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Enticing Player-NPC Dialogue System in a Visual Novel Game Using Intent Recognition with BERT

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A R T I C L E I N F O

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A B S T R A C T

This study aims to develop a visual novel game in which the user can actively interact with an NPC by entering their own response rather than selecting dialogue options, as well as to improve the immersion of the Player-NPC dialogue system by obtaining the player's in-game text inputs while using intent recognition with the BERT transformer model. The researchers developed two different versions of the visual novel game to achieve their goal. The first version of the game uses the standard visual novel game mechanics, while the second version uses text input to communicate with NPCs, and the BERT algorithm was integrated in this version for the intent recognition of the player's text inputs. The retraining of the model achieved an accuracy of 0.9375. To measure the players' immersion in both versions, a Modified Immersion Experience Questionnaire was given to the players to complete after each playthrough of the visual novel games. Based on the research findings, the researchers concluded that when participants played the game that uses Intent Recognition with BERT, their level of immersion significantly improved.

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INTRODUCTION

In recent years, many video games have become intricate. Video games have improved on many aspects such as graphics, gameplay mechanics, and game difficulty. This includes the implementation of a storyline. In classic video games from the past, such as Super Mario Brothers, and Donkey Kong, they usually had a simple storyline of the protagonist going through different hurdles and challenges in order to save the damsel in distress or reach a goal. Current day video games now have overarching storylines, which can even take days or weeks to finish. Some popular titles even have a storyline that spans into different games in a whole series. With the improvement of story writing over the years, video games have become more immersive than before. Story writing became an integral part in developing a game. With the use of a story, players can grow attached to characters involved in the game. Some games even focus on socializing with the characters in a game. An example of this is the Persona series, where each game encourages the player to interact and become close with the main characters.

A player can discover more about a non-player character (NPC) by interacting with them in in-game conversations. In most story-based games, the player can speak to a NPC by picking a dialogue option that is presented in-game. Choosing a certain dialogue can affect the response or attitude of the NPC towards the player. This adds to the immersion of a game where the player can feel involved in the story by conversing with a NPC. An example of this are visual novel games. These games are mostly text-based where the ending or outcome is dependent on the choices of the player. Several visual novels have many twists in them but their main mechanic stays the same; the narrative flow will stop and options will appear, giving the player a choice to make, which will alter the flow of the story (Carrera, 2019).

The goal of this study was to improve the immersion in a visual novel game. Visual novels have predetermined choices for the player that the player can choose from but at the same limits other possibilities the player can do. The player can only choose dialogue options provided in a visual novel. This study aims to create a visual novel game where the player can actively converse with a NPC by typing down their own response instead of choosing dialogue options. The NPC should be able to categorize the player’s response and react accordingly. This study focuses on intent recognition with the BERT transformer model. This was used to classify the player’s responses so that the NPC will be able to give an appropriate response for the situation.

LITERATURE REVIEW

A player can discover more about a non-player character (NPC) by interacting with them in in-game conversations. In most story-based games, the player can speak to a NPC by picking a dialogue option that is presented in-game. Choosing a certain dialogue can affect the response or attitude of the NPC towards the player. This adds to the immersion of a game where the player can feel involved in the story by conversing with a NPC. An example of this are visual novel games. These games are mostly text-based where the ending or outcome is dependent on the choices of the player. Several visual novels have many twists in them but their main mechanic stays the same; the narrative flow will stop and options will appear, giving the player a choice to make, which will alter the flow of the story (Carrera, 2019).

METHODOLOGY

The focus of this study is to determine whether players would be more immersed with their interaction with NPCs through the means of text-input as compared to the traditional point-and-click style of gameplay. In order to do so, the researchers developed two versions of the visual novel game. The first version was developed without the implementation of intent recognition, that is, it has the default mechanics of a normal visual novel game. The common gameplay of visual novel games is through the use of a point-and-click input for the players to choose dialogue options. This version was developed using Ren'Py, a free game engine which is used to create standard visual novels.

The second version of the game has the same mechanic but with a different input style i.e., using text-input to interact with NPCs. This version of the game is also where the BERT algorithm was integrated for the intent recognition of the player text-inputs. This version was developed using the Unity game engine. To utilize the algorithm on the said game engine, the researchers used the Hugging Face Inference API and PyTorch machine learning framework to import the BERT model. Along with this, the researchers also opted to use different external and built-in libraries which relate to implementing the algorithm. Since the game developed has a conversational approach in the gameplay, a dataset that focuses on natural human dialogue would be essential for the study.

