Classy Trash Monster: An Educational Game for Teaching Machine Learning to Non-major Students

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Figure 1: ***Title screen of Classy Trash Monster, a defense game for machine learning education,*** **2021.**

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ABSTRACT

As machine learning (ML) became more relevant to our lives, ML education for college students without technical background arose important. However, not many educational games designed to suit challenges they experience exist. We introduce an educational game *Classy Trash Monster* (CTM), designed to better educate ML and data dependency to non-major students who learn ML for the first time. The player can easily learn to train a classification model and solve tasks by engaging in simple game activities designed according to an ML pipeline. Simple controls, positive rewards, and clear audio-visual feedback makes game easy to play even for novice players. The playtest result showed that players were able to learn basic ML concepts and how data can impact model results, and that the game made ML feel less difficult and more relevant. However, proper debriefing session seems crucial to prevent misinterpretations that may occur in the learning process.

CCS CONCEPTS

• **Applied computing** → **Computer games**.

KEYWORDS

Game Design, Educational Games, Machine Learning Education

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1 INTRODUCTION

Along with the increasing relevance of artificial intelligence (AI) and machine learning (ML) technology in our lives, tackling the general public misunderstanding of AI through education is becoming a great concern [13]. Despite its growing importance, research on ML education for people with non-technical background remains less explored [12, 13]. As more non-major students learn ML in college, teaching standards and components adjusted to their needs became a developing research area [4]. Games possess potential for lowering barriers for ML education [7, 8, 14], supported by its effective use in computer science (CS) education [15, 16, 21]. However, the educational game for ML education targeted for non-major students is hard to find. In this paper, we introduce an educational game *Classy Trash Monster* (CTM) designed to teach ML to non-major students and help them overcome barriers and misconceptions discovered by [18].

2 RELATED WORKS

2.1 ML Education Tactics for Non-major students

How to effectively educate ML to people without CS knowledge is an emerging area of research [4, 12, 13]. A survey by Wollowski *et al.* revealed the learning goals of ML instructors in practice ranging from the general introduction on the capability of ML to teaching knowledge for practical implementation [20]. A study conducted by Sulmont *et al.* went a step further and also investigated the preconceptions and barriers that non-major students encounter in the introductory ML courses [18]: 1) students often start with preconceptions that rises from the media reputation of ML, such as that ML is not accessible without CS background; 2) students face several barriers while developing ML knowledge, including having difficulty acknowledging that ML processing is different from human thinking, believing that ML does not require much human effort, and not recognizing the limits of ML applications easily. Adequate teaching standards or components for this population, however, is still under development [12].

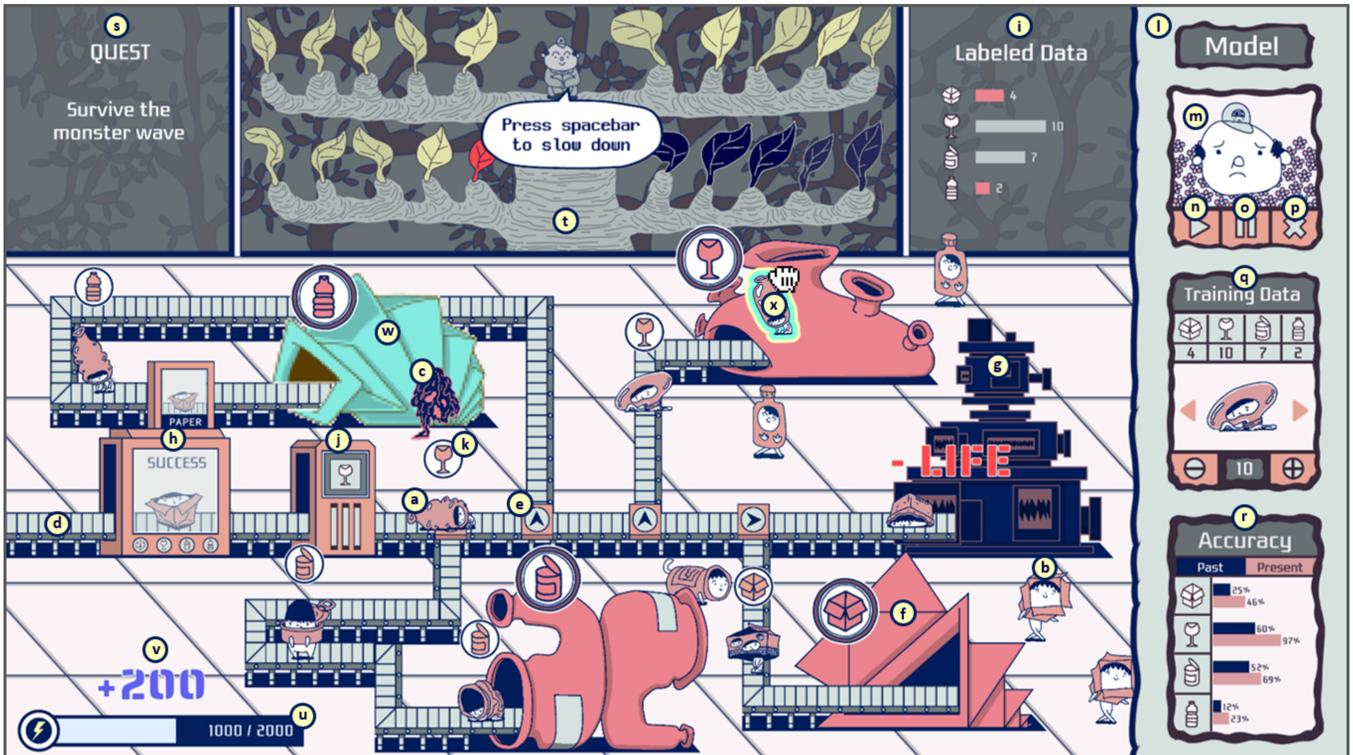
2.2 Interactive Approach on ML Education for Non-major Students

