When to generate hedge in peer-tutoring interactions?

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Abstract

This paper explores the application of machine learning techniques to predict hedging in peer-tutoring interactions. The study uses a spontaneous face-to-face dataset featuring natural language turns, conversational strategies, tutoring strategies, and nonverbal behaviors. These elements are processed into a vector representation of the previous turns, which serves as input to various machine learning models, including MLP and LSTM. The results show that embedding layers, capturing the semantic information of the previous turns, significantly improves the model's performance. Additionally, the study provides valuable insights into the importance of various features, such as rapport and nonverbal behaviors, in predicting hedges by using Shapley values (Hart, 1989) for feature explanation. Our research uncovers that the eye gazes of both the tutor and the tutee could have a significant impact on the hedges prediction. We further validate this observation through a follow-up ablation study.

1 Introduction

Effective communication involves various conversational strategies that help speakers convey their intended meaning and manage social interactions at the same time. These strategies can include the use of self-disclosure, praise, violation of social norms, etc. (Zhao et al., 2014). Hedges are one of those strategies that is commonly used in dialogues. Hedges are words or phrases that convey a degree of uncertainty or vagueness, allowing speakers to soften the impact of their statements and convey humility or modesty (or avoid face threats). Although hedges can be effective in certain situations, understanding when and how to use hedges is essential and challenging.

The use of hedges is especially significant in tutoring interactions. However, the prevalent use of hedges is not limited to only expert educators. They also abundantly found in peer-tutoring setting. (Madaio et al., 2017a) found that confident tutors tend to use more hedges, to help the tutee solve more problems correctly, when the rapport is low. Hence, the detection and also use of hedges in the right time is not just beneficial, but crucial for the development of effective intelligent tutoring systems.

While the use of hedges in conversation is an important aspect of effective communication, generating appropriate hedges in real-time for the dialogue system can be a challenging task. In recent years, there have been several studies on automatic hedge detection (Raphalen et al., 2022; Goel et al.), particularly in the context of natural language processing. However, despite the significant advances in these technologies, there are still limitations in generating hedges in a timely and appropriate manner. For example, the RLHF-based training method enables the development of robust language models that align with human preferences (Ouyang et al., 2022). However, this approach does not explicitly instruct large language model (e.g., ChatGPT) in pragmatic and social skills, such as the appropriate use of hedges during communication. This lack of specific training can result in a gap in the model's ability to effectively integrate these crucial conversational nuances into its responses. This limitation can affect the quality of communication and highlights the need for further research on effective hedge strategies used in real-time communication, that is, to generate hedges at the right time.

Despite the widespread use of hedges in communication, there is still much to learn about the timing and effectiveness of their use, particularly in peer-tutoring environments.

To address this gap in the literature, our research will focus on two key questions below:

RQ1: First, can we predict when hedges should be generated in peer-tutoring environments?

This question aims to investigate whether it is possible to identify the moments to introduce hedges during a conversation.

RQ2: Second, what features contribute more to these predictions?

This question focuses on the explainability of classification models using Shapley values (Sundararajan and Najmi, 2020) .

2 Related Work

2.1 Hedges

What is the hedging in the conversation? Hedge is a common rhetorical device used to diminish the effect of an utterance to avoid unnecessary embarrassment and being interpreted as rudeness. In linguistic term, Hedge is a rhetorical technique that diminishes the full semantic value of an expression (Fraser, 2010). Hedges are typically divided into two primary categories: propositional hedges and relational hedges (Prince et al., 1982). **Propositional hedges**, also called *Approximators*, refers to the use of uncertainty (Vincze, 2014), vagueness (Williamson, 2002), or fuzzy language (Lakoff, 1975), such as "sort of" or "approximately". On the other hand, **Relational hedges** are used to convey the subjective or opinionated nature of a statement, such as "*I guess* it will be a raining day tomorrow.". Another type of hedge is Apologizer, which is an expression used to mitigate the strength of an utterance by using apologies, such as "*I am sorry*, but you shouldn't do that." Although various types of hedges function differently, they all share a common role of mitigation in conversation. Therefore, in this paper, we embark on our initial effort to predict only hedges and non-hedges.

