A Bayesian Network Approach for Predicting Social Interactions in Shared Spatial Environments

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Abstract

Modeling and predicting social interactions within shared physical spaces is key to understanding human spatio-temporal behavior. Such models are essential for optimizing the spatial design of the built environment, achieving human-centric objectives, and improving the objectives of physical processes, such as improving the energy efficiency of buildings. This paper presents a modular Bayesian Network (BN) approach for predicting the probability of both pairwise and group social interactions of humans in dynamic environments, using sensor data to enable near real-time updates. The proposed modular structure integrates distinct components, each consisting of specific sets of nodes and edges that represent individual, interpersonal, contextual, and physical factors, allowing for flexible customization and expansion of the model. By incorporating observed and latent variables, the BN approach dynamically adapts as new data becomes available, making it well-suited for simulations in dynamic environments. Through an illustrative example involving four individuals in a room, we demonstrate the system's ability to infer interaction probabilities in scenarios where partial information is received and propagated through the network, updating beliefs about unobserved variables, such as the probability of interaction. Our results highlight the BN's potential for modeling and predicting social interactions in physical spaces. This work contributes to helping bridge the fields of social network analysis, agent-based modeling, and cyber-physical-social systems.

CCS Concepts

• **Applied computing → Sociology**; • **Computing methodologies → Modeling and simulation**; **Model development and analysis**.

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Bayesian Networks, Social Interaction Prediction, Spatio-temporal Behavior, Link Prediction, Probabilistic Modeling, Social Networks, Group Dynamics, Interaction Probability.

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1 Introduction

Spatial behavior includes the actions and movements of individuals or groups within a physical environment, leading to shifts in their location or situation within that space [19]. Models that capture this behavior over time, also referred to as spatio-temporal behavior models, are valuable across a variety of domains as they simulate how individuals interact with one another and their physical environment. For example, optimizing office layouts based on occupant movement patterns can improve workplace satisfaction and reduce energy consumption by aligning occupant activities with energy-intensive building systems [25]. Other applications include but are not limited to the design and operation of cyber-physical-social (or "cyber-physical-human") infrastructure systems [6, 7], optimizing energy use [8], enhancing architecture and interior design [24], improving emergency response strategies [26], managing healthcare systems [5], and urban planning [13].

One of the key factors influencing spatio-temporal behavior is the structure and strength of social ties [1, 9, 27]. Direct measurement of social ties, such as through surveys or self-reported data, can offer insights into these relationships but is often associated with several limitations [21]. These methods are typically time-consuming, costly to administer, and subject to biases such as social desirability, recall errors, or the influence of self-perception. Additionally, they tend to capture static snapshots of social ties, which do not accurately capture the evolving nature of relationships [4, 10, 14, 16].

Using indirect methods to infer social ties can overcome these limitations. Social ties influence how people interact with others and how they navigate and occupy shared spaces. Stronger social ties often result in more frequent interactions, creating specific spatial patterns. For example, in work environments or social gatherings, individuals with strong connections tend to cluster, forming denser interaction zones. In contrast, weaker ties result in greater physical distance and less frequent interaction, shaping different spatial dynamics. Therefore, social interactions can be measured as an indirect indicator of social ties [11, 25].

Recent advancements in sensor technology enable the near real-time capture of spatio-temporal behavior and social interactions, providing an indirect, less biased, and dynamic approach to inferring social ties. This rich sensor data can be used to estimate quantities of interest such as the frequency, duration, and proximity of interactions, as well as the nature of these engagements—whether positive, negative, or neutral—serving as indirect indicators of the underlying social ties [17]. Despite its advantages, this approach presents challenges. Privacy concerns remain a critical issue, as continuous tracking of social interactions may raise ethical considerations. Interpreting raw sensor data to detect activities and interactions while preserving privacy requires advanced computational techniques and the use of more privicy-preserving sensing devices such as depth-based sensors [18, 20]. In addition, sensor coverage may be limited in certain environments, resulting in incomplete or uncertain data. Despite these limitations, the use of *in-situ* sensing provides a more efficient, timely, scalable, and a less biased tool for studying social networks in dynamic contexts.

