ML MODELS FOR DATA CLASSIFICATION IN VR

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INTRODUCTION

As VR continues to advance, there is a growing need to **enhance user experiences** and **personalize content** to individual preferences

Machine learning (ML) plays a crucial role in achieving these objectives by enabling **the analysis and classification** of vast amounts of data

Goals:

- **enhance player experience** by keeping players engaged and immersed is essential for creating enjoyable and memorable gaming experiences
- **personalize adaptation** by understanding individual player preferences and emotions, for the customization of VR content to meet specific needs and enhance overall satisfaction

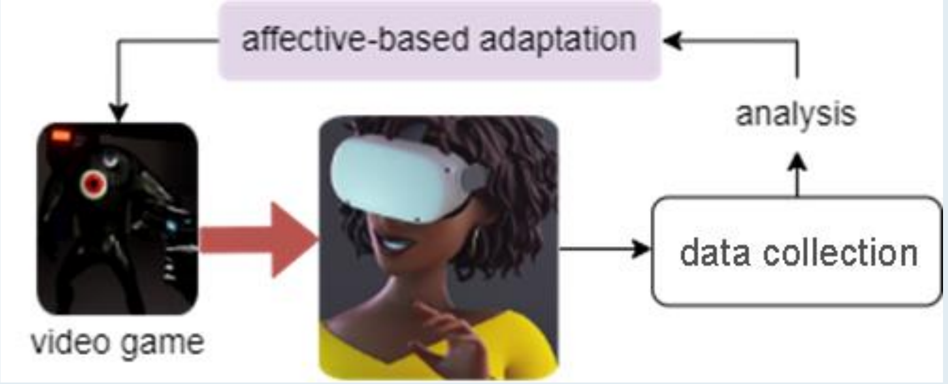
ENHANCING PLAYER EXPERIENCE IN VR

Flow (CSIKSZENTMIHALYI, 1990):

- a **state of complete absorption and engagement** experienced by users

***Affective-based Game Adaptation*:**

- recognizing the importance of individual **player emotions and preferences** in shaping their gaming experiences
- **customizing game content and challenges** based on real-time analysis of player affective states



