Large Language Models are Pretty Good Zero-Shot Video Game Bug Detectors

Mohammad Reza Taesiri  Finlay Macklon  Yihe Wang  Hengshuo Shen
Cor-Paul Bezemer
University of Alberta
{taesiri,macklon,yihe2,hengshuo,bezemer}@ualberta.ca

Abstract

Video game testing requires game-specific knowledge as well as common sense reasoning about the events in the game. While AI-driven agents can satisfy the first requirement, it is not yet possible to meet the second requirement automatically. Therefore, video game testing often still relies on manual testing, and human testers are required to play the game thoroughly to detect bugs. As a result, it is challenging to fully automate game testing. In this study, we explore the possibility of leveraging the zero-shot capabilities of large language models for video game bug detection. By formulating the bug detection problem as a question-answering task, we show that large language models can identify which event is buggy in a sequence of textual descriptions of events from a game. To this end, we introduce the GameBugDescriptions benchmark dataset, which consists of 167 buggy gameplay videos and a total of 334 question-answer pairs across 8 games. We extensively evaluate the performance of six models across the OPT and InstructGPT large language model families on our benchmark dataset. Our results show promising results for employing language models to detect video game bugs. With the proper prompting technique, we could achieve an accuracy of 70.66%, and on some video games, up to 78.94%. Our code, evaluation data and the benchmark can be found on https://asgaardlab.github.io/LLMxBugs

Introduction

Similar to other software products, a video game must be thoroughly tested to assure its quality. Game testing is an umbrella term for many types of tests that cover different aspects of the game. For example, a rendering test aims to verify the visual quality of the output, whereas a gameplay test assesses whether the game is engaging enough. While it is possible to automate some game testing elements, e.g., by using advanced vision models to detect graphical issues automatically (Taesiri, Macklon, and Bezemer 2022), most game testing aspects still require a human tester (Pascarella et al. 2018). Two of the main challenges that prevent the automation of game testing are the difficulty to automate (1) knowledge about the game context and (2) common sense reasoning (Politowski, Petrillo, and Guéhéneuc 2021).

Many video games rely on a physics engine that defines the rules of the world in which the game is situated (Millington 2007). For some games, there are sharp contrasts between the game world and the natural laws of the real world. These differences make it hard to reason about events in video games without knowing the game context. For example, is it a bug that the player survives after falling from a very high height? Answering such a question is impossible without having knowledge about the target video game.

In this study, we propose using the game context knowledge and common sense reasoning capabilities of large language models (LLMs) to identify buggy events in video games and classify their bug type. Recent revolutions in nat-
ural language processing (NLP) show that scaling up language models is beneficial in many tasks (Vaswani et al. 2017; Devlin et al. 2018; Rae et al. 2021; Chowdhery et al. 2022; Thoppilan et al. 2022), such as few-shot and zero-shot learning (Brown et al. 2020; Kojima et al. 2022). Having been trained on very large datasets, LLMs have the potential to capture many details about topics in their training set, including video games. Figure 1 shows an example of successful bug detection by a language model.

We are the first to empirically evaluate the capability of LLMs as zero-shot video game bug detectors. Our main contributions are as follows:

1. We present the GameBugDescriptions dataset, the first dataset of videos of game bugs with a step-by-step textual description for bug detection purposes. This dataset can serve as an out-of-distribution (OOD) challenge for LLMs.

2. We are the first to show that large language models have promising capabilities to detect video game bugs.

3. We extensively evaluate the performance of two families of large language models on the bug detection and bug type classification tasks: InstructGPT (Ouyang et al. 2022) and OPT (Zhang et al. 2022).

4. We analyze the robustness of language models to different descriptions of the same event for these tasks.

Our study demonstrates the promising capabilities of LLMs to play an important role in the automation of the game testing process.

**Background and Related Work**

Our work bridges the language modeling, video game, and software engineering research communities. In this section, we provide a brief overview of the relevant literature across these disciplines, in particular, on large language models and prompt engineering, and automated game testing.

**Large Language Models and Prompt Engineering**

The training objective in a language model is to learn a probability distribution over some text corpus. Such a simple training objective combined with sufficient model scaling can yield large language models that are successful even for tasks for which the model was not explicitly trained (Kaplan et al. 2020; Brown et al. 2020; Chowdhery et al. 2022; Thoppilan et al. 2022).

Prompting or prompt engineering (Liu et al. 2021) is an effective technique wherein we condition a language model on a set of manually handcrafted (Schick and Schütze 2020; Kojima et al. 2022) or automated (Gao, Fisch, and Chen 2020) templates to solve new tasks. That is, new tasks can be solved by giving natural language instructions to a pre-trained model without any further training, e.g., by providing sample reasoning steps to the model (Wei et al. 2022) in a few-shot setting. Moreover, Kojima et al. (2022) showed that even with a prompting technique as simple as adding “Let’s think step by step” to the beginning of the answer, it is possible to trigger the reasoning in language models, which leads to higher accuracy improvement on multiple benchmarks in zero-shot setting. Using graphical models Dohan et al. (2022) introduced a general formulation for prompted models, enabling probabilistic programming with LLMs.