Collected sensor data serves as a key input for computational models designed to predict social interactions. A well-established area of research, known as link prediction, refers to the process of forecasting potential connections between nodes in a network based on existing structural patterns and known interactions. Advances in the aforementioned sensing technologies stand to support radical advancements in the area of link prediction, such as for extracting social networks from spatio-temporal data. In this paper we explore the potential of probabilistic graphical models for predicting interaction probabilities between individuals from spatio-temporal behavior data in a modular and interpretable way.

While previous Bayesian Network (BN)-based link prediction models, such as those proposed by Kumar et al. (2020) [15] and Xiao et al. (2018) [28], have been successful in predicting binary links between users, they primarily focus on pairwise interactions in digital environments. This emphasis on pairwise connections is rooted in their application within social networks, where predicting links between individual pairs typically suffices. However, in the context of spatio-temporal behavior, which is deeply intertwined with physical space, the nature of interactions is more complex and influenced by factors absent in digital settings. Interactions can occur both at the pairwise and group levels, making it essential for predictions to extend beyond individual connections to include group dynamics. This broader scope is critical for understanding behaviors in shared physical spaces.

We propose a modular BN approach to infer the probability of social interactions in dynamic physical environments, utilizing sensor data and near real-time updates. This data may include activity recognition, individual locations (e.g., from various presence detection technologies), and other observed interactions. This method enables the continuous adjustment of predicted interaction probabilities and supports the exploration of various "what-if" scenarios through simulation. The model is designed to estimate interaction probabilities between individuals—even in situations where there is only partial information—by calculating posterior probabilities based on observed interaction data.

The structure of the remainder of this paper is as follows: Section 2 outlines the methodology behind the proposed modular BN approach, including the network design, sensor data parameterization, and the inference process for near real-time interaction probabilities under uncertain conditions. In Section 3, we present an illustrative example, detailing the creation of the synthetic dataset used in our experiments, as well as the BN's structure and parameterization. Section 3.3 discusses the results, offering insights from preliminary "what-if" scenarios, interaction predictions, and the system's capacity to manage partial information and group dynamics. Finally, Section 4 concludes by addressing the limitations of the current approach and proposing future research directions.

2 Methodology

BNs are probabilistic models that represent dependencies between random variables through directed acyclic graphs. Nodes in a BN represent random variables while the edges capture the causal relationships between them. Each node in the network is associated with a conditional probability table (CPT), which quantifies the strength of the causal relationships between the node and its parent nodes. BNs ensure that variables are arranged in a hierarchical manner without any feedback loops, thus allowing for efficient computation of joint probability distributions by factoring them into smaller, conditional probabilities. BN's major strength lies in its ability to perform near real-time updates as new evidence—potentially uncertain—becomes available, and to infer latent variables [12].

In this section, we present our modular BN approach for predicting social interactions in dynamic physical spaces, using *in-situ* sensor data. The methodology is divided into several stages: the definition of network modules, data collection and parameterization, and the process of inferring interaction probabilities.

2.1 Modular BN Structure

The proposed BN framework is designed to predict interaction probabilities by incorporating both individual and interpersonal factors within shared physical environments. The network is modular, composed of five core modules: Physical Space, Global Features, Individual Features, Interpersonal Features, and Interaction. Each module is designed to capture specific elements influencing the probability of interaction. Each module can represent a complex model comprising multiple nodes and edges, which are selected based on factors influencing interactions, such as available sensor data, the specific social or environmental variables included, and the level of granularity desired by the modeler. These interconnected components form a flexible framework that can predict social interactions in dynamic environments and adapt to various contexts and complexities.

