Project Report
Predictive Movement Modeling Using HMMs and DBNs

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1 Objective

The objective of this project is to construct a predictive model capable of forecasting a user's next location and intended activity within a smart home ecosystem, based on temporal sequences of historical sensor activations and contextual variables. The model leverages Hidden Markov Models (HMMs) to model sequential dependencies between latent states (representing location and activity) and observed sensor events, while Dynamic Bayesian Networks (DBNs) extend this by incorporating richer temporal dynamics and multi-variable dependencies. This approach enables the system to predict future states with higher granularity, thereby supporting intelligent decision-making for automated control systems, improving home security through anomaly detection, and enabling energy-efficient management by preemptively adjusting environmental settings based on predicted user behavior.

2 Introduction and Motivation

Smart home automation aims to provide an environment that is adaptive, comfortable, energy-efficient, and secure. A truly intelligent system should not only react to commands but proactively predict and prepare for the user's needs. My vision is to build a comprehensive automation system that anticipates user behavior to deliver personalized care and optimal environmental control.

Imagine a system that can:

- Automatically lock the door when the user leaves for work.
- Brew coffee just before the user wakes up.
- Adjust lighting and air conditioning in anticipation of the user's movement.
- Prepare the bathroom or kitchen depending on the user's internal state.

To enable this, the system must understand what the user is feeling now (e.g., sleepy, hungry, needing to use the restroom) and predict their next move. This is not simply activity recognition—it is intention prediction based on sequential observations over time.

In such a scenario, the human experience can be modeled as a graph of mental or physical states (e.g., Working $\rightarrow$ Sleepy $\rightarrow$ Sleeping) where each state emits observable actions like sitting down, turning off a laptop, or lying on a bed. If we can infer the current internal state based on sensor observations, we can predict the most probable next state, thus unlocking advanced automation potential.

3 The Challenge

The core challenge lies in learning these hidden user states and transition patterns from historical sensor data. We need a probabilistic model that:

- Represents hidden internal user states (intentions or feelings).
- Captures the sequence of transitions over time.
- Learns the relationship between observed actions and internal states.
- Can operate under uncertainty and in real time.

4 Why Hidden Markov Models (HMMs)?

This leads us to Hidden Markov Models (HMMs), which offer a natural and mathematically sound framework for this problem:

- Hidden states represent the user's internal condition (e.g., active, idle, sleepy).
- Observations represent sensor-detected behavior (e.g., movement, location).
- Transition probabilities model how users move from one state to another.
- Emission probabilities model how likely a certain observation is given a hidden state.

HMMs strike a balance between model interpretability, computational efficiency, and real-time capability, making them well-suited for smart environments with sparse but structured data.

5 From HMM to DBN: The Need for Contextual Awareness

While initial implementation with Hidden Markov Models (HMMs) showed promise in modeling human behavior through sequential observations, the limitations became evident during evaluation. The HMM was trained using observation pairs consisting of user activity and location, such as:

- (Cooking, Kitchen) — could correspond to the user being hungry or preparing food
- (Sleeping, Bedroom) — indicative of a resting or sleeping state

Although the HMM could infer probable hidden states and predict subsequent user locations, its predictions lacked granularity and contextual awareness, leading to less accuracy in forecasting the user's actual next state. It became clear that (activity, location) pairs alone do not adequately capture the nuances of user behavior in a dynamic environment like a smart home.

5.1 The Missing Variables

Upon further analysis, it was found that human decisions and behavior patterns are strongly influenced by contextual cues such as:

- Time of Day – Sleeping and eating behaviors follow natural circadian cycles.
- Temperature – Environmental comfort often influences movement or rest decisions.

These variables, although not directly part of the user's activity stream, modulate behavioral patterns in subtle but consistent ways. Incorporating such context is crucial for accurate and personalized predictions.

5.2 Enhanced Model with Dynamic Bayesian Networks (DBNs)

To overcome these limitations, the architecture was extended using Dynamic Bayesian Networks (DBNs). In the refined pipeline:

- The HMM outputs the top-3 most probable user states based on (activity, location) sequences.
- These candidate states are passed to the DBN, which incorporates quantized contextual variables — time of day and temperature — to produce a refined prediction.