In a paper by Saravia et al. (2018), they presented the Emotions dataset which is an already preprocessed dataset containing tweets annotated with six different emotions. The authors created a set of hashtags to collect an English dataset of tweets from the Twitter API which belongs to eight basic emotions i.e., sadness, joy, anger, fear, disgust, trust, anticipation, and surprise. This dataset was also modified to narrow down the domain of the proposed game's storyline. It was used for training the model by treating the emotion labels as the utterance intents of the users, i.e. Sadness, Joy, Love, Anger, Fear, and Surprise.

To quantitatively analyze game immersion, the players were asked to answer a questionnaire after playtesting which evaluates the player's game immersion experience. The questionnaire used in this experiment was developed based on the findings of the previous research based on the Immersive Experience Questionnaire by Jennett et al. (2008). The gathered data was analyzed by first evaluating whether it has a normal distribution using the Shapiro-Wilk test. Based on the results of the normality test, either the paired t-test or Wilcoxon signed rank test was conducted to further analyze the data.

RESULTS

Sampling and Data Gathering Procedure

In order to gather data for the study, an ideal minimum of 30 participants was required. The sample size is limited to those aged 18 to 25, primarily UST Computer Science students under the Game Development Track. A modified version of the Immersive Experience Questionnaire by Jennett et al. (2008) and Wong et. al (2017) was used to gather data on the player's level of immersiveness. It was utilized to determine whether or not the player's interaction with the NPC dialogue system was immersive in the game. In this study, stratified sampling was utilized to choose samples from the population. The total number of samples is determined using Slovin's Formula:

$$n = \frac{N}{1+Ne^2}$$

where:
n = sample size
N = population size of UST CS students under the GD Track
e = margin of error (5% or 0.05)

Statistical Treatment of Data

The researchers used statistical treatments for both the evaluation of the player's game immersion and the performance of the model used for the second version of the game. Since intent recognition is a multi-class classification task, the metrics for accuracy, precision, recall, and F1 score will be used to evaluate the performance of BERT.

A 6×6 confusion matrix was used to illustrate the true positives, false positives, true negatives, and false negative values. This shows the classification per intent and performance of the model.

Accuracy can be defined as the percentage of times wherein the predictions were correct. As a mathematical equation, it is defined as:

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

Precision can be defined as the percentage of correct predictions out of the total positive predictions. As a mathematical equation, it is defined as:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

For Recall, it is the percentage of correct predictions out of the total actual positive predictions. As a mathematical equation, it is defined as:

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

F1 Score would be the measurement of balance between recall and precision. As a mathematical equation, it is defined as:

$$F_1\ \text{Score} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

On the evaluation of the player immersion, the results of the modified IEQ deployed for the respondents were computed and evaluated using the Shapiro-Wilk test to check for the normality of the difference in the score distributions. Based on the computed results, this determines whether the paired t-test or Wilcoxon signed rank test will be used. In the normality test, the formula for getting the test statistic W value is denoted as

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where:
n = sample size
xi = ordered random sample values
ai = constants generated from means, variances, covariances of n

The null hypothesis for the Shapiro-Wilk normality test assumes that the data is normally distributed. If the difference between the pair of scores are normally distributed, the paired t-test will be used which is denoted as:

$$t = \frac{\Sigma d}{\sqrt{\frac{n(\Sigma d^2) - (\Sigma d)^2}{n-1}}}$$

where:
d = difference per paired value
n = number of samples

On the instance wherein the data is not normally distributed, a non-parametric test is needed to compare the data. The researchers will use the Wilcoxon signed-rank test which is denoted as:

$$W = \sum_{i=1}^{N_r} [\text{sgn}(x_{2,i} - x_{1,i}) \cdot R_i]$$

where:
Nr = sample size, excluding pairs where x1=x2 sgn = sign function
x1,i, x2,i = corresponding ranked pairs from two distributions Ri = rank i