- Physical Space module: This module comprises the characteristics of the physical environment where interactions occur, such as locations, layout, and the presence of obstacles. As the module with no parent, it serves as a foundation for other modules by providing a spatial context for the entire system. For instance, if temperature variations across different locations are relevant, additional nodes can be introduced to represent temperature at specific locations. To account for the spatial dependencies of temperature, one can model this using a random field approach, similar to the work by Bensi et al. [2], where a BN was employed to model the random field of earthquake intensity. This allows for capturing the physical dependencies of environmental variables in a structured manner.

- Global features module: This module accounts for factors that apply universally across the environment, such as time and social norms. These features are common for all individuals and they influence how interactions manifest in the given space.
- Individual features module: Each person in the environment is modeled with an associated Individual Features module, capturing unique attributes such as personal preferences, current activity, physical location, and behavioral traits. This module is dependent on both the Physical Space and Global Features modules to account for their influence on individual features. For example, the location of each individual is affected by the Physical Space module.
- Interpersonal features module: This module models the degree of similarity or compatibility between pairs of individuals, which is an influential factor in predicting the likelihood of interaction. For each pair of individuals, the interpersonal features module takes as input the individual features of all involved individuals in an interaction. Interpersonal features are computed based on shared or complementary characteristics, such as interests, line of sight, activities, and spatial proximity.
- Interaction module: For each combination of individuals, the Interaction module computes the probability of interaction, based on inputs from the interpersonal features module. Various nodes within this module can represent different aspects of interactions, such as probability of the interaction occurring, duration of interaction, and interaction type. This module allows for near real-time predictions of both pairwise and group-level interactions, dynamically updating probabilities as new sensor data becomes available.

This modular design supports flexibility and scalability, allowing for easy incorporation of additional nodes or variables as the social network expands.

2.2 Data Collection and Parameterization

Sensor data plays an important role in parameterization of the BN. Using various sensors such as RGB cameras and depth sensors, data capturing the movements and interactions of individuals within the shared space can be systematically collected while preserving privacy [18, 20]. The dataset should capture key information, including the time, location and/or proximity of individuals, the activities they are engaged in, and the nature and type of social interactions, among other relevant observable metrics.

This data is processed and fed into the network, where it is used to estimate the CPTs for each node. In cases where data is incomplete or uncertain (e.g., due to sensor occlusion or noise), the BN framework's ability to handle partial information becomes advantageous. The breakdown of the joint probability distribution into smaller conditional probability tables allows for the node CPTs, whose values and those of their parent nodes are recorded, to be populated independently of missing data in other parts of the network. This ensures that the model can still benefit from incomplete data [12].

2.3 Inference and Near Real-time Updates

The BN framework is capable of inferring interaction probabilities in near real-time. During each simulation episode, or near real-time situation in the real world, the system updates the posterior probabilities of interactions between individuals based on simulated or observed data. This enables the model to adapt dynamically as the environment or individual behaviors change. The interaction probabilities are inferred through the following steps:

(1) Initial probabilities: Before any interactions occur, the BN uses the prior distributions defined by the sensor data and the network structure to estimate the likelihood of interactions.
(2) Data integration: As interactions are observed (through sensors or simulation), the network uses Bayes theorem to calculate the posterior probabilities by updating priors with new evidence. This allows the system to continuously refine its estimates of future interactions in real time. For example, the sensors might observe the location of individuals and or the activity they are engaged in and predict the probability of interactions between those individuals. In addition to pairwise interactions, the model is capable of handling group dynamics by predicting

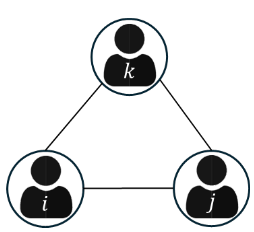

Figure 1: Social network of three individuals i, j, and k, with pairwise connections representing social ties.