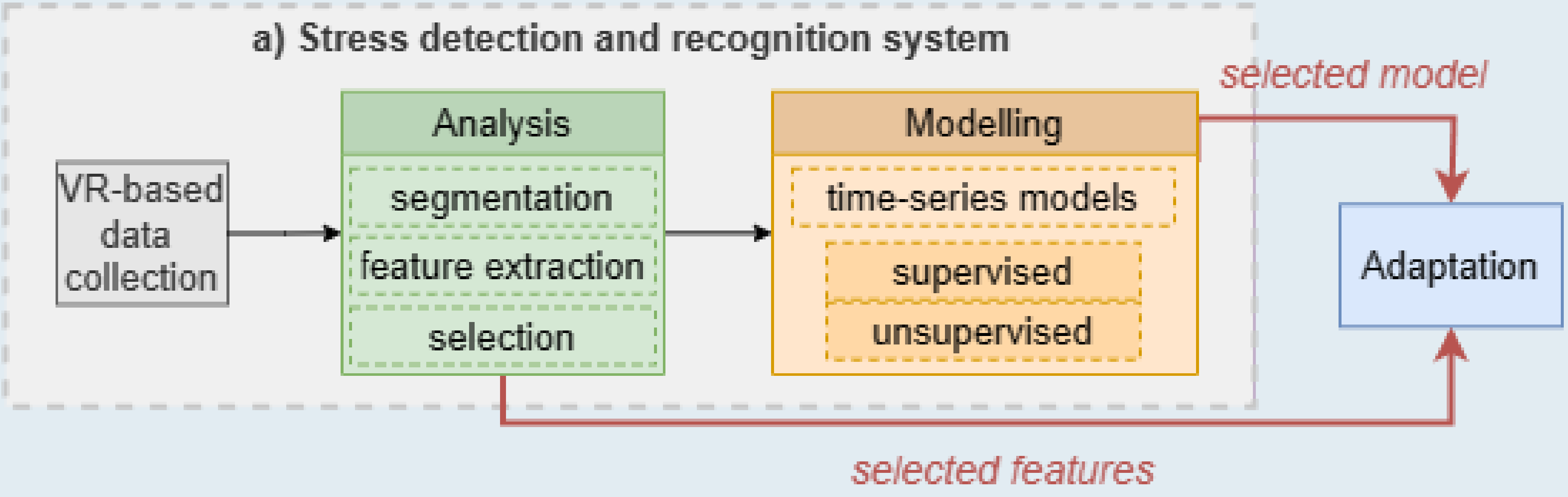
DATA COLLECTION IN VR

Collecting data from VR environments involves capturing various types of information related to user interactions and experiences

Inputs:

- users' **movements and interactions** within the virtual environment
- **button presses,** and other actions
- **gaze and face tracking** data collected from devices like Meta Quest Pro: gaze tracking enables analysis of users' visual attention, while face tracking provides insights into emotional expressions and engagement levels.
- User’s **speech data**

PIPELINE


a) Stress detection and recognition system
VR-based data collection
Analysis
segmentation
feature extraction
selection
Modelling
time-series models
supervised
unsupervised
selected model
Adaptation
selected features

MODELS

INTRODUCTION TO ML MODELS

ML models enable us to **uncover patterns, make predictions, and extract meaningful insights** from complex VR datasets

Objectives:

- Understand the fundamental principles of ML models used in VR data analysis
- Explore how these models can be applied to enhance user experiences and personalize VR content

Models:

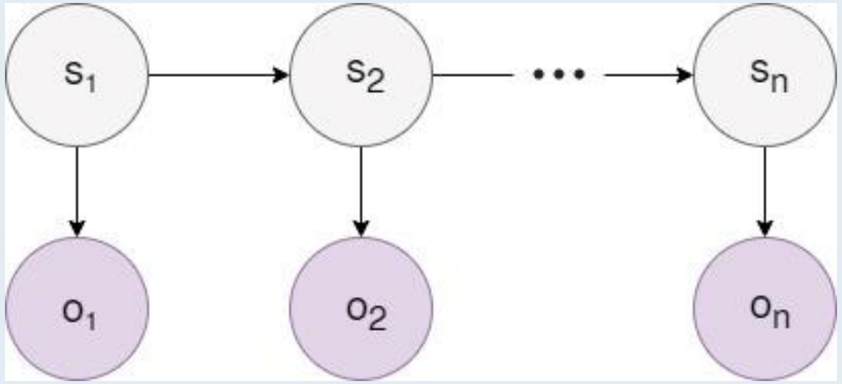
- *Kalman Filter*
- *Kalman Filter with Controller Input*
- *Long Short-Term Memory (LSTM)*

KALMAN FILTER (KF)

The Kalman Filter is a widely used algorithm for state estimation and prediction in dynamic systems

Key Principles:

- **Recursive estimation**: updates its estimate of the system state based on new measurements (observations) and predictions
- **State-Space Representation**: operates within the framework of state-space representation, where the system is modeled as a set of latent variables (states) evolving over time



KF MATHEMATICAL MODEL

1. **Prediction Step:**

next state and errors estimation using current state and error covariance

State Prediction:

$$\hat{x}_{t|t-1} = F_t \cdot \hat{x}_{t-1}$$

Covariance Prediction:

$$P_{t|t-1} = F_t \cdot P_{t-1} \cdot F_t^T + Q_t$$

2. **Update Step:**

estimates correction using the measurement observation

Kalman Gain Calculation:

$$K_t = \frac{P_{t|t-1} \cdot H_t^T}{H_t \cdot P_{t|t-1} \cdot H_t^T + R_t}$$

State Update:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \cdot (z_t - H_t \cdot \hat{x}_{t|t-1})$$

Covariance Update:

$$P_{t|t} = (I - K_t \cdot H_t) \cdot P_{t|t-1}$$

$\hat{x}_{t|t-1}$ is the predicted state estimate at time t given information up to time $t-1$.