Currently, several approaches that aim for a more interactive approach to ML education for the general public exist. Massive Online Open Courses (MOOC) such as Elements of AI and AI for Everyone [1, 2] encourage active learning through quizzes and exercises. The more interactive approaches include visualizations such as Tensorflow Playground, GAN Lab, and CNN Explainer [3, 11, 17, 19]. While visualizations were reported to be good for building intuition through dynamic experiments, beginners may need a step-by-step guide to fully engage and learn through them [10]. Game-based learning in CS education were reported to be beneficial in increasing students' motivation and participation as well as encouraging positive attitude towards the subject, including that of beginners [9, 15, 21]. Recent ML education research also found the game's potential as a 'soft' option for explaining ML concepts and procedures for beginners [7, 8, 14]. However, many existing games that can be used for the ML education target pre-adult population or do not specify target [8], and we could not find many empirical examples of educational games that indicate being designed to adjust the needs of our specific target population: adult non-major students who begin to learn ML.

3 GAME DESIGN

CTM is a kind of defense game where player should properly classify incoming trash monsters and put them in matching recycling facility. Players can either manually move monsters, or train and install a model that automatically classifies monsters. Increasing pace of incoming monsters guide players towards training more models. We designed theme, rule, and game elements to lower two barriers that players can encounter when they learn ML through game: barriers to understanding and using ML in game, and barriers to playing the game. Below are the design rules we set up in light of those considerations.

- **Easy to play**: Players do not need extensive math or programming knowledge to understand the game, and those who are not familiar with the game can play without difficulty.
- **Easy to understand**: ML elements translated to game elements are easy to understand. Each step of ML sequences are separated into distinct game activities to help players' understanding. Success / failure of model training is easy to recognize.
- **Overcoming barriers**: Players can recognize both the importance and limitations of ML while navigating the game with models. Players can also feel the importance of human decision in ML as they can experience the model's data dependency in a simulated environment.



a. Trash monster
b. Recycled monster
c. Mutant
d. Conveyor belts
e. Direction changer
f. Recycling machine
g. Euthanizer
h. Data collector
i. Data UI
j. Label generator
k. Generated label
l. Model training UI
m. Boss face
n. Start button
o. Pause button
p. Delete button
q. Data controller
r. Accuracy graph
s. Quest screen
t. Life tree
u. Timer energy gauge
v. Text effect
w. Color change
x. Mouse interaction

Figure 2: Game Overview

3.1 Lowering Barriers to Understand and Use ML

One design objective of the CTM was to make learning ML as simple and easy as possible, without delivering inaccurate knowledge. To do so, we translated the basic task and steps of the ML classification model into the core game activities and mechanics. We designed game objects, activities, and mechanics to be casual and easy to understand so that learning ML through the game would not feel burdensome.