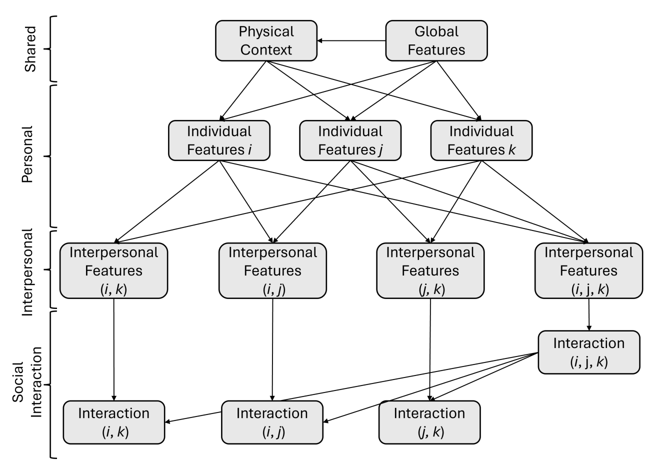

Figure 2: Proposed modular BN for predicting likelihood of social interactions between individuals i, j, and k.

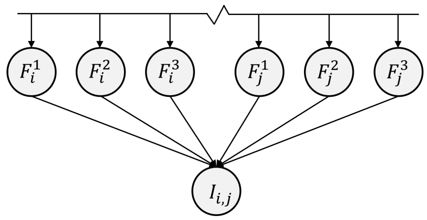

Figure 3: Features directly connected to the interaction node.

the likelihood of multi-person interactions and thus capturing the collective behaviors that emerge in shared physical spaces.

2.3.1 Handling Computational Complexity. The model's ability to provide near real-time inference is essential in dynamic environments, where individual movements, physical space, social norms, and interactions constantly evolve. The time complexity of updating a node in a BN is directly related to the size of its CPT, which grows exponentially with the number of parent nodes. Specifically, if a node has n parent nodes each having m state, the size of its CPT is $O(m^n)$, meaning that for timely updates, it is essential to limit the maximum number of parent nodes for each node in the network.

One effective approach to controlling the number of parent nodes is by introducing intermediate nodes, a role played by the interpersonal features module. While it is possible to link all influential factors, including the characteristics of each individual involved in the interaction, directly to the interaction node, this approach would lead to an excessive number of parent nodes, particularly in group interactions involving multiple individuals. By adding an interpersonal features module to compare pairs of individuals, we can significantly reduce the number of parent nodes.

For example, in Figure 3, using a Naive Bayes approach, all six features (three from each individual i and j, shown as F_i and F_j) are directly connected to the interaction node, $I_{i,j}$, resulting in six parent nodes. However, in Figure 4, intermediate interpersonal nodes, $A_{i,j}$, are introduced to compare each corresponding pair of features. After incorporating these pairwise intermediate nodes, a similar strategy can be extended to model group interactions. This method introduces intermediate nodes that compare two pairwise interpersonal nodes, ultimately producing a single interpersonal node that models interactions within a group of three individuals, and so forth. Doing so, reduces the size of the CPTs, and thus both computational time and memory usage [3].

Additionally, most root nodes in higher-level modules, such as physical space and global features (e.g., current time or physical layout), are easily observed with certainty. These root nodes have fixed values during inference, as they represent background data rather than query or observation nodes. When a root node is observed with certainty, it no longer contributes to the network's uncertainty and acts as a deterministic value. This allows for pruning, where these nodes are effectively removed, and their observed values are propagated to child nodes, further reducing computational complexity [12].