In the setting of peer tutoring, hedges are frequently used and have been found to have a positive impact on performance (Madaio et al., 2017a). This could be because hedges reduce the embarrassment of the tutee when they do not know the correct answer. Therefore, it is important to understand the role of hedges in communication and explore ways to generate them at the right time. Numerous powerful language models such as GPT-4 (OpenAI, 2023) and ChatGPT (OpenAI, 2022) are now capable of generating hedges at appropriate prompts, but these language models do not actively generate hedges (Abulimiti et al., 2023). For example, when engaging in face-threatening behaviors such as instructions or bad humors. In other words, the question of how to use the correct hedge strategy (i.e., hedges / non-hedges) in the next conversational action is an unsolved problem.

2.2 Conversational Strategies Prediction

The development of approaches for predicting conversational and emotion strategies has advanced progressively over the years in the field of dialogue systems research. Early research like COBBER framework, which leverages Conversational Case-Based Reasoning (CCBR) with an affective approach, applying causal loops from system dynamics theory to design conversation strategies tailored to specific domains (Gómez-Gauchía et al., 2006). Subsequent years saw the introduction of reinforcement learning techniques, such as a policy learning was introduced in non-task-oriented dialog systems (Yu et al., 2016).

More sophisticated approaches emerged recently, like the Estimation-Action-Reflection (EAR) framework, which combines conversational and recommender systems by learning a dialogue policy based on user preferences and conversation history (Lei et al., 2020). Building on this concept of adaptive interactions, the field has ventured into reinforcement learning. Researchers explored reinforcement learning for training socially interactive agents that maximize user engagement (Galland et al., 2022), as well as the Sentiment Look-ahead technique, which models users' future emotional states and rewards generative models that improve user sentiment (Shin et al., 2020). The rewards include response relevance, fluency, and emotion matching. These rewards are built using a reinforcement learning framework, where the model learns to predict the user's future emotional state. Romero et al. (2017) designed a social reasoner that can manage the rapport between user and system by reasoning and applying different conversational strategies. Most recent advancements in the field have focused on how to create an empathetic dialogue system. MIME (Majumder et al., 2020) used the emotion mimicry strategy to match the user's emotion based on the text context. EmpDG (Li et al., 2020) generated empathetic responses using interactive adversarial learning method to identify whether the responses evoke emotion perceptivity in dialogues. The Mixture of Empathetic Listeners (MoEL) (Lin et al., 2019) model, which aimed to generate empathetic responses by combining the output states of multiple listeners, each optimized to react to certain emotions, and generated an empathetic response based on the user's emotions as tracked by the emotion tracker. Despite the notable success of MIME and MoEL in predicting emotions or conversational strategies, they do not incorporate social context (e.g., the relationship between speakers) or nonverbal behaviors into reasoning and decision-making processes. However, such elements are fundamental in the realm of social language, and their missing potentially limits the effectiveness and naturalness of these models. This paper aims to bridge this gap by integrating social context and nonverbal behaviors as predictive features to construct predictive models for hedges.

Predicting the appropriate emotion or conversational strategies in a conversation is a challenging task. This is mainly because determining what is "appropriate" in a conversation is highly subjective and context dependent. For example, EmpDG (Li et al., 2020) model achieved an accuracy of approximately 0.34 across the 32 evenly distributed labels in the Empathetic Dialogue dataset (Rashkin et al., 2019). indicating the complexity of the problem at hand. Similarly, MoEL (Lin et al., 2019) model achieved varying degrees of accuracy in the same dataset - 38% for the top 1, 63% for the top 3, and 74% for the top 5 for emotion detection, further emphasizing the difficulty of the task.

3 Methodology

3.1 Task Description

Suppose we have a set of dialogues $D = \{d_1, d_2, d_3, ...d_n\}$. Each dialogue $d = \{u_1, u_2, u_3...u_m\}$ consists of m turns, with u_i representing a specific turn. Both tutor and tutee turns within these dialogues can be categorized as either hedges or non-hedges. However, for the purposes of our analysis, we will primarily focus on the tutor's turns. The label of a particular turn u_i is denoted as l_i. Furthermore, every turn can be depicted as a feature vector X, composed of elements $(x_1, x_2, ..., x_N)$. Here, N signifies the total number of features used to characterize a turn. Each turn in the dialogue is assigned a fixed window size (ω) of the dialogue history, represented as: $h_i = \{u_{max(1,i-\omega)}, u_{i-\omega+1}, ...u_i\}$. The primary objective of this research is to develop a model, denoted M, capable of predicting the type of hedge l'_{i+1} that a tutor will use next, based on the dialogue history h_i. The effectiveness of the model is measured using standard classification metrics, such as precision, recall, and the F1 score.