This approach enables a two-stage reasoning process:

- HMM models user state transitions over time using observable actions.
- DBN uses external context to weigh and refine these predictions more precisely.

5.3 Quantization of Contextual Variables

Since time and temperature are continuous, they were quantized into discrete categories to reduce noise and enhance learning:

Feature	**Categories**
Time	Morning, Afternoon, Evening, Night
Temperature	Cold, Moderate, Hot

6 Dataset Description and Preprocessing

6.1 Dataset Overview

To train and evaluate the predictive models, this project initially explored datasets from the CASAS Smart Home Project at Washington State University, a leading initiative in the field of smart home research. CASAS provides real-world datasets collected through long-term deployments of sensor-based monitoring systems in residential environments. These datasets include detailed logs of user activity, sensor activations, and environmental conditions—making them well-suited for behavior modeling and automation tasks.

During early experimentation, multiple CASAS datasets were analyzed and partially merged. The merging process required aligning sensor formats, normalizing timestamps, and resolving inconsistencies across different deployment settings. After a rigorous preprocessing phase, a unified dataset was curated to support the modeling goals of this project.

6.2 Final Dataset Structure

The final dataset used in this study includes four key features:

Column	**Description**
Activity	The user's inferred or labeled action (e.g., Cooking, Sleeping, Eating).
Location	The room or area associated with the activity (e.g., Kitchen, Bedroom).
Temperature	The ambient temperature at the time of the activity (inferred from context).
Time	Timestamp or categorized time of day (e.g., Morning, Afternoon, Evening).

Each record represents an observation collected from a smart home environment, enriched with contextual variables that influence user behavior.

This format supports both:

- Sequential modeling of (activity, location) transitions using HMMs.
- Context-aware reasoning through DBNs using temperature and time categories.

By combining real sensor observations with curated context features, this dataset provides a rich foundation for building predictive models that reflect natural indoor behavior patterns.

7 Theoretical Foundations

In this section, we present the theoretical framework underpinning the models employed in this study: the **Hidden Markov Model (HMM)** and the **Dynamic Bayesian Network (DBN)**. These models have been selected for their ability to capture temporal dependencies and contextual factors inherent in human behavior within smart home environments. While HMMs provide a robust foundation for sequential modeling of location and activity transitions, DBNs extend this capability by incorporating additional contextual variables, enhancing predictive accuracy.

7.1 Hidden Markov Model (HMM)

The Hidden Markov Model (HMM) is a generative probabilistic framework that models sequential data with unobserved (hidden) states. In this project, the hidden states correspond to the overall **state of the user**, which reflects the user's internal intent or condition, while the observations are a combination of **location** and **activity** detected at each time step.

7.1.1 Model Specification

The HMM is defined by:

- Hidden states $S = \{S_1, S_2, ..., S_N\}$ representing the user's internal state (e.g., active, idle, resting).
- Observations $O = \{(L_1, A_1), (L_2, A_2), ..., (L_T, A_T)\}$ where L_t is the location and A_t is the activity at time t.
- Initial state distribution $\pi(i) = P(S_1 = s_i)$.
- Transition probabilities $a_{ij} = P(S_t = s_j \mid S_{t-1} = s_i)$, describing the likelihood of transitioning between user states.
- Emission probabilities $b_j(l, a) = P(O_t = (l, a) \mid S_t = s_j)$, the probability of observing a specific location-activity pair given the user's state.

The joint probability of the state sequence S and observation sequence O is given by:

$$P(O, S) = \pi(S_1) \cdot b_{S_1}(L_1, A_1) \prod_{t=2}^{T} a_{S_{t-1}S_t} \cdot b_{S_t}(L_t, A_t)$$

7.1.2 Key Algorithms

Forward Algorithm Computes the probability of observing the first t steps and being in state i at time t:

$$\alpha_t(i) = \left[\sum_j \alpha_{t-1}(j) \cdot a_{ji}\right] \cdot b_i(L_t, A_t)$$