2.3.2 Handling Noisy Sensor Readings. One of the key challenges in modeling social interactions in physical space is dealing with

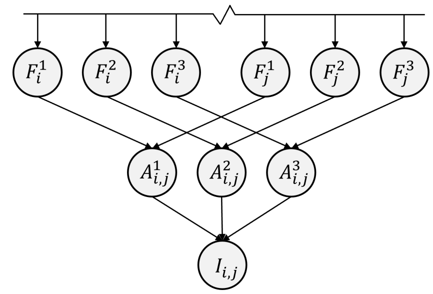

Figure 4: Intermediate similarity nodes to reduce the number of parent nodes for the interaction node.

uncertain sensor data (i.e., observations). This uncertainty may arise from individuals being occluded by others or by objects. In such cases, observations are not certain, but rather represent likelihood findings, associated with a likelihood ratio. Unlike certain observations, likelihood evidence is specified without a prior. When propagating likelihood evidence, the network considers the existing beliefs about the variable before the evidence is introduced. As a result, the belief in the variable can be updated with additional evidence from other variables. For instance, information about the location of other individuals can influence the probability distribution of another person's location if it was with uncertainty, which in turn affects the likelihood of interactions. To incorporate likelihood observations in a BN, a virtual node is introduced as a child of the observed node. This virtual node serves as a placeholder for the observation, while its parent represents the real value. The virtual node's CPT encodes the likelihood of the observed value given values of its parent. The observation is then entered as if it were a certain observation for the virtual node [22].

3 Illustrative Example

To demonstrate our approach, we use a simple yet representative example involving a conference room where four PhD students from the Civil and Environmental Engineering (CEE) department at Carnegie Mellon University (Pittsburgh, PA) interact with each other during lunch time.

The *physical layer* consists of the layout of the conference room, shown in Figure 5, which includes a single entrance/exit, a central desk, six chairs, and a couch for casual seating. This setting provides a manageable space for observing and simulating interactions among the students. The *social layer* involves four PhD students, each affiliated with a different subgroup within the CEE department: Mechanics, Chemistry, and Materials (MCM), Sustainable Energy and Transportation Systems (SETS), Climate-resilient Environmental Systems and Technologies (CREST), and Intelligent Engineered Systems and Society (IESS). These subgroups represent distinct research focuses, which influence the students' communication and work styles. Each student's characteristics, represented as S_i (student i in Figure 6), are outlined in Table 1. These include their subgroup affiliation, personality type (extrovert/introvert), communication style, work style, interaction preferences, and seating preferences (chair or couch).

Table 2 presents the group dynamics, including the primary topics discussed during interactions (whether work related or personal), the nature of the discussions (whether driven by friendship or professional collaboration), and the strength of friendships between student pairs. These dynamics provide insight into the factors that influence both individual and group behaviors within the conference room.

The features presented in the tables are not directly utilized as known variables for training the BN parameters. Instead, they serve as prompts for generating the synthetic dataset using GPT-4 [23], as explained in the following section.

3.1 Creating Synthetic Dataset

In the absence of a real-world dataset that captures all the relevant features for this illustrative example, we generated a synthetic dataset that mimics realistic behaviors, interactions, and environmental factors. Using GPT-4, a large language model, we generated descriptive interaction scenarios based on the students' characteristics and environment. The interactions between the four students were simulated over 30 consecutive days during lunch times. From these scenarios, a dataset was created, containing details such as time of day, location of each student, whether an interaction occurred, the type of interaction (e.g., positive, negative, or neutral), the students involved, and their activities at the time. This synthetic dataset can be easily replaced with real-world data when available.

The synthetic dataset captures essential interaction parameters, including the time of interactions, the spatial arrangement within the room (e.g., desk, chair, couch), and interaction outcomes (whether social or work-related). By leveraging this dataset, we can show scenarios for demonstrating the framework's ability to model and predict human interactions.

3.2 BN Structure

The BN structure for this illustrative example is shown in Figure 7. For clarity, nodes within each module (i.e., global features, physical context, individual features, interpersonal features, and interaction modules) are grouped together using distinct boxes in the figure, as described in the methodology section. Here, we have selected a subset of representative nodes for each module to illustrate the functionality of the network.

The global features module includes a time node, denoted as T, which represents the time of day. For this example, we discretized each one-hour period into four 15-minute intervals, defining the states of the time variable. The node T influences other temporal aspects of the network, such as activity and location. In the physical context module, we introduce a constraint node C, which is a child of the location nodes of all students. This node enforces the rule that

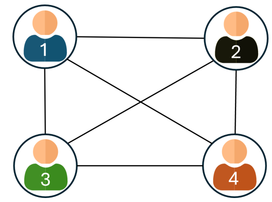

Figure 6: Social network of the four PhD students.