The task of predicting the use of hedges in a peer-tutoring interaction can be formalized as a binary classification problem, where the input features are derived from the turns and (see below in Section 3.3) in the interaction and the output is a binary variable indicating the presence or absence of hedges in each turn.

3.2 Corpus

The peer tutoring corpus is a subset of a larger investigation into the phenomenon of goal-oriented dialogue. The dataset consists of face-to-face interaction recordings from 40 American teenagers, with an average age of 14.3 years (ranging from 13 to 16 years), evenly gender-balanced. These participants paired with a same-age, same-gender stranger, resulting in 20 dyads. However, due to video technical issues, only 14 dyads' data were usable. The participants were asked to do linear algebra peer-tutoring for 2 sessions. Each hour-long session was structured into various phases: an initial social period for acquaintance, followed by first task period, then a second short social period, and finally, second task period. The roles of tutor and tutee were interchanged after the second social period. In total, 28-hour long dataset face-to-face interactions were recorded. The recorded video and audio data were transcribed, resulting in approximately 9479 turns. These included 8399 non-hedges and 1080 hedges. We also retained non-speech segments such as laughter and fillers. Given that the participants were minors, the dataset is subject to a Non-Disclosure Agreement (NDA). However, a sample of the dataset will be made available[1].

Peer tutoring is a popular teaching method used in many schools and educational settings. Previous research (Madaio et al., 2017b) has shown that even though these teenagers may be inexperienced, when they use hedges during tutoring, their tutees are encouraged to attempt more problems and succeed in solving more of them. This positive outcome justifies the use of our dataset for studying hedges in tutoring interactions. While we recognize the importance of exploring the use of hedge with expert tutors, our current focus on untrained peer tutors provides a unique perspective on how hedges can impact learning, even when the tutors themselves are not highly experienced. The methods and results from our study can be used as a foundation for future research, which could include the investigation of expert tutors and the potential differences in their use of hedges.

[1] github.com/AnonymousHedgePrediction

3.3 Features

In this section, we outline the features used as input vectors (i.e., u_i vector) for our prediction model, which seeks to properly predict the hedging strategy for the tutor's upcoming turn. In total, we have a vector with a length of 438 to represent a turn.

3.3.1 Turn embedding

Turn embedding is a common technique in natural language processing that involves representing a turn as a vector. In this study, we apply a sentence transformer (Reimers and Gurevych, 2019) to generate turn embeddings of the tutor-tutee conversation. This feature enables us to capture the semantic meaning of the turn in the context of the conversation, which can be helpful for predicting hedges.

3.3.2 Conversational Strategies (*CS*) of the previous turns

Conversational strategies refer to the different ways of speaking used by both speakers to manage social interaction. Strategies considered in this study are self-disclosure, praise, violation of social norms, and hedges. Self-disclosure (Derlega et al., 1993) is a form of disclosure in which the tutor or tutee shares personal information about themselves, which is often used to build rapport. Praise (Brophy, 1981) is a form of positive feedback that acknowledges and reinforces the other person's behaviors or attributes. Violation of social norms (Zhao et al., 2014) is a strategy in which the tutor or tutee behaves in a way that is unexpected or not in line with social norms. In terms of hedges, note that we only use previous hedges strategies of speakers to predict the next tutor's hedge strategy. This does not indicate any issue with predicting label leakage.

3.3.3 Tutoring Strategies (*TS*) of the previous turns

Tutoring strategies (Madaio et al., 2016) refer to the different techniques applied by the tutor and tutee to facilitate learning. Strategies considered in this study include deep / shallow questions, meta-communication, knowledge building, and knowledge telling. The deep question encourages critical thinking and higher-order cognition. The shallow question is used to confirm or clarify understanding. Meta-communication is a strategy where the tutor or tutee communicates about the tutoring process or the tutor / tutor's self-evaluation of his own knowledge, which can help to clarify misunderstandings and promote effective communication. Knowledge building involves introducing new concepts or ideas, discussing the reasoning-mathematical solving steps, and providing examples. Knowledge telling is to provide information (i.e., simply stating numbers, variables).