3.1.1 Theme and Artwork. Considering that our target players are beginners with less programming knowledge, we excluded detailed ML algorithms. We tried to make ML in the game usable without programming knowledge, just like using calculators without knowledge in electronic circuits. Trash monsters are the main object that player plays with in CTM. There are four types of trash monsters in the game: paper, glass, cans, and plastic. Each monster type is designed with two different forms to give variations. The concept is that incoming monsters are sad trash monsters with a sullen look, shunned by the society, but they transform into happy and confident form once the player classifies them right and put them to the right recycling facility. With this concept we tried to deliver that ML can be used to help society when used right. Also, we designed trash monsters in a cute form and warm color to make the game feel more casual despite the difficult theme, ML.

3.1.2 Game Rule. We set game rules so that success and failure of the main task, classification through model training, is tied to the success and failure of the game. When the game starts, trash monsters (Fig. 2. a.) enter the scene following the conveyor belt (Fig. 2. d.). When players correctly classify monsters, they become recycled monsters (Fig. 2. b.) and the player earns time energy (Fig. 2. u.). But if they fail to classify monsters correctly, mutants (Fig. 2. c.) appear and the player loses a life unless they put them in the ‘Euthanizer’ (Fig. 2. g.). If the player does not classify and let monsters reach Euthanizer, the player loses a life. Game is over when the player loses all lives. Players can manually classify monsters instead of using a model in the beginning when they learn model training sequences, but as the game progresses, players are encouraged to use the model as the number and speed of incoming monsters increase. Players can easily engage in model training following simple steps, which are explained in the below section.

3.1.3 Game Elements Related to ML. We separated each step of model training sequence into different game activities that involve using different game objects. In the game, data collection is done via using Data Collector (Fig. 2. h.), model training can be done via operating Model Training UI (Fig. 2. l.) using the data player collected (Fig. 2. i.), and the player can observe the performance of the model he or she trained by installing it on the label generator (Fig. 2. j.). By repetitively engaging in above activities in a sequential process, the player can learn the basic ML sequence.

- **Data collector**: When a trash monster enters the Data Collector, the player presses the appropriate Numeric key (paper: 1, glass: 2, can: 3, plastic: 4) to collect data and label it with that type. It's different from the actual one, but if the player labels incorrectly, the player loses one data corresponding to the pressed key. This represents a potential problem that could lead to more quality data being needed due to mislabeled data.
- **Model Training UI**: The Model Training UI consists of sections for model training. First, the player can make a dataset one wants to use for model training by setting the type and number of monster data on the Data Controller (Fig. 2. q.). Then the player can simply click on a start button (Fig. 2. n.) to proceed with training. On the backside, the server receives the number of each trash monster type data that the player set and creates the training dataset with the pre-made dataset. The server then trains ResNet18, an image classification model, with the training dataset. The player can check if the training is going well by checking the prediction accuracy graph (Fig. 2. r.), which is updated whenever an epoch of training progresses. The player can use the boss' face (Fig. 2. m.) on the top corner as an additional cue; as the average accuracy increases, the face will turn into a happy face. Based on the feedback, the player can choose whether to pause training (Fig. 2. o.) and install the model on the label generator, or to delete the model (Fig. 2. p.) to train a new one.
- **Label Generator**: When the player installs the model he or she trained, the label generator (Fig. 2. j.) creates and puts labels (Fig. 2. k.) on the trash monsters according to the model's prediction results. When the labeled trash monster reaches the direction changer (Fig. 2. e.), it is sent to the recycling machine (Fig. 2. f.) that matches the label unless the player interrupts. By observing where the labelled monster goes, the player can check whether the model is classifying monsters right and see if any improvements should be made.

3.2 Lowering Barriers to Playing the Game

We believed that making the game playable for a wide range of students, regardless of their game skills, is essential to provide optimal learning experience for all. Therefore, we added the following features to make the game easy to play.

3.2.1 Simple Control. In order to make control as intuitive and easy as possible, we limited the main control to mouse clicking and key pressing. To grab and drop objects (trash monsters or mutants), players can simply click on them (Fig. 2. x.). The objects are then attached to the pointer unless the player clicks again, so it is easy to move. objects. Collecting and labeling different types of monster data is simplified to pressing a corresponding numeric key(1-4).

3.2.2 Slow Mode. Every time players classify trash monsters correctly, they obtain the time energy that stacks on the gauge (Fig. 2. u.). Using the time energy, players can slow down the time and make monsters move slower. This acts as a positive reward which serves two roles: 1) it reduces the burden on players and gives time to learn through trial and error, and 2) reinforce desired behavior (correct classification).