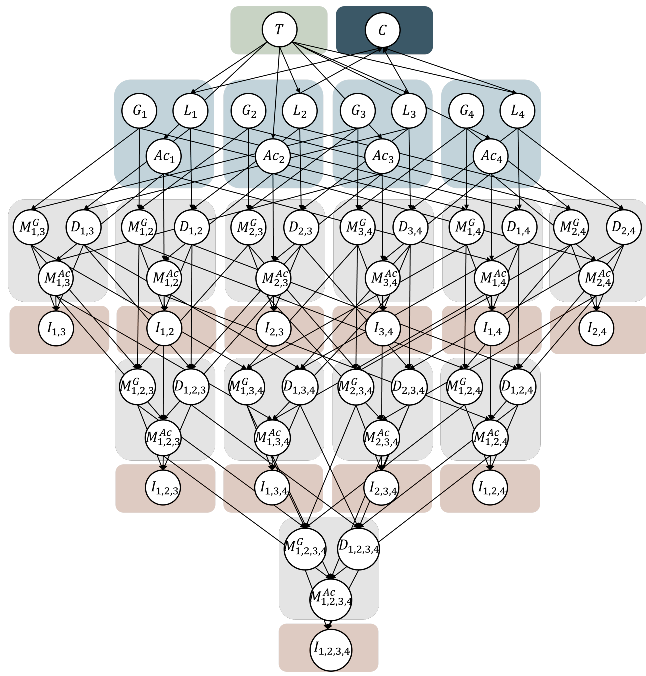

Figure 7: Bayesian network of the illustrative example.

only one student can occupy any given cell in the environment. The node C has two states: *valid* and *invalid*. If more than one student is located in the same cell, the probability of C being in the *invalid* state is 1, and otherwise 0. To ensure valid inferences, we impose the condition $C(valid) = 1$ as evidence in all scenarios. The individual features module includes three nodes per student. G_i represents the subgroup affiliation of student i within the CEE department. It can take one of four possible states (MCM, IESS, SETS, or CREST). L_i denotes the location of student i, with as many states as there are grid cells in the room. The node L_i is dependent on time T, as the distribution of student locations changes throughout the day. Ac_i corresponds to the activity of student i. It can take one of the following values: *Studying*, *Moving*, *Eating*, *Waiting*, *Leaving*, and *Eating and Studying*. The activity node Ac_i depends on both the time of day and the student's location.

The interpersonal features module captures the relationships between pairs of students. Three key nodes in this module are $M^G_{i,j}$, $M^{Ac}_{i,j}$, and $D_{i,j}$. $M^G_{i,j}$ compares the subgroups of students i and j, with states *same* or *different*, indicating whether their affiliations within the CEE department match. $M^{Ac}_{i,j}$ evaluates the compatibility of

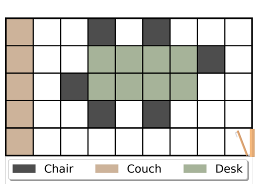

Figure 5: Layout of the conference room.

Table 1: Characteristics of the Four Students

Student	Affiliation	Personality Type	Communication Style	Work Style	Seating Preference
S_1	SETS	Extrovert	Direct, Formal	Collaborative	Chair
S_2	IESS	Introvert	Indirect, Reserved	Independent	Couch
S_3	CREST	Extrovert	Casual, Open	Flexible	Chair
S_4	IESS	Introvert	Formal, Structured	Collaborative	Couch