3.3.4 Dialogue Act (*DiaAct*) of the previous turns

Dialogue acts (Searle, 1965) are various types of speech acts used by tutors and tutees during their interactions. In our study, we use the widely-used DAMSL (Dialogue Act Markup in Several Layers) (Jurafsky, 1997) coding schema to annotate dialogue turns by using a state-of-the-art dialogue act classifier with context-awared self-attention (Raheja and Tetreault, 2019). In our dataset, only 6 dialogue acts were found, they are Abandoned or Turn-Exit (*%*) , Acknowledge (Backchannel) (*b*), Backchannel in question form (*bh*), Yes-No-Question (*qy*), Statement-non-opinion (*sv*) and Statement-opinion (*sd*).

3.3.5 Rapport in the previous turns

As the level of rapport is expected to be an important factor influencing the use of hedges in the peer-tutoring setting, we include it as a feature in our study. Rapport is "The relative harmony and smoothness of relations between people" (Spencer-Oatey, 2005). In this study, we operationalize rapport level as a 7 point Likert scale, where a higher score indicates a stronger level of rapport. For the annotation of rapport, we employ the "thin slice" method (Ambady and Rosenthal, 1993), segmenting each video into multiple 30-second clips. To ensure the quality of rapport annotations, we used Amazon Mechanical Turk for the annotation task and applied the inverse-biased correction method (Parde and Nielsen, 2017) for selecting the qualified rapport annotations. When the dialogue history is contained within a single slice, we directly use the annotated rapport level of that particular slice as the historical rapport level. However, if the dialogue history extends over two slices, we select the rapport level of the slice containing the majority of the dialogue history.

3.3.6 Nonverbal Behaviors (NB)

Nonverbal behaviors, such as head nod, smile, and gaze, are an essential aspect of interpersonal communication that can also contribute to the development of rapport (Tickle-Degnen and Rosenthal, 1990). We include nonverbal behaviors that annotated by human evaluators with Krippendorff's alpha > 0.7. We collected all nonverbal behaviors that occur during one turn and encode them using one-hot encoding. For head nods and smiles, we used a binary labeling approach, marking 1 for their occurrence and 0 for non-occurrence. As gaze serves as a potent indicator of attention, we categorized it into 4 distinct types: no gaze appeared in the video, gaze at partner, gaze at worksheet, and gaze elsewhere.

Mutual gazes, smiles, and nods serve as great indicators of alignment and rapport in communication. These are not encoded separately, as our encoding process for nonverbal behaviors capture the behaviors of both participants within a turn, not only the current turn's holder. Our current approach successfully captures these important mutual signals.

3.3.7 Contextual Information (*ConInfo*) in the previous turns

Our model also incorporates contextual information that outlines the discourse environment between the two interlocutors. Specifically, we include features such as the session and period numbers, which help to encapsulate the temporal dynamics of the tutoring interactions. We also consider the problem ID and the correctness of the current problem response, which act as markers of the present learning context. These features can illuminate the complexity of the ongoing problem and the students' performance, potentially influencing their use of hedges. The tutee's and tutor's pre-test scores are also included, serving as initial measures of their knowledge before the tutoring session. This data can help to identify the starting knowledge disparity between the tutor and the tutee. It is plausible that these pre-test scores might also be linked with the students' level of confidence, which could subsequently impact their use of hedges. (Madaio et al., 2017a).

Norman et al. (2022) stated a link has been established between verbal alignment signals, such as backchannels (e.g., "um", "hhm", "oh.."), and learning gains in a cooperative learning environment. Given the role of hedging as a social language skill that improves learning performance, we hypothesize its connection to dynamic learning gains. Consequently, we incorporated the frequency of these verbal alignment signals from the previous four conversational turns into our model input.

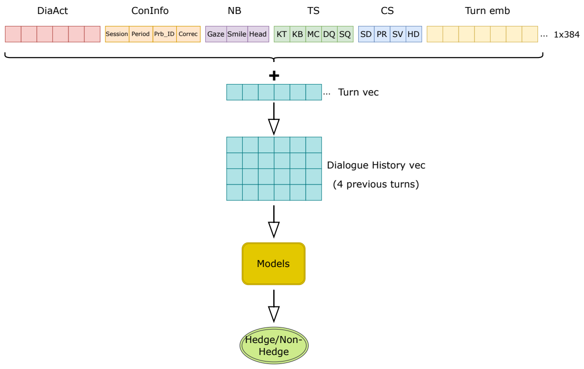

Figure 1: Vector Representation

3.4 Vector Representation

Before presenting the specific models, we first describe how to convert each sequence of turns into a vector representation. Our vector representation consists of three basic parts: turns as a sequence of tokens, annotations based on the turn (e.g., conversational strategies), and the nonverbal behaviors. Figure 1 shows that we divide a vector of turns into 6 parts: turn embedding, conversational strategies (*CS*), tutoring strategies (*TS*), nonverbal behaviors (*NB*), contextual information (*ConInfo*) and dialogue acts (*DiaAct*). After encoding each turn in this fashion, we use the four previous turns as a history tensor of a turn. This history ten tensor will be the input to the prediction models, and the model's output will be this turn's hedge label.