3.2.3 Clear Audiovisual Feedback. We designed feedback to be as clear as possible so that even the novice players can understand the result of their actions without difficulty. Players can determine whether they succeeded or failed from the changing color of machines(Fig. 2. w.), sound effects, and text effects(Fig. 2. v.). The color change and sound effects from the background, life tree (Fig. 2. t.) and quest screen (Fig. 2. s.), also help players check their progress.

3.3 Level Design according to the Learning Curve

The game is divided into four levels that are designed according to the learning curve of the ML beginner. Players start from learning a basic element one at a time guided step-by-step, and as the level progresses and the player develops more knowledge, they are introduced to more complex concepts with opportunities for free exploration.

- **Tutorial**: In the tutorial, players can learn the basic concept and steps of ML. They can learn the basic ML steps by practicing the controls of ML-related game elements (refer to section 3.1.3 for the explanation). In the game, the boss character also explains how the ML model operates differently from human thinking and why it requires players' efforts. We tried to explain with easy words and metaphors suited to a beginner's knowledge level. At the end, players are introduced to the data shortage problem by training the model with too small amounts of data and experiencing the consequences.
- **Day 1 Stage**: In Day 1, players practice the model training steps they learned in the tutorial again. They are also introduced to the data imbalance problem in the form of quests: training both biased model and unbiased model and experiencing the consequence.
- **Day 2 and 3 Stage**: Day 2 and Day 3 are stages where players can take free-form explorations incorporating the ML knowledge they learned in game. The sole mission is to survive the monster wave, and players can train their own model to survive using what they learned.

In order to aid the learning progress of the players, we used quests and recap texts in the tutorial and day 1 stage. When learning basic ML sequences, the player can engage in each step by doing mini-quests sequentially. When a player is introduced to a more complex concept of data shortage and data imbalance, the quest reduces learning load by making players naturally experience the problem as they follow the quests sequentitally. To help players connect in-game situations with the corresponding ML concept, we inserted recap texts at the end of main quests that explain what happened and why it happened in relation to the ML concept. In addition, statistics are provided at the end of each stage for self-feedback. By checking statistics such as the number of correct labels and the total number of recycled monsters, the player can check how well they performed the classification task.

3.4 Technical Note

The authors developed the game using Unity 2021 game engine in Visual Studio 2019, and created all visual assets in Clip Studio. The training model was developed with python using the PyTorch library. Unity and the python server operate through socket communication. The game build supports both Windows and Mac OS.

4 PLAYTEST

4.1 Iterative Process

We conducted iterative playtests during the development in reference to [6] to check if the game delivered our intended experience to players. Due to the length constraint, we only present the final playtest procedure and result in this paper.

4.2 Test plan

4.2.1 Participant. 6 players participated in the playtest (3 female, 3 male). All participants were undergraduate or graduate students in their 20s, did not major in CS, and never used ML or took related courses. From pre-test survey results we identified that the participants had no or very little prior knowledge on ML and that they shared some misconceptions mentioned in [18]. Participants' game skill varied (3 participants (2 female, 1 male) with a relatively lower game expertise and 3 participants (1 female, 2 male) with relatively higher game expertise)

4.2.2 Method. The playtest involved three stages. First, participants took a pre-play survey that collected their basic demographics, ML knowledge, and perception on ML. Afterwards, they played the game from start to end on the provided PC. When they finished playing, they answered the post-play survey which consisted of four sections: 1) ML knowledge; 2) ML perception; 3) Educational game enjoyment using E-gameflow scale[5]; 4) Questions on the game elements and stage design.

4.3 Result

4.3.1 Learning ML and Data Concepts. Overall, participants were able to describe the ML steps, the role of data in ML, what trained ML model does, and the consequences of training models with too small amounts or unbalanced data in a more accurate, detailed way after playing the game. Their answers changed less vague and more specific; for instance, when asked "what would the model trained with unbalanced data do?", answers changed from "wrong result" to "biased result","cannot classify certain data types well". However, some participants used vague or inaccurate terms when they described ML concepts in game. For instance, 2 participants described the model training process as "creating a model", although such a term was never mentioned in the game.

4.3.2 Change in Perception. Participants answered that ML felt less difficult, more agreed that ML needs human efforts, and felt more confident about learning ML, saying that the game "created a more concrete image of ML, which lowered my barrier to ML". Also, five out of six participants agreed that ML felt more relevant and helpful to their daily lives, saying that they found recycling with ML model "impressive that ML can be used in such basic daily works". The result showed that aforementioned changes in perception was more evident in participants who answered that ML seemed too difficult or overwhelming.