Table 2: Group Dynamics

Student Pairs	Primary Interaction Topic	Interaction Type	Friendship Strength
S_1–S_2	Work-related	Collaborative, Formal	Moderate
S_1–S_3	Social, Casual	Friendly, Open	Strong
S_1–S_4	Work-related	Formal, Structured	Weak
S_2–S_3	Work-related	Collaborative, Reserved	Moderate
S_2–S_4	Social, Casual	Friendly, Relaxed	Strong
S_3–S_4	Work-related	Formal, Structured	Moderate

the activities of students i and j, assessing the likelihood that their activities will result in an interaction. This node has three states: *low*, *moderate*, and *high*. For example, if one student is studying while the other is eating, the compatibility is likely to be *low*; however, if both are eating, the compatibility may be considered *high*. $D_{i,j}$ measures the physical distance between students i and j, with the students' locations as parent nodes.

For simplicity, the interaction module focuses on a single interaction occurrence node $I_{i,j}$, which is a combination of interaction occurrence and type. This node has four states: *No Interaction*, *Positive Interaction*, *Negative Interaction*, and *Neutral Interaction*. The interaction node depends on the three nodes from the interpersonal features module: $M^{G}_{i,j}$, $M^{Ac}_{i,j}$, and $D_{i,j}$, representing subgroup similarity, activity compatibility, and distance between students, respectively. For interactions involving three or more students, the same structure used for pairwise interactions is extended. For example, when modeling interaction between three students, the interpersonal nodes from the pairwise modules are used as parents for the corresponding interpersonal nodes in the three-student module. Similarly, interactions involving four students incorporate interpersonal nodes from all combinations of three students as parents. The distance node in these multi-student interpersonal features modules represents the largest distance among the students, essentially capturing the diameter of the group interaction space.

3.3 Results and Discussion

The results are generated through a hypothetical scenario, where observations are introduced incrementally in multiple stages, and the network is updated at each stage using Bayesian updating as shown in Figure 8.

3.3.1 Stage 0: Initial Prior Inference. The scenario begins by performing a marginal inference over the *interaction nodes* in the BN, resulting in prior interaction probabilities. These priors reflect the baseline likelihood of interactions between each pair of students, as well as potential group interactions, before any evidence is introduced. At this point, the priors are driven solely by the structure of the BN and the conditional dependencies encoded in the CPTs. For instance, the inferred prior probability of interaction between S_1 and S_2 is 0.441, while the prior for a group interaction between S_1, S_2, and S_3 is 0.154.

3.3.2 Stage 1: Observing Locations of S_1 and S_2. The first observation is provided in the form of evidence on the location nodes L_1 and L_2, indicating that S_1 and S_2 are in close proximity. This evidence conditions the BN on the observed values for L_1 and L_2, causing the network to perform an updated belief propagation across the interaction nodes. As a result, the posterior probability of interaction between S_1 and S_2 increases from 0.441 to 0.833, reflecting the stronger likelihood of interaction due to their proximity.

3.3.3 Stage 2: Observing S_3's Location. Next, the location node L_3 is updated with evidence placing S_3 near S_1 and S_2. The BN performs belief updating, recalculating the posterior distributions for the relevant interaction nodes. The probabilities for pairwise interactions between S_1 and S_3 and between S_2 and S_3 increase from 0.863 to 0.971 and from 0.629 to 0.758, respectively. Additionally, the posterior for group interaction between S_1, S_2, and S_3 rises significantly, increasing from 0.334 to 0.593, as proximity now favors a group dynamic. This demonstrates how the BN captures multi-agent dependencies through joint probability distributions.

3.3.4 Stage 3: Observing Activity for S_1, S_2, and S_3. Subsequent evidence pertains to the activity nodes Ac_1, Ac_2, and Ac_3, representing the activities of S_1, S_2, and S_3. Evidence is set such that S_1 is engaged in *Studying*, while S_2 and S_3 are *Eating*. The conditional dependencies encoded in the CPTs of the activity and interaction nodes lead to a recalibration of interaction probabilities. Specifically, the posterior probability of group interaction among S_1, S_2, and S_3 decreases from 0.593 to 0.036, as S_1's activity is not conducive to group interaction. Also, the pairwise interaction probabilities between S_1–S_2 and S_1–S_3 drop from 0.889 to 0.167 and from 0.971 to

0.28, respectively, due to S_1's solitary activity. In contrast, the probability of interaction between S_2 and S_3 increases from 0.758 to 0.98, reflecting their shared social activity, which is highly compatible with interaction.