3.5 Prediction as Classification

We mentioned in the previous section that we transform the prediction problem into a classification problem. This means that the corresponding hedge strategy is obtained by classifying different previous interactions (i.e., dialogue history) and historical characteristics (e.g., rapport, etc.). The classification models used are presented here.

3.5.1 LightGBM

In this work, we used LightGBM (Ke et al., 2017), a gradient boosting framework known for its efficiency. We use it to predict hedges in dialogues, relying only on dialogue features such as conversational strategies, tutoring strategies, nonverbal behaviors, and contextual information, while turn embeddings are not included.

3.5.2 XGBoost

We also used the Extreme Gradient Boosting (XGBoost) algorithm (Chen and Guestrin, 2016), which is a decision tree-based ensemble machine learning algorithm that uses a gradient boosting framework. Similar to LightGBM, the turn embedding is not used.

3.5.3 Multi-layer perceptron (MLP)

We constructed a multi-layer perceptron using two sets of features. These included a pre-trained contextual representation of the turn, specifically from the SentBERT model (Reimers and Gurevych, 2019) which is the most prevalent sentence embedding tool, and the concatenation of all the features mentioned in Section 3.3.

3.5.4 Long Short-Term Memory (LSTM)

We use the same features and apply them to LSTM (Hochreiter and Schmidhuber, 1997) and also LSTM with attention (Bahdanau et al., 2015). LSTM has a good ability to capture temporal correlations, and we expect this ability to enhance prediction performance.

3.6 Implementation Details

In order to address the imbalance in our dataset, where the ratio of hedge to non-hedge instances is approximately 1:10, we used the Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al., 2002) for each model to augment our learning process. SMOTE is a popular method that generates synthetic examples in a dataset to counteract its imbalance. Given the variable nature of model performance, we implemented a 5-fold cross-validation strategy to evaluate the models. The model that delivered the best performance during this cross-validation process was then chosen to make predictions on the test set. For the neural models, we adjusted the loss function to account for class imbalance, thereby compelling the models to accommodate less frequent classes more effectively.

4 Results

4.1 Classification Results

To answer the research question 1, we conducted classification experiments on different models. Table 1 offers an in-depth comparison of multiple machine learning models for predicting hedges in a peer-tutoring dataset. We also incorporated a dummy classifier for comparison, which generates predictions in accordance with the class distribution observed in the training set. The performance metrics are accuracy, F1 score, precision and recall, all of which include confidence intervals ($\alpha = 0.05$). The dataset is composed of several types of input features described in Section 3.3. The models used different combinations of these inputs. (w/o emb) indicates that the model uses only the features without turn embeddings. If not specified, the model uses all features plus turn embeddings.

From Table 1, although the Dummy classifier achieved the highest accuracy of 78%, its performance on other metrics was the worst. However, note that all other models obtained significantly better results than the dummy classifier when considering the F1 score. The relatively high accuracy of the dummy classifier stresses that a class imbalance in the dataset is significant. This result also confirms the complexity of the hedge prediction task. The LightGBM and XGBoost models without embeddings achieved relatively low scores for F1 scores, precision and recall, indicating limited performance in terms of balanced precision and recall. The MLP models, particularly those using only embeddings, showed a remarkable recall of 74%, but at the cost of reduced accuracy and precision. The LSTM model using only turn embeddings demonstrated balanced performance across all metrics, achieving the highest precision of 19% and a competitive F1 score of 0.28. However, the attention-based LSTM (AttnLSTM) model did not significantly outperform the standard LSTM model in any metric.

The inclusion of turn embeddings significantly impacts model performance. Models with only embeddings perform better in terms of F1 score and recall, suggesting that the semantic information captured in these embeddings, which represented the semantic information of turns, is crucial for hedge prediction. Second, models without embeddings also performed reasonably well in F1 score, implying that other features such as rapport, conversational strategies, tutoring strategies, nonverbal behaviors, and contextual information are also important. These features should not be overlooked.