4.3.3 Game Enjoyment. To assess players' enjoyment, the mean scores for each section of the EGameFlow scale was calculated on a 1-7 Likert type scale. The 'Social interaction' section and two questions from the 'Challenge' section was deleted in the analysis process as they dealt with features not present in our game. Participants generally agreed that the game provided clear goal and feedback to determine their status (Feedback = 6.06, Goal Clarity = 6.29), helped increasing their knowledge on ML (Knowledge Improvement = 5.77), and they were generally able to stay concentrated without feeling stressed (Concentration = 4.89) which indicates good learning experience. They also agreed that the game provided an immersive experience where they can take initiative (Immersion = 5.05, Autonomy =5.06). However, some players experienced the game to be challenging compared to their skill level (Challenge = 4.5).

4.3.4 Game Elements. Participants were generally positive about the completeness of the game. They received the overall game elements (look and feel, UI and control, the audiovisual feedback / reward / penalty on the task) to be harmonious, easy to understand, and helpful in learning. They also agreed that stages were well designed according to their learning progress and helped them learn. Regarding feedback on model training and performance (graphs, text effects, boss' facial expression), players agreed that they were helpful, but suggested complementing them with other sensory feedback as visual feedback was not easy to comprehend quickly especially when they were busy with the classification task.

5 CRITICAL REFLECTION

We developed CTM in consideration of the challenges that non-major students encounter when they learn ML for the first time. Based on existing literature[18], we defined the challenges to address as follows: 1) students experience difficulty in correctly understanding the importance of human effort and limitations of ML when learning ML, 2) they enter learning process with misconceptions which needs to be debunked with correct understanding of how ML works. To tackle these challenges, we aimed to make learning ML with this game easy, enjoyable, and interactive. We found that playing CTM helped players get a better understanding of the ML and data dependency. Playing the game helped participants to get a more clear picture of what ML is and what it can do. Also, playing the game helped ameliorate their fear towards ML and relate ML to their everyday life. Learning concepts by handling ML themselves, even in a very simplified form, was received positively. It seems that CTM can be a good beginning step for those who learn ML for the first time to get a grasp of what ML is and how data the model is trained on can influence the model's outcome. However, we also found that the CTM alone may not be sufficient when the learning objective is to educate more complex ML concepts. Players' reflection on the gained ML knowledge was sometimes vague or inaccurate, as illustrated in the playtest results. The game can be good for understanding the big picture, but it would best achieve its full educational potential when accompanied by debriefing sessions or quizzes where players can learn to interpret in-game situations more accurately in relation to the ML knowledge.

6 LIMITATION AND FUTURE WORK

During the development, we deliberately limited some features for technical issues. For example, we blocked players from labeling the same monster multiple times due to the concern that it might make the game too easy, reducing the fun of overcoming challenges. However, we acknowledge that this can make the game monotonous and thus difficult to engage in long-term. We plan to address this problem in the future by adding new stages and features, such as stopping time to allow more sophisticated training or stages that require crafting strategies to clear, like creating biased dataset or using a generative model. Also, we blocked training the ResNet18 with the image data the player captured and used the pre-made image dataset, therefore only using the number data that the player set in the game, due to data transfer delay and environment setting issues. However, we can undo this in future developments for more realistic portrayal of ML process. Moreover, CTM currently covers only supervised learning and a single modal classifier. Exploring game design considerations for educating more extensive ML concepts such as considerations for the multimodal data processing can be discussed in the future. Also, testing the game's educational effect in the real class environment can be explored to overcome small sample size and verify statistical effects.

7 CONCLUSION

CTM is designed to help college students without a CS background who learn ML for the first time. We made ML sequences easier to understand by designing each step as a different game activity. By engaging in them sequentially, the player can easily train a model and solve tasks. We also simplified controls, reinforced positive rewards, and provided clear audiovisual feedback to make the game easy to understand and play even for novice players. Stages are designed according to a beginner's learning curve so that players can start from learning simple concepts to more complex one. From the playtest, we discovered that playing CTM helped players better understand ML and data dependency in relation to basic ML steps. Also, participants felt that ML is less difficult and more relevant after playing. However, playing CTM alone may not be sufficient when the learning objective is to educate more complex ML concepts, so we suggest accompanying debriefing sessions when using it in a class environment.

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