Backward Algorithm Calculates the probability of observing the future sequence given the current state:

$$\beta_t(i) = \sum_j a_{ij} \cdot b_j(L_{t+1}, A_{t+1}) \cdot \beta_{t+1}(j)$$

Expectation Values (Posterior Probabilities) State occupancy probability:

$$\gamma_t(i) = \frac{\alpha_t(i) \cdot \beta_t(i)}{P(O)}$$

Transition probability:

$$\xi_t(i,j) = \frac{\alpha_t(i) \cdot a_{ij} \cdot b_j(L_{t+1}, A_{t+1}) \cdot \beta_{t+1}(j)}{P(O)}$$

Viterbi Algorithm (Decoding) Finds the most likely sequence of hidden user states:

$$\delta_t(i) = \max_j \left[\delta_{t-1}(j) \cdot a_{ji}\right] \cdot b_i(L_t, A_t)$$

Backtracking is then applied to reconstruct the optimal user state sequence.

Algorithm 1 Forward-Backward Algorithm for HMM

Input: Observation sequence $O = \{(L_1, A_1), ..., (L_T, A_T)\}$, parameters π, A, B
Initialization:
for each state i **do**
    $\alpha_1(i) = \pi(i) \cdot b_i(L_1, A_1)$
    $\beta_T(i) = 1$
end for
Forward Pass:
for $t = 2$ to T **do**
    for each state i **do**
        $\alpha_t(i) = \sum_j \alpha_{t-1}(j) \cdot a_{ji} \cdot b_i(L_t, A_t)$
    end for
end for
Backward Pass:
for $t = T - 1$ down to 1 **do**
    for each state i **do**
        $\beta_t(i) = \sum_j a_{ij} \cdot b_j(L_{t+1}, A_{t+1}) \cdot \beta_{t+1}(j)$
    end for
end for
Output: $\alpha_t(i)$ and $\beta_t(i)$ for all states and times

Algorithm 2 Baum-Welch Algorithm for HMM Training (Location + Activity Observations)

Input: Observed sequence $O = \{(L_1, A_1), ..., (L_T, A_T)\}$
Initialize: Parameters π, A, B
repeat
    Compute forward probabilities $\alpha_t(i)$
    Compute backward probabilities $\beta_t(i)$
    Estimate $\gamma_t(i)$ and $\xi_t(i, j)$
    Update $\pi(i) = \gamma_1(i)$
    Update $a_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}$
    Update $b_j(l, a) = \frac{\sum_{t:(L_t,A_t)=(l,a)} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}$
until Convergence
Output: Estimated parameters π, A, B

Algorithm 3 Viterbi Algorithm for HMM Decoding (Location + Activity Observations)

Input: Observation sequence $O = \{(L_1, A_1), ..., (L_T, A_T)\}$, parameters π, A, B
Initialization:
for each state i **do**
    $\delta_1(i) = \pi(i) \cdot b_i(L_1, A_1)$
    $\psi_1(i) = 0$
end for
Recursion:
for $t = 2$ to T **do**
    for each state i **do**
        $\delta_t(i) = \max_j [\delta_{t-1}(j) \cdot a_{ji}] \cdot b_i(L_t, A_t)$
        $\psi_t(i) = \arg\max_j [\delta_{t-1}(j) \cdot a_{ji}]$
    end for
end for
Termination:
$S_T^* = \arg\max_i \delta_T(i)$
Backtracking:
for $t = T - 1$ down to 1 **do**
    $S_t^* = \psi_{t+1}(S_{t+1}^*)$
end for
Output: Most likely state sequence $\{S_1^*, S_2^*, ..., S_T^*\}$

7.2 Dynamic Bayesian Network (DBN)

7.2.1 Model Specification

To enhance the predictive capabilities of the HMM, this project integrates a Dynamic Bayesian Network (DBN) that models the joint probability distribution over multiple contextual and behavioral variables. Unlike HMMs, which focus solely on state-to-observation mappings, DBNs enable reasoning over multivariate temporal dependencies.

In this setup, the DBN is used to learn the joint distribution:

$$P(\text{Activity}_t, \text{Location}_t, \text{Time}_t, \text{Temperature}_t)$$

This distribution captures real-world behavioral tendencies—for instance, activities like Eating are more likely during Morning or Evening, and Sleeping may be more frequent when Temperature is cold and Time is night.