3.3.5 Stage 4: Observing Interaction Between S_2 and S_4. In this stage, evidence is provided directly on the interaction between S_2 and S_4, indicating the occurrence of an interaction. However, the sensor is unable to classify the interaction as positive, negative, or neutral. To incorporate this partial observation into the network, a child node $I^o_{i,j}$ is added to the interaction node $I_{i,j}$, representing a binary distinction between *Interaction* and *No Interaction*. The CPT of $I^o_{i,j}$ is deterministic, assigning a probability of 1 to the *No Interaction* state when $I_{i,j}$ is in the *No Interaction* state, and 0 otherwise. The evidence is then enforced by setting the child node $I^o_{i,j}$ to the *Interaction* state, effectively conditioning the BN on the observed interaction. This leads to belief updating across the network, particularly for the interaction and location nodes. Given that interaction implies physical proximity, the posterior distribution for the location node L_4 shifts accordingly, indicating that S_4 is now likely to be in close proximity to S_2. This update reflects the constraints imposed by the observed interaction, refining the BN's estimates of the spatial configuration and interaction dynamics. Additionally, this update introduces indirect effects, shifting probabilities for other nodes; for example, the probability of S_2 and S_4 having the same affiliation increases from 0.717 to 0.742 due to subgroup similarity being positively correlated with interactions.

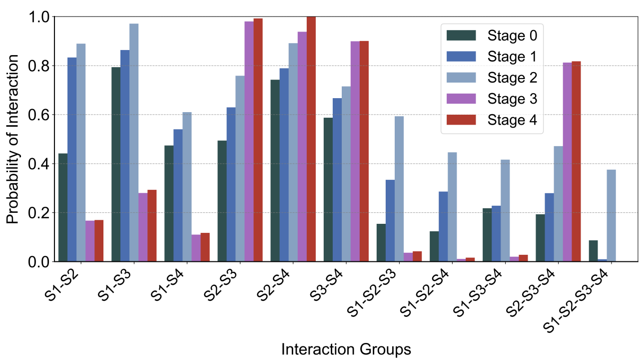

Figure 8: Probability of interaction across different stages for pairwise, trio, and four-student groups.

This scenario illustrates the flexibility of BN in dynamically updating interaction probabilities based on incremental evidence, utilizing belief propagation.

4 Conclusion

The modular BN approach proposed in this paper demonstrates its potential to model and predict social interactions in dynamic physical spaces, both by enabling near real-time updates through sensor data and supporting simulations in "what-if" scenarios. Through an illustrative case study, we highlight the model's flexibility in managing variable dependencies, partial information, and updating beliefs about unobserved variables.

Future research directions include incorporating real-world datasets for parameterizing and validating the model's predictions. Second, extending the model to include a temporal dimension by upgrading it to a dynamic BN will allow for the incorporation of memory and interaction history, enabling the model to capture not only the effect of social ties on interaction, but also the formation of new social ties over time through repeated interactions. Improving the model's scalability to handle larger populations and more complex social networks will also be a priority. This will require the development of efficient algorithms to manage computational complexity, particularly in near real-time scenarios involving multi-agent group interactions. This includes testing the model in larger and more complex environments, such as urban areas or multi-floor buildings, where factors like crowd density and environmental conditions come into play. Finally, future research should also focus on addressing ethical considerations related to privacy during data collection and data security, especially regarding the inferences made through the BN framework. By addressing these challenges, the BN model has the potential to improve the understanding of human interactions within the built environment, helping to bridge the social science and human spatial behavior modeling fields.

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