The LightGBM and XGBoost models, which only use features without turn embeddings, also display competitive performance compared to the MLP, LSTM, and AttnLSTM models using all fea-

Models	Acc.	F1-score	Precision	Recall
LightGBM (w/o emb)	**0.60** (±0.02)	0.24 (±0.07)	0.17 (±0.03)	0.45 (±0.07)
XGBoost (w/o emb)	0.59 (±0.03)	0.24 (±0.07)	0.16 (±0.03)	0.45 (±0.07)
MLP	0.56 (±0.03)	0.25 (±0.06)	0.16 (±0.03)	0.52 (±0.07)
MLP (only emb)	0.38 (±0.07)	0.26 (±0.05)	0.16 (±0.02)	0.74 (±0.06)
MLP (w/o emb)	0.54 (±0.07)	0.26 (±0.06)	0.17 (±0.06)	0.56 (±0.07)
LSTM	0.56 (±0.07)	0.25 (±0.06)	0.16 (±0.03)	0.50 (±0.07)
LSTM (only emb)	**0.60** (±0.07)	**0.28** (±0.07)	**0.19** (±0.08)	0.52 (±0.07)
LSTM (w/o emb)	0.34 (±0.07)	0.25 (±0.05)	0.15 (±0.02)	**0.75** (±0.06)
AttnLSTM	0.47 (±0.07)	0.24 (±0.06)	0.15 (±0.03)	0.57 (±0.07)
AttnLSTM (only emb)	**0.60** (±0.06)	0.25 (±0.07)	0.17 (±0.03)	0.45 (±0.07)
AttnLSTM (w/o emb)	0.45 (±0.07)	0.23 (±0.06)	0.15 (±0.07)	0.57 (±0.07)
Dummy	0.78 (±0.02)	0.11 (±0.08)	0.14 (±0.06)	0.10 (±0.04)

Table 1: Comparison of MLP and LSTM models for predicting hedges

tures. This suggests that although turn embeddings provide valuable information for hedge prediction, models can still achieve satisfactory results even without them. The AttnLSTM models, which incorporate attention mechanisms, do not show significant improvements over the regular LSTM models. This could be due to the limited amount of data available, which cannot unleash the potential of the attention mechanism.

Since good performance can also be achieved using the extracted features, in order to answer our research question 1, in the next subsections we will mainly investigate the importance of features in predicting hedges.

4.2 Features Explanation with Shapley values

Shapley values (Hart, 1989), originating from cooperative game theory, have emerged as a powerful tool to explain the predictions of machine learning models. This approach provides a way to fairly distribute the contribution of each feature to the overall prediction for a specific instance. By calculating the Shapley value for each feature, we gain insight into the importance of individual features within the context of a specific prediction. This interpretability technique has been widely adopted across various machine learning models, enhancing the transparency and trustworthiness of their predictions. In this study, we will use Shapley values to interpret the contributions of extracted features in our classification models using the SHAP python package (Lundberg and Lee, 2017).

Figure 2 in the Appendix A illustrates the importance of each feature for prediction when only features are used as input to different prediction models. The importance of features within the models can differ depending on their architectures. For simplicity, we identify the features that frequently appear in these 4 figures as significant indicators. Therefore, we have selected some of the most representative features in predicting hedges in Table 2.

Features	Valence
correctness	+
no gaze from tutor	-
problem id	-
rapport	-
tutee's deep question	-
tutee's gaze at tutor	-
tutee's pre-test	-
tutor's gaze at elsewhere	-
tutor's praise	-

Table 2: Features and their Valences

Based on Table 2, certain features have a significant impact on the likelihood of using hedges in tutoring conversations. Rapport has a negative valence, suggesting that higher rapport between the participants results in a lower likelihood of hedges being used. This reconfirms the previous finding that hedges are frequent in low rapport interaction (Madaio et al., 2017c). Interestingly, the "problem id" feature also has a negative valence, indicating that as the complexity or difficulty of the problem increases, the likelihood of using hedges decreases. This could be because tutors tend to be more assertive or confident when addressing more challenging problems.

