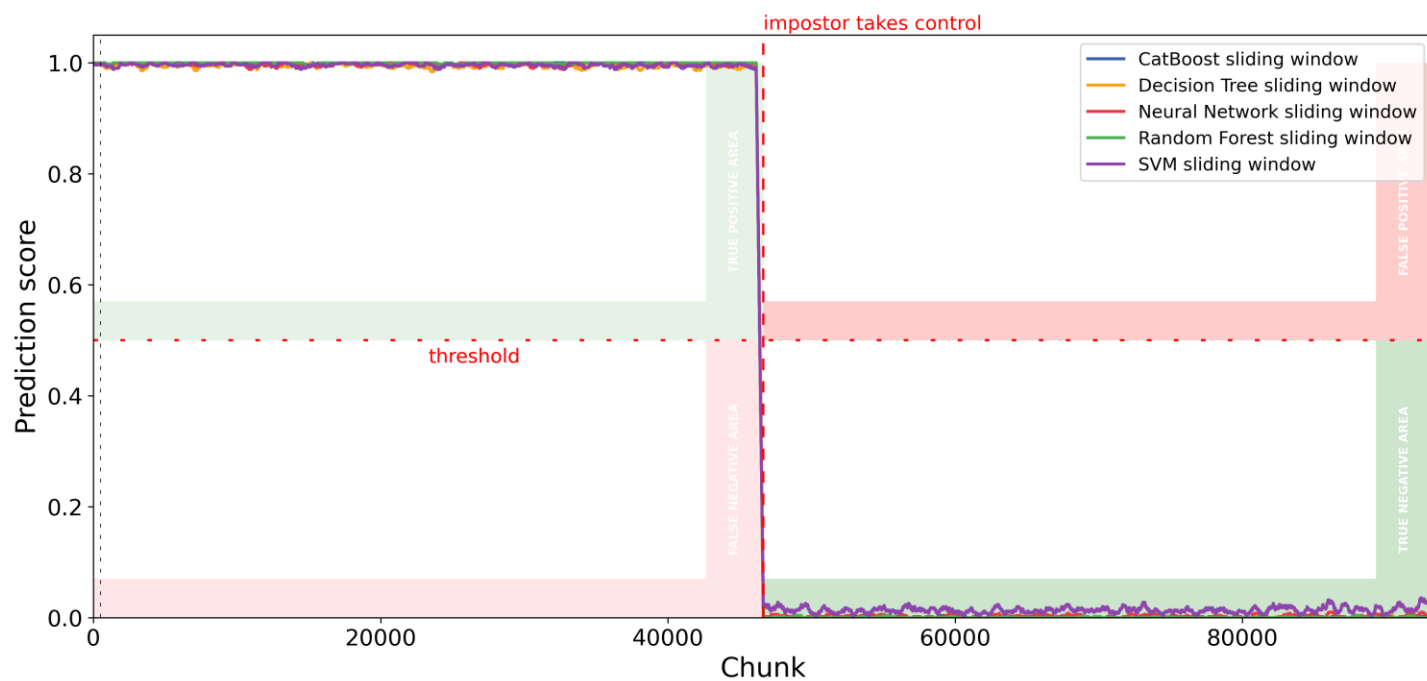
Rejection Test





Results

Rejection Test Comparison between models





Results

User	Organization	App Version	Operating System	Prediction ↑	Model version	Base Model	Retrain	Last sending of data	Details
 User 1	Organization 1	3.2.2.0b	Windows 10	60,52 %	v1	MLP		31 Jul. 2024 13:10:30	
 User 2	Organization 1	3.2.2.0b	Windows 10	61,07 %	v4	MLP		31 Jul. 2024 13:11:24	
 User 3	Organization 1	3.2.2.0b	Windows 11	63,52 %	v1	MLP		31 Jul. 2024 13:10:42	
 User 4	Organization 1	3.2.2.0b	Windows 10	65,52 %	v4	MLP		31 Jul. 2024 13:11:03	
 User 5	Organization 1	3.2.2.0b	Windows 10	67,38 %	v4	MLP		31 Jul. 2024 13:10:58	
 User 6	Organization 2	3.2.2.0b	Windows 11	75,02 %	v1	MLP		31 Jul. 2024 13:11:01	
 User 7	Organization 2	3.2.2.0b	Windows 10	75,41 %	v1	MLP		31 Jul. 2024 13:11:07	
 User 8	Organization 3	3.2.1.0	Windows 10	79,46 %	v3	MLP		31 Jul. 2024 13:10:41	
 User 9	Organization 1	3.2.2.0b	Windows 11	79,50 %	v1	MLP		31 Jul. 2024 13:10:42	
 User 10	Organization 2	3.2.1.2b	Windows 11	80,05 %	v1	MLP		31 Jul. 2024 13:11:15	
 User 11	Organization 1	3.2.2.0b	Windows 10	80,34 %	v1	MLP		31 Jul. 2024 13:09:42	
 User 12	Organization 2	3.2.2.0b	Windows 11	83,05 %	v1	MLP		31 Jul. 2024 13:11:12	
 User 13	Organization 1	3.2.2.0b	Windows 10	84,21 %	v4	MLP		31 Jul. 2024 13:10:43	