System Architecture

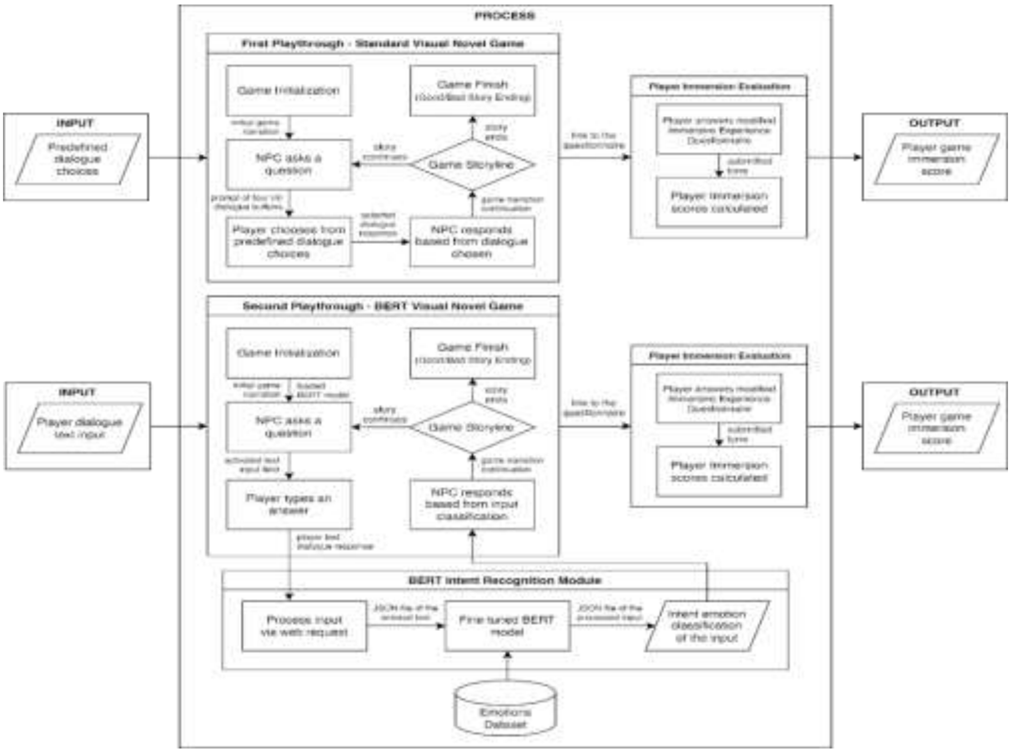

Figure 1. Illustrates the System Architecture

Figure 1 illustrates the system architecture, which shows the process of when the first and second versions of the game would be played by a player. The researchers prepared two visual novel games to compare which version would render higher game immersion scores from the players.

DISCUSSION

The BERT Model was fine-tuned on the Emotions dataset using the Hugging Face Trainer. The model achieved an accuracy of 0.9375 in the emotion intent classification task. For both the first and second playtests, the game was distributed to forty-three (43) players. In the second playtest, only 30 of the 43 players who took part in the first playtest answered. Furthermore, in order to determine the player's level of game immersion, the results of the modified Immersive Experience Questionnaire (IEQ) were gathered after players had finished playing both game versions.

A. Fine-Tuning of the BERT Model

Table 1. Evaluation Metrics of Retraining the BERT Model

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1-score
1	No log	0.236529	0.933000	0.935431	0.933000	0.933570
2	0.089900	0.205222	0.936000	0.937783	0.936000	0.935284
3	0.089900	0.200994	0.934000	0.933499	0.934000	0.933539
4	**0.069900**	**0.195542**	**0.937500**	**0.938704**	**0.937500**	**0.937092**
5	0.069900	0.225181	0.936500	0.937029	0.936500	0.936636
6	0.037300	0.247025	0.936500	0.937840	0.936500	0.936960
7	0.037300	0.254642	0.934000	0.934005	0.934000	0.933832
8	0.022100	0.260248	0.933000	0.933345	0.933000	0.933135

Table shows the training results in fine-tuning the BERT model. The training loss and validation loss converges at epoch = 4, which yielded an F1- score of 0.937092. Therefore, the chosen model for the final trained intent classifier is when the epoch = 4.

The BERT model was retrained on the Emotion dataset (Saravia et. al., 2018) with 20,000 preprocessed Twitter messages labeled with emotions, where 80% of the dataset was split for training, 10% for validation, and the remaining 10% for testing. Table illustrates the frequency distribution of emotions of the training set, where approximately 33% of the inputs were classified under Joy.

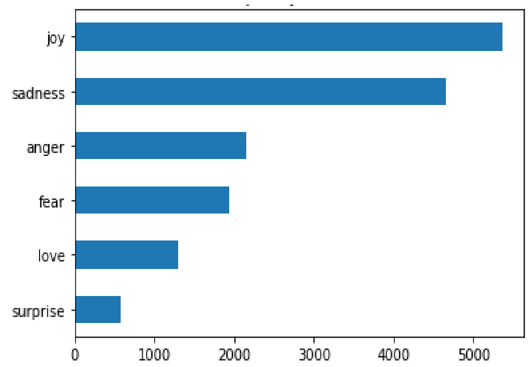

Figure 2. Bar Graph of the Training Set Emotion Frequency Distribution

Table 2. Confusion Matrix of the Fine-Tuned BERT Model

		Predicted					
		Sadness	Joy	Love	Anger	Fear	Surprise
Actual	Sadness	528	3	0	10	9	0
	Joy	4	675	14	2	5	4
	Love	2	29	146	1	0	0
	Anger	5	3	0	263	4	0
	Fear	7	1	0	6	189	9
	Surprise	1	2	0	0	5	73

This table illustrates the confusion matrix of the model's performance for the task of emotion intent recognition. Discrepancies on the performance of the fine-tuned model may be attributed to the uneven distribution of inputs in the training data. The model achieved an accuracy and recall of 0.9375, precision of 0.9387, and F1-score of 0.9371.