Several successful applications of LLMs include program synthesis (Jain et al. 2022), code generation (Chen et al. 2021) or chatbots (Thoppilan et al. 2022). However, we are the first to apply LLMs to detect bugs in video games.

**Automated Game Testing**

As shown by prior work, automated game testing is challenging because game-specific knowledge and common sense reasoning are required to detect and report bugs (Pasquarella et al. 2018; Politowski, Petrillo, and Guéhéneuc 2021). The majority of prior work on automated game testing focuses on methods to automatically play games, such as heuristic search strategies (Keehl and Smith 2019). Automated play techniques using reinforcement learning or evolutionary strategies (Zheng et al. 2019; Vinyals et al. 2019; Berner et al. 2019; Justesen et al. 2019) allow the testing of video games from different perspectives, such as playability, game balance, and even predicting user churn rate (Roohi et al. 2020, 2021). However, these methods are often designed to maximize a certain reward function, which might lead to progress in the game in an unintended manner and even break the game’s rules or physics engine (Baker et al. 2020; Clark and Amodei 2019). More importantly, these methods do not have common sense reasoning.

Other prior work has leveraged computer vision and NLP techniques for automated video game testing. Several studies have proposed approaches for graphical bug detection using deep learning (Ling, Tollmar, and Gisslén 2020; Taesiri, Habibi, and Fazli 2020) or digital image processing (Macklon et al. 2022). However, these approaches do not require common sense reasoning. For example, Macklon et al. (2022) rely on graphical assets of the game as a test oracle.

Several other studies have proposed approaches to retrieve moments from gameplay videos based on text queries (Zhang and Smith 2019; Taesiri, Macklon, and Bezemner 2022). However, to detect bugs with these approaches the bug instance must be known in advance, and therefore these gameplay event retrieval approaches do not allow for automated detection of (previously undiscovered) bugs. Our approach does not have this requirement and can therefore be used to identify previously undiscovered bugs.

Finally, prior work has proposed NLP-based approaches to automatically improve test case descriptions for manual playtesting of games (Vigliato et al. 2022a,b), but we are the first to leverage LLMs for bug detection in video games.

**Bug Detection with Large Language Models**

To automatically identify buggy events in a video game, we propose using LLMs to reason about sequences of textual descriptions of game events. We formulate the problem as a question-answering (Q&A) task (Srivastava et al. 2022) for LLMs. Here, we explain how we convert textual descriptions of a sequence of game events into a multiple-choice question and use a language model to identify the buggy event. In addition, we discuss how LLMs can assist us to classify the bug.
Game Mechanics - text-curie-001

How does the player level up their attributes in the Red Dead Redemption 2 video game?
A: The player levels up by gaining experience points. Experience points are gained by killing enemies, completing missions, or trading with merchants. Completing these challenges and tasks will increase the player’s attributes, such as their health, strength, and shooting accuracy.

Game Mechanics - text-davinci-002

Explain the mechanics of the grappling hook in Just Cause 3 video game:
The grappling hook is a tool that allows the player to attach themselves to objects and then swing from them. It can be used to reach high places, travel across large distances, or to simply cause havoc. The hook can be attached to almost any object, including vehicles, and can be used to pull them towards the player or to swing them around.

Figure 2: Examples of the game knowledge of LLMs.

Multi-Stage Prompting
Following Kojima et al. (2022), we propose a two-stage prompting technique for eliciting reasoning in language models. This technique enables LLMs to provide step-by-step reasoning for their answer, leading to higher accuracy and better interpretability, which allows us to debug the final answer and understand in which step the model goes wrong.

Stage 1 - Elicit Reasoning: Similar to prior work (McCann et al. 2018; Radford et al. 2019; Schick and Schütze 2021) for each triplet (Q, S, A), we use a string template “Q: [X], [Z]” in which [X] is the input slot for concatenation of a question template Q containing the game name, and the sequence of events S. The “[Z]” text in the template is a fixed string that implies we are asking a question. The [Z] slot is for the trigger sentence added to the beginning of the answer. The purpose of the trigger sentence is two-fold: (1) to assist the language model in reaching the answer progressively, and (2) to inject different perspectives in the classification, e.g., to see events as a game designer, player, or compared with the real world.

We feed the question and trigger sentence to a language model to provoke step-by-step reasoning and use the generated text in Stage 2.

Stage 2 - Answer Extraction: We rely on the language model to extract the final answer from the generated text, given the intermediate results, instead of performing text processing. To this end, we concatenate the inputs and results from the previous stage and append an ‘answer extraction’ prompt to the end. We can use different answer extraction prompts depending on the format of the final answer. Since we have a multiple choice format, we use the “Among (a) through (d), the answer is” prompt.