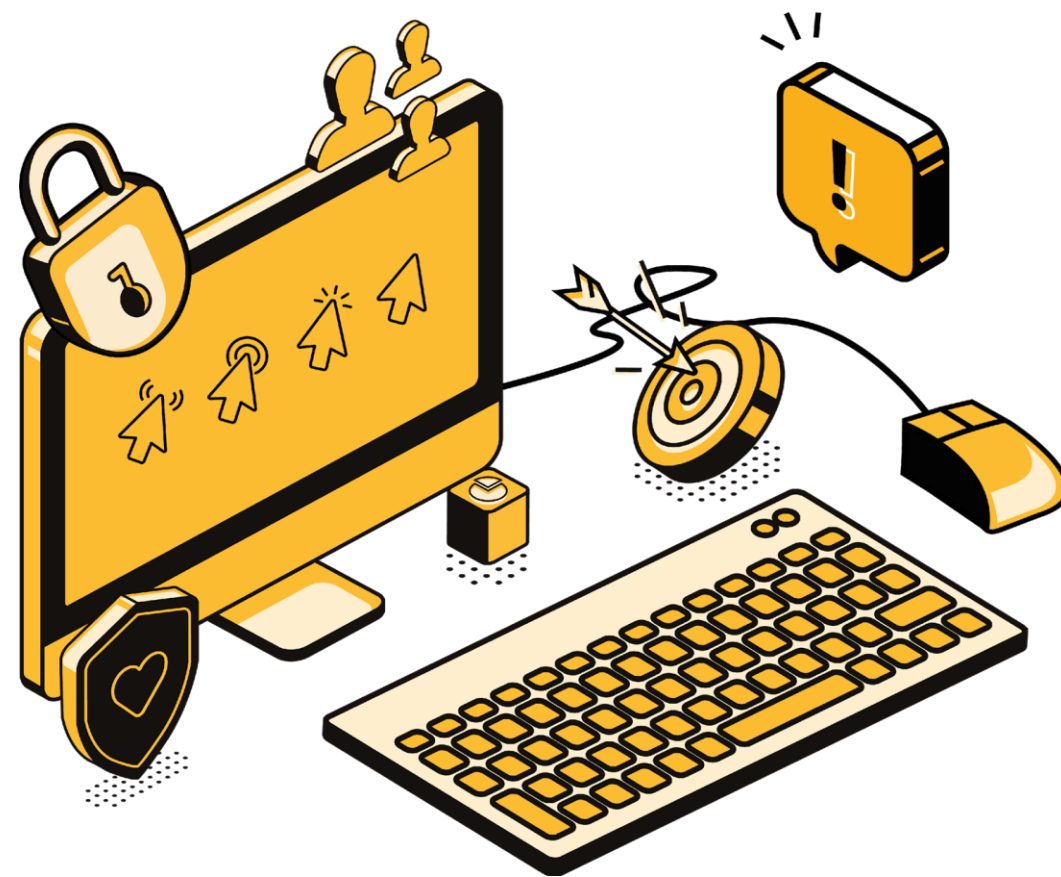
Conclusions

- Advances in attacks against traditional authentication systems have underscored the need for more dynamic and secure mechanisms to guarantee user identity, not only at the beginning of the interaction with a system but also throughout active sessions.
- The identity verification through mouse dynamics is feasible and offers strong potential as a complementary mechanism to traditional authentication methods.
- The results obtained confirm that mouse dynamics can achieve high levels of accuracy, precision, and recall, positioning them as a reliable basis for continuous authentication.



Future work

- A systematic performance evaluation of the platform, instrumenting the pipeline to measure how resource consumption evolves as data volume and user concurrency increase.
- Expand the range of behavioral features and validate the platform with larger and more heterogeneous populations.



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