Table 3. Evaluation Results of the Fine-tuned BERT for Intent Recognition.

Model	Accuracy	Precision	Recall	F1-score
BERT Base (uncased)	0.9375	0.9387	0.9375	0.9371

B. Presentation of Gathered Data

Table 4. Average Length of Gameplay for both Game

	Length of Gameplay
Normal VN	14.36
BERT VN	10.09

The visual novel game's normal and bert versions' gameplay durations are presented in Table 4. The average amount of time spent playing the Normal version of the game is 14.36 minutes, compared to 10.09 minutes for the BERT version.

Table 5. Recorded BERT VN Text Inputs of the First Three (3) Players

Player	Question	Input	Sadness	Joy	Love	Anger	Fear	Surprise
Player 1	Q1	i m doing good	0.001071	0.997503	0.000337	0.000677	0.000225	0.000187
	Q2	okie	0.006282	0.721930	0.142319	0.109006	0.014209	0.006253
	Q3	ok feed me	0.001010	0.993339	0.001219	0.003716	0.000428	0.000288
	Q4	bro i don t remember that	0.859725	0.008578	0.003047	0.094207	0.008246	0.026198
	Q5	okie ill stay with u	0.037480	0.816099	0.067299	0.063714	0.014733	0.000676
Player 2	Q1	im doing great but not that great	0.014071	0.982168	0.000666	0.001838	0.000928	0.000330
	Q2	oh i can but i might be a convenience here	0.001300	0.987784	0.002706	0.005633	0.000658	0.001919
	Q3	sure let s hve bfast	0.000228	0.998044	0.000910	0.000564	0.000121	0.000133
	Q4	i feel bad that i left	0.999209	0.000155	0.000145	0.000284	0.000078	0.000129
	Q5	i ll be happy	0.002499	0.996037	0.000899	0.000276	0.000176	0.000113
Player 3	Q1	fine	0.027231	0.942977	0.003146	0.023407	0.002647	0.000592
	Q2	sure	0.001370	0.994721	0.001113	0.002001	0.000398	0.000397
	Q3	im not sure	0.003169	0.008570	0.000816	0.002334	0.975259	0.009851
	Q4	not that great	0.867362	0.017400	0.001969	0.093646	0.018406	0.001216
	Q5	i ll think about it	0.019949	0.024417	0.003976	0.041918	0.905788	0.003952

This table shows the actual responses of the first three (3) participants during the playtest for the Version 2 and its predicted score for each of the six basic emotions. Preprocessing techniques, i.e. removal of punctuation marks and conversion of characters to lowercase, were applied to the responses before they were passed to the BERT tokenizer to match the training data used in the fine- tuned model.

Table 6. Modified Immersive Experience Questionnaire (IEQ) Scores and Score Differences of the first Ten (10) Players

Player	Normal VN Immersion Score	BERT VN Immersion Score	Score Difference
Player 1	51	62	-11
Player 2	70	66	4
Player 3	64	56	8
Player 4	79	96	-17
Player 5	82	68	14
Player 6	72	77	-5
Player 7	47	53	-6
Player 8	88	92	-4
Player 9	62	67	-5
Player 10	72	73	-1

This table displays each player's overall score for both game versions after answering the modified Immersive Experience Questionnaire. The difference between the outcomes of the first and second playtests is shown in the table. Moreover, the gathered data indicate a significant effect on the player's game immersion.

Computation of Statistical Tests

The data extracted from the Modified Immersive Experience Questionnaire were used in order to identify the Immersion Score and Average of each version of the Visual Novel, where the first version (Version 1) is the Normal Visual Novel and the second version (Version 2) is the Visual Novel with the integration of BERT with Intent Recognition. The Immersion average of the two versions are represented by Table IV-12 and as for the Immersion score of each version.