The DBN structure allows us to represent dependencies such as:

- $\text{Location}_t \sim P(\text{Location}t \mid \text{Location}t - 1, \text{Time}_t, \text{Temperature}_t)$
- $\text{Activity}_t \sim P(\text{Activity}_t \mid \text{Location}_t, \text{Time}_t)$

These conditional distributions are estimated from historical data using the Expectation-Maximization (EM) algorithm.

7.2.2 Refinement of HMM Output

The primary role of the DBN in this system is to refine the prediction output generated by the HMM. While the HMM identifies the top-most probable next (activity, location) pairs based on transition probabilities:

$$P((\text{Activity@Location})t \mid (\text{Activity@Location})t - 1)$$

The DBN scores each of these candidates using contextual knowledge:

$$\text{Final Score} = P_{\text{HMM}} \times P_{\text{DBN}}(\text{Activity}_t, \text{Location}_t, \text{Time}_t, \text{Temperature}_t)$$

This allows the system to prioritize predictions that are both behaviorally and contextually valid, improving real-world accuracy and reliability.

8 Notation Summary

Table 1: Notation Summary

Symbol	**Description**
S_t	Hidden state at time t (user location)
O_t	Observation at time t (user activity)
C_t	Context at time t (time of day, temperature)
$\pi(i)$	Initial probability of state i
a_{ij}	Transition probability from state i to j
$b_j(k)$	Emission probability of observing activity k in stat
$\alpha_t(i)$	Forward probability of state i at time t
$\beta_t(i)$	Backward probability of state i at time t
$\gamma_t(i)$	State occupancy probability at time t
$\xi_t(i,j)$	Transition probability between states at time t
$P(Activity_t \mid Location_t, Time_t)$	DBN conditional probability of activity
$P(Location_t \mid Location_{t-1}, Time_t, Temperature_t)$	DBN conditional probability of location

9 Architecture and Workflow

9.1 System Architecture

The proposed system is designed as a modular pipeline that transforms raw smart home sensor data into intelligent, real-time predictions of user behavior. This is achieved through a hybrid probabilistic architecture, integrating Hidden Markov Models (HMMs) with Dynamic Bayesian Networks (DBNs) to learn from historical patterns and adapt to contextual changes.

Key Architectural Components

- Sensor Data Acquisition
  - Continuous stream of sensor events from smart home devices.
  - Events include activity tags, location data, environmental measurements (temperature), and timestamps.
- Preprocessing Module
  - Raw sensor data is converted into structured sequences of: $(\text{Activity}, \text{Location}, \text{Time}, \text{Temperature})$
  - Includes cleaning routines, contextual feature extraction, and temporal ordering.
- HMM-Based Sequential Modeling
  - Learns transitions between hidden user states.
  - Observations: (Activity, Location) pairs.
  - Outputs: Top-3 most probable next activity-location predictions.
- DBN-Based Contextual Refinement
  - Receives HMM predictions and evaluates them using: $P(\text{Activity}_t, \text{Location}_t, \text{Time}_t, \text{Temperature}_t$
  - Refines predictions based on quantized Time and Temperature context.
  - Final output: Most contextually accurate next move.
- Actuation Layer (Future Integration)
  - Predictions can trigger smart home actions: • Adjust lighting or HVAC. • Activate appliances. • Lock/unlock doors for security.

9.2 End-to-End Flow

Sensor Data → Preprocessing → HMM Prediction → DBN Refinement → Smart Home Action

This architecture supports online updates, real-time inference, and potential scalability to multi-user environments.