$P_{t|t-1}$ is the predicted state covariance at time t given information up to time $t-1$.

F_t is the state transition matrix describing the evolution of the system over time.

Q_t is the process noise covariance.

K_t is the Kalman gain matrix.

H_t is the observation matrix mapping the state into the observation space.

R_t is the measurement noise covariance.

z_t is the measurement at time t.

KF APPLICATION

In the context of VR, the KF can be employed to track and predict user affective state with high accuracy

Application in VR:

1. **Tracking user affective states**: can predict the hidden states (affective state) of VR users based on data collected from Oculus sensors (observations)
2. **Real-time interaction:** enables real-time predictions in virtual environments
3. **Unsupervised:** it does not need labels

KALMAN FILTER WITH CONTROL INPUT

The KF with **control input** extends the basic KF by incorporating additional input from VR

By integrating **external data**, this model enhances the accuracy of motion tracking and prediction in VR environments

Integration of control input:

- **External data integration:** incorporates additional input variables, such as environmental factors, into the KF

Application in VR:

- Enables the Kalman Filter to adaptively adjust its predictions based also on external control signals, **enhancing responsiveness and accuracy**

KF WITH CONTROL INPUT MATHEMATICAL MODEL

Prediction Step:

State Prediction:

$$\hat{x}_{t|t-1} = F_t \cdot \hat{x}_{t-1} + B_t \cdot u_t$$

Covariance Prediction:

$$P_{t|t-1} = F_t \cdot P_{t-1} \cdot F_t^T + Q_t$$

Update Step:

Kalman Gain Calculation:

$$K_t = \frac{P_{t|t-1} \cdot H_t^T}{H_t \cdot P_{t|t-1} \cdot H_t^T + R_t}$$

State Update:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \cdot (z_t - H_t \cdot \hat{x}_{t|t-1})$$

Covariance Update:

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H_t is the observation matrix mapping the state into the observation space.

R_t is the measurement noise covariance.

z_t is the measurement at time t.

B_t is the control matrix mapping the control input u_t into the state space.

LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to process sequential data with long-range dependencies

Key Characteristics:

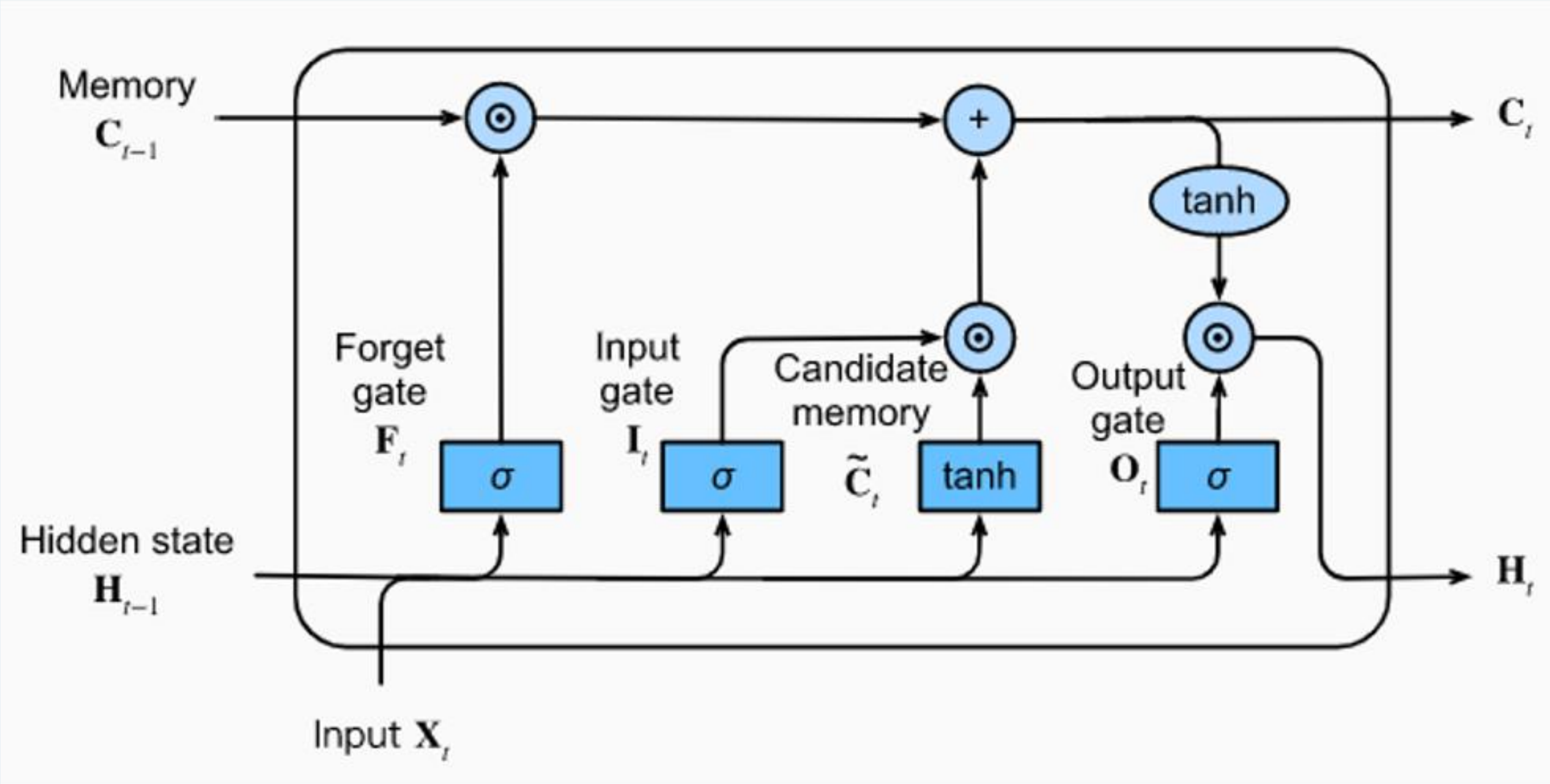
- **Memory cells:** LSTM units contain memory cells capable of retaining information over extended time intervals
- **Gating mechanisms:** LSTM incorporates gating mechanisms to regulate the flow of information, facilitating the selection and use of relevant features

LSTM COMPONENTS

Components of LSTM:

- **Memory Cells**: LSTMs contain memory cells that can maintain information over long periods, allowing for the capture of long-term dependencies
- **Gates:** LSTM units have three types of gates: input gate, forget gate, and output gate
  - *Input Gate:* Controls the flow of new information into the memory cell, determining which information should be stored
  - *Forget Gate:* Decides what information from the previous cell state should be forgotten or discarded
  - *Output Gate*: Regulates the flow of information from the memory cell to the output, determining the next hidden state
- **Activation Functions**: LSTMs use activation functions, such as the sigmoid and tangent functions, to control the flow of information through the gates and memory cells, allowing for non-linear transformations of the input data

LSTM STRUCTURE



MODELS COMPARISON

Model	Advantages	Disadvantages
Kalman filter	• Requires minimal training data due to its recursive estimation approach • Provides real-time tracking • Can be used on a single subject • No need for labels	• Limited ability to capture complex temporal dependencies • Assumes linear dynamics, may not fully capture nonlinear relationships
Kalman filter with control input	• Same advantages as Kalman Filter • Incorporates external control inputs for improved predictions	• Requires tuning of control input parameters
Long short-term memory	• Captures long-term dependencies in sequential data • Effective for modeling complex temporal dynamics in VR interactions	• Difficult to be tuned on one single person • Requires labeling

CONCLUSION

Considerations:

- KF is suitable for real-time motion tracking with minimal training data requirements
- Kalman Filter with Control Input enhances prediction accuracy but may increase complexity
- LSTM excels in capturing complex temporal dynamics but may require larger datasets and computational resources

Impact on VR experiences:

- Personalized interactions: by understanding user preferences and behaviors, VR applications can tailor experiences to individual users.
- Adaptive content: ML enables real-time adaptation of VR content based on user actions and affective states, maximizing engagement