Moreover, certain conversational features such as "tutee's deep question" and "tutor's praise" have a negative valence, implying that these actions tend

Model \ Feature	*N/A*	*Rapport*	CS	*TS*	*NB*	*ConInfo*	*DiaAct*
XGBoost	0.24 (±0.07)	0.15 (±0.08)	0.10 (±0.08)	0.15 (±0.09)	**0.08** (±0.07)	0.10 (±0.08)	0.12 (±0.08)
LightGBM	0.24 (±0.07)	0.16 (±0.08)	**0.09** (±0.08)	0.10 (±0.07)	0.10 (±0.10)	0.12 (±0.09)	0.13 (±0.08)
LSTM	0.25 (±0.05)	0.24 (±0.05)	0.26 (±0.06)	0.24 (±0.06)	0.22 (±0.06)	0.25 (±0.07)	**0.21** (±0.06)
AttnLSTM	0.23 (±0.06)	**0.20** (±0.06)	0.22 (±0.05)	0.25 (±0.05)	0.24 (±0.05)	0.23 (±0.07)	0.22 (±0.06)
MLP	0.26 (±0.06)	0.25 (±0.06)	0.25 (±0.06)	0.26 (±0.06)	0.25 (±0.06)	0.27 (±0.06)	**0.21** (±0.07)

Table 3: F1 scores after the feature ablation, *CS*: Conversational Strategies; *TS*: Tutoring Strategies; *NB*: Nonverbal Behaviors; *ConInfo*: Contextual Information; *DiaAct*: Dialogue Act.

to decrease the likelihood of hedges. This could be because deeper questions or praise might foster a more open and confident dialogue, thus reducing the need for hedges.

The table also reveals a negative correlation between various non-verbal cues such as "no gaze from tutor", "tutee's gaze at tutor", and "tutor's gaze at elsewhere", and the occurrence of hedges. When the tutor is not gazing, the likelihood of hedges decreases. The tutee's gaze at the tutor and the tutor's gaze at elsewhere are negatively associated with the use of hedges. This could mean that when attention is focused elsewhere, the conversation tends to be more direct. To our best knowledge, this is the first demonstration that specific nonverbal cues substantially influence the likelihood of a hedge being used in the succeeding turn of peer-tutoring interactions.

4.3 Ablation Study

Ablation study plays a crucial role in machine learning research, which provides a systematic approach to understand the value contributed by individual features or sets of features within a model. Therefore, we examine aforementioned models with different features ablated from input. This approach allows us to identify which features, when absent, led to the best or worst performance in each model, implying that these features may not have contributed positively (or negatively) to the model's performance. Our study considered 6 groups of features: Conversational Strategies (*CS*), Tutoring Strategies (*TS*), Nonverbal Behaviors (*NB*), Contextual Information (*ConInfo*), Dialogue Act (*DiaAct*), and Rapport.

Table 3 shows the different F1 scores when removing the different features. For XGBoost and LightGBM, the worst performance observed when *NB* and *CS* were removed, respectively, which implies that these features may provide important information for these models. The LSTM and MLP models showed a significant drop in performance when the *DiaAct* feature was removed, suggesting a substantial dependency of these models on the *DiaAct* feature for their prediction capabilities. Interestingly, the best performance of AttnLSTM was achieved when the rapport feature was removed, suggesting that the attention mechanism could compensate for loss of rapport, which has been shown to be an important factor to predict hedges in peer-tutoring interactions (Madaio et al., 2017a).

5 Conclusion and Future Work

This study presents an effective approach to predict hedges in peer-tutoring interactions using classic ML models. Our results show the importance of considering various types of input features, such as turn embeddings, rapport, conversational strategies, tutoring strategies, nonverbal behaviors, and contextual information. Moreover, we applied the Shapley value study to explain the predictions of the ML models. Notably, we found for the first time that the gaze of both tutor and tutee may play a critical role in predicting hedges. This observation is substantiated by subsequent ablation studies, where classic classification models, like XGBoost and LightGBM, experienced a significant decline in F1 score when removing nonverbal behavior features.

For future work, several directions can be pursued. First, the investigation of hedge generation in the context of expert tutors could provide valuable insights into how experienced tutors use hedges differently and how these differences might affect learning outcomes. Second, incorporating reinforcement learning techniques to enhance specific aspects of the interaction, such as learning performance, could improve the practical applications of our findings.