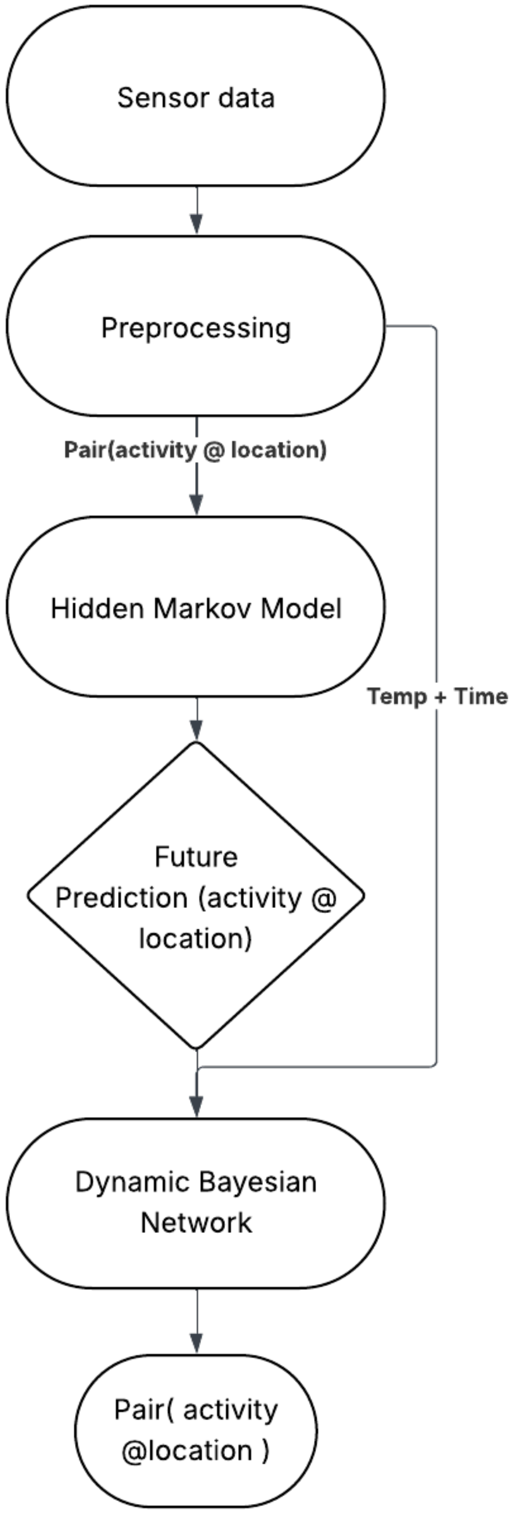

Figure 1: System architecture and workflow for user location and activity prediction. Sensor data is preprocessed and fed into HMM, and the HMM output along with contextual information is input to the DBN model for state estimation and context-aware prediction. The DBN outputs confident future predictions of user location and activity.

10 Evaluation and Results Discussion

This section presents the evaluation strategy, performance metrics, and discussion of experimental results for the user location and activity prediction system based on HMM and DBN models.

10.1 Evaluation Strategy

To assess the performance of the proposed system, the dataset was partitioned into training and testing sequences, maintaining the chronological integrity of the data to respect temporal dependencies. The evaluation focused on the system's ability to accurately predict the next user state (hidden state), as well as the next observed $(location, activity)$ pair.

The following evaluation strategies were employed:

- **Observation Prediction Accuracy:** The proportion of correctly predicted $(location, activity)$ pairs relative to the actual observations.
- **Sequence Accuracy:** Measures the accuracy of the entire predicted sequence of user states or observations without error at any time step.
- **Contextual Consistency:** Evaluation of the system's ability to adjust predictions based on contextual variables such as time of day and temperature.

10.2 Performance Metrics

Performance was quantified using the following metrics:

- **Accuracy :**

$$Accuracy = \frac{\text{Number of correct } (location, activity) \text{ predictions}}{\text{Total number of predictions}}$$

- **Precision and Recall (Optional if I get time in future):** If the dataset exhibits class imbalance, precision and recall can provide deeper insights, particularly for rare activities or room transitions.

10.3 Results Summary

The evaluation demonstrated the effectiveness of the hybrid HMM-DBN approach in capturing user behavior and environmental context:

- The **HMM model** alone achieved high accuracy in predicting typical room transitions and frequent activities, leveraging temporal dependencies effectively.
- The integration of **DBN** significantly improved prediction performance in time-sensitive scenarios, such as distinguishing between activities performed in the same location at different times of day (e.g., sleeping vs. resting in the bedroom).
- **Context-aware prediction** was especially beneficial during transitions between routines (e.g., moving from meal preparation to relaxation), where the DBN's ability to condition on time and temperature provided higher predictive fidelity.