Table 7. Average Level of Immersion Scores per each Game Version

Level of Immersion	
Version 1 (Normal)	3.08
Version 2 (BERT)	3.26

To check for the normality of the data, the researchers have decided to use the Shapiro-Wilk test for testing. If the P-value is less than the alpha, in this case 0.05 or 5% is used, then the Wilcoxon Signed Rank test will be used, otherwise the Paired T-test will be used. Additionally, for this testing, the difference between the Immersion Scores of both versions is used for the statistical treatment.

Table 8. Shapiro-Wilk Test Results

Shapiro-Wilk Test Results	
W	0.98558
P-value	0.9467
Alpha	0.05
Results	0.9467 > 0.05

Given the results in Table 8, the P-value with 0.9467 is greater than the alpha, therefore, the null hypothesis for the Shapiro-Wilk test is accepted and the data is normally distributed. Given that the data are normally distributed, the Paired T-test is used to determine whether there are differences in the levels of immersion between the two Visual Novel game versions.

The Paired T-test is the statistical treatment used for normally distributed data with the conditions, rejecting the null if the computed P-value is less than the given alpha. In this study, this test will be used in determining if there is an improvement in the immersion if BERT with intent recognition is implemented. The hypotheses are as follows:

H0: There is no difference in the player's immersion in the game's dialogue with the NPCs by using text input through intent recognition.

Ha: There is a significant improvement in the player's immersion in the game's dialogue with the NPCs by using text input through intent recognition.

Table 9. Paired T-test Results

Paired Sample T-test	
t	-2.4348
df	29
P-value	0.02128
alpha	0.05
Result	0.02128 < 0.05

Given the results in Table 9, the P-value with 0.02128 is less than the alpha, therefore, rejecting the null hypothesis and concluding that there is a significant improvement in the level of immersion of the participants when they played the game with implemented BERT with Intent Recognition.

CONCLUSIONS AND RECOMMENDATIONS

The researchers developed a visual novel game using intent recognition with BERT to enable the player to communicate with NPCs via text input and classify its intents to generate the appropriate responses from the NPCs. The BERT model was fine-tuned for intent recognition using the Emotions dataset, which is divided into six primary emotions—joy, love, sadness, anger, surprise, and fear. The modified Immersive Experience Questionnaire (IEQ) responses from players who have completed both versions of the visual novel game were utilized to determine the game immersion scores. According to the study, the inclusion of BERT-enabled intent recognition in a visual novel game has an impact on the player's overall game immersion experience. Further, the researchers arrive at the following conclusions:

a) In the normal version of the game, the player's level of immersion averaged 3.08, whereas it averaged 3.26 for the version of the game that used intent recognition with BERT. Therefore, the player's immersion in the game will be significantly affected if intent recognition with BERT is implemented.
b) The BERT model was retrained to do the task of classifying intended emotions of the input sentences using the Emotions dataset. With this, the model

The study focused on the player’s immersion based on the modification and improvement of the dialogue system from predetermined choices to giving players freedom to put their desired input and let BERT and intent recognition handle the player’s answer and respond accordingly in a visual novel game. As BERT and other NLP have not been used often as an algorithm to the Video Game Industry, this research can be used as a guide for future researchers who want to tackle the same path for their research. With that, based on the yielded results and drawn conclusions, the researchers would like to recommend the following for future studies, whoever will make this study a reference:

a) As this study specifically used BERT for Intent Recognition in order to respond to player's answers to the given questions, future studies may try other NLP tasks for BERT, such as Question Answering, Named-entity recognition etc.
b) The researchers have chosen BERT as the transformer model for this study because of the model achieving state-of-the-art results for various NLP tasks, one of which is the Text Classification class and under it would be the Intent Recognition. Even though that is the case, it is also recommended to test other more recent transformer models such as XLNet, GPT-3 etc. in the context of Intent Recognition applied in dialogue systems.
c) Since the focus of this study relies on single emotion classification for each input, there are instances where two or more emotions have closely related classification scores which may cause discrepancies in the accuracy of the classifier. In light of this, it is recommended that future researchers explore the use of multiple or mixed emotions rather than concentrating on just one emotion in the task of intent recognition.
d) Since this study is only focused on the immersion of the dialogue component in a visual novel game, the games developed only consisted of 4 story endings, good and bad for each NPC route, and used a linear way of storytelling. It is recommended for future studies to explore more than 4 endings with a complex story that consists of branching dialogue to observe the relationship between the players' immersion and their interaction with the game's storyline.

FURTHER STUDY

This study was done remotely, where the researchers were not able to observe and see how the players are doing during their playtesting, which may have led to distractions or external factors that the researchers were not aware of. In this event, it is recommended for future studies to set a controlled environment for the players, in which players are invited into a place where the external factors may not be present so that they will not be distracted and focus more on the game.

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