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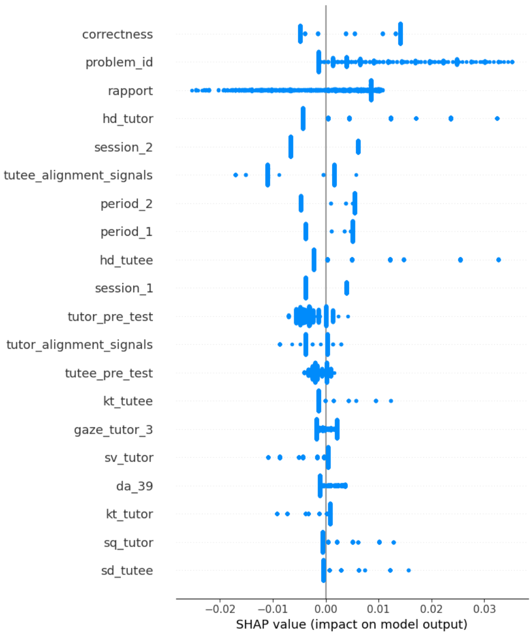
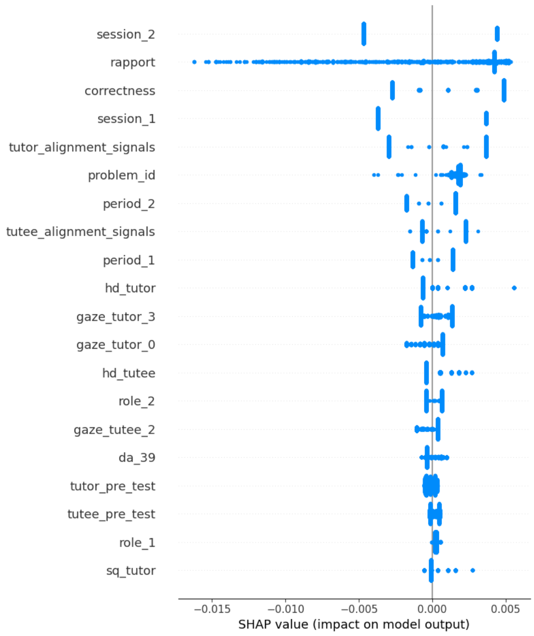
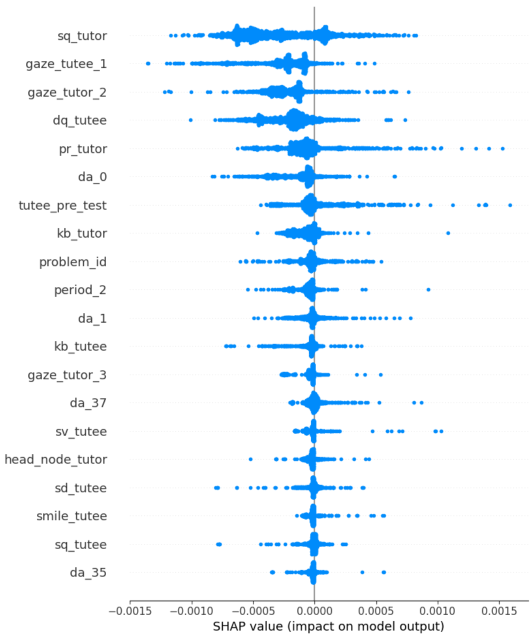
A Shap Value Graphs



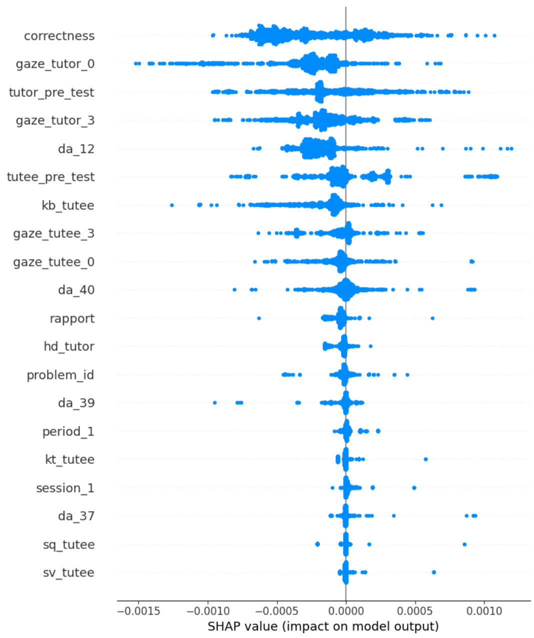
(a) Feature Importance for AttnLSTM (without emb)



(b) Feature Importance for MLP (without emb)



(c) Feature Importance for XGBoost



(d) Feature Importance for LightGBM

Figure 2: Feature Importance for Different Model