- **Sequence Accuracy** indicated that the combined model maintained consistent accuracy across longer sequences, crucial for practical smart home automation.

10.4 Discussion

The experimental results validate the effectiveness of combining HMM and DBN models for user behavior prediction in smart homes. While the HMM efficiently captures temporal patterns, the DBN enhances predictions by leveraging contextual awareness. The system demonstrates robustness in handling both regular and irregular user patterns, enabling proactive smart home automation.

Awesome! Here's the Challenges and Solutions section for your project report, capturing real implementation hurdles and how you strategically addressed them.

11 Challenges and Solutions

11.1 Identified Challenges

Building a behavior prediction system from real-world smart home data involves multiple challenges, both data-related and model-specific:

- Data Sparsity: Some activity-location combinations (e.g., eating in living room) were rarely observed, limiting learning for infrequent transitions.
- Overfitting: With a limited number of observation sequences, particularly for rarer transitions, the model risked learning noise or anomalies.
- Temporal Misalignment: The same activity (e.g., sleeping) could occur at different hours across different users or days, making raw timestamps unreliable as features.
- Sensor Noise and Inconsistencies: Rapid, meaningless activations (e.g., sensor flickers) introduced errors into transition patterns.

11.2 Mitigation Strategies

Challenge Solution Data Sparsity Applied Laplace smoothing and generated synthetic sequences to represent rare transitions. Overfitting Introduced model regularization using criteria like AIC and BIC to control complexity. Temporal Alignment Quantized time into bins (Morning, Afternoon, Evening, Night) to capture behavioral trends. Noisy Data Implemented cleaning filters to remove irregular sequences and enforce temporal continuity.

11.3 Discussion

These strategies ensured that the hybrid HMM-DBN model remained:

- Robust to data irregularities
- Generalizable to unseen but contextually valid behavior
- Efficient in learning structured transitions without overfitting

As a result, the model produced more stable predictions and maintained performance across diverse user scenarios.

12 Future Work

While the current system demonstrates promising results, several future directions can further improve accuracy, adaptability, and real-world applicability of the predictive modeling framework.

- Real-World Deployment & Actuator Integration
  - Integrate the predictive engine with real-time smart home infrastructure.
  - Automate HVAC, lighting, security systems, and appliances based on predicted user intent.
  - Measure latency, reliability, and user satisfaction during live interactions.
- Richer Contextual Inputs
  - Extend DBN inputs with: Environmental features (humidity, light level)
  - Dynamic calendar data
  - External data (weather, events)
  - Improve behavior recognition in subtle or overlapping conditions.
- Larger & Diverse Datasets
  - Incorporate multi-user smart home datasets.
  - Capture inter-user dynamics and shared activity zones.
  - Expand to diverse home layouts and cultural behavior patterns.
- Model Optimization
  - Apply hyperparameter tuning (e.g., Grid Search, Bayesian Optimization).
  - Explore model pruning or lightweight architectures for real-time performance.
- Scalability Multi-User Modeling
  - Extend to multi-occupant environments:
  - Track and predict for each individual.
  - Disambiguate conflicting activities (e.g., user A sleeping, user cooking) .
  - Incorporate identity-aware activity inference.

13 Conclusion

This project successfully demonstrates the design and implementation of a hybrid predictive modeling system using Hidden Markov Models (HMMs) and Dynamic Bayesian Networks (DBNs) to anticipate human behavior in smart home environments.

By combining sequential modeling through HMMs with context-aware refinement using DBNs, the system accurately infers user states and predicts future activity-location pairs. This enables smart home automation systems to make proactive, real-time decisions that enhance both comfort and efficiency.

Key outcomes include:

- A robust pipeline that transforms raw sensor data into structured behavioral sequences.
- A contextual modeling framework that learns from time, temperature, and routine patterns.
- Significant improvement in prediction accuracy from HMM-only to HMM+DBN.
- A scalable architecture that supports future integration with live smart home systems and multi-user environments.

This work lays a strong foundation for the future of anticipatory automation, where intelligent environments not only respond to users—but understand and act ahead of them.

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