Bug Type Classification
In addition to identifying the buggy event, classifying the type of bug is helpful for bug prioritization, as described by Truelove, de Almeida, and Ahmed (2021). Therefore, as a secondary objective, we are interested in determining if language models can correctly classify video game bug types. To this end, we design another question template in which we provide the event description and the ground truth and ask the model to classify the type of the video game bug.

In the [C] video game, the following sequence of events happened:
[C]

What is the type of bug?

[C]

In which O contains the bug types as multiple choice options, and e_b is the buggy event in the original sequence.

Dataset
To evaluate the capabilities of LLM for identifying game bugs, we created the GameBugDescriptions dataset, a collection of videos of real game bugs. Our dataset consists of a collection of 167 buggy gameplay videos, each with 2

Problem Formulation: For a sequence S of textual descriptions of events e_i in a video game G (S = \{e_1, e_2, \cdots, e_n\}) we design the triplet (Q, S, A), in which Q is a question template and A is the correct answer (i.e., the buggy event). By presenting S as multiple choice options (e.g., (a) through (d) in Figure 1), this triplet allows us to use a language model to detect bugs in a game event sequence.

We leverage Q to provide context information to the language model. Identifying buggy events in a video game requires context, because events in a video game can be unrealistic yet valid for that game. For example, in the Grand Theft Auto V video game, a player would die when they fall from a height, while in the Marvel’s Spider-Man game, the player would not take any damage. Therefore, we modify Q to include a string template G, which is a placeholder for the game’s name, which is used by the language model as a reference point. We design each question as follows:

In the [G] video game, the following sequence of events happened:
[S]

Which event is a bug?
textual descriptions of the events in the videos, and a bug-type label per video. Each description includes up to four sentences describing the events in the video without reasoning about their bugginess. To assess the robustness of language models to different descriptions, we provide two descriptions written by two authors for each video. Each description is converted into a question-answering format as explained above, resulting in 334 question-answer pairs. We also classify all 334 descriptions into 9 different bug types.

**Data Collection:** We start with the GamePhysics dataset (Taesiri, Macklon, and Bezemer 2022), a collection of gameplay videos from different games. Following prior work (Taesiri, Macklon, and Bezemer 2022), we focus on eight popular video games (see Table 4) from this dataset and sample a total of 200 videos. We define several exclusion criteria to manually filter out videos that are unsuitable for our study: (1) The video does not showcase a bug (but instead, e.g., a funny moment or impressive playing skills), (2) The video showcases a severe graphical bug (e.g., a glitch) and (3) The video is related to a game modification (e.g., the contents or logic of the game were changed through manual modification of the game files).

**Labeling:** After filtering, our dataset contains 167 videos, with an average of 20 videos per game. Two of the authors labelled each video separately without exchanging information during the labelling. Each label contains step-by-step textual descriptions of events in the video without interpretation or reasoning about the events. The resulting dataset contains a total of 334 descriptions with an average of 3.9 sentences per video. In the rest of the paper, we denote each set of the descriptions as Descr1 and Descr2.

We also provide one bug type for each video in our dataset. One of the authors manually classified each video into a single bug type, and another author finalized the classification by combining similar bug types while confirming that each video was suitably classified. During the classification process, nine different bug types were extracted:

- **Player Animation:** When the player’s body or limb is animated incorrectly, such as twisted to an abnormal angle or moving uncontrollably.
- **Teleportation:** An instantaneous movement of an object or character from one point to another.
- **Graphics:** Objects or backgrounds are displayed incorrectly on the screen, e.g., showing the wrong color, texture, or with the screen flickering.
- **(De)Spawning:** An object suddenly appears in (or disappears out of) sight.
- **Collision:** Objects are clipping through each other, or objects have interactions they are not supposed to have, like hitting an invisible wall.
- **Irregular force:** An object is acted upon by a force in a way that disobeys the game’s physics, such as an object suddenly starting to float.
- **Logic:** Non-player characters (NPCs) do things that seem illogical, such as an ambulance driving on the sidewalk or running over pedestrians.

The **Irregular force** type is the most common bug type among all videos. Figure 3 shows the distribution of bug types in the GameBugDescriptions dataset.

**Average CLIP Score:** To estimate the similarity between the descriptions and videos (and hence the quality of the descriptions), we calculated the CLIP Score (Radford et al. 2021) between each sentence in the event description and all frames in the video. We record the maximum similarity among frames for each sentence and report the average score for all sentences as a final score. The median CLIP Score for all 334 video descriptions in our dataset is 0.30, which has been previously used as a reasonable similarity threshold (Schuhmann et al. 2021) based on human inspection.

**Experimental Setup**

We executed two tasks in our experiments: (1) buggy event identification and (2) bug type classification. In this section, we discuss the experimental setup.

**Models:** We tested six models from the InstructGPT (Ouyang et al. 2022) and OPT (Zhang et al. 2022) families of models. We tested all four InstructGPT models (ada, babbage, curie and davinci), which contain 0.3B to 175B parameters. We also ran our experiments on OPT models with 66B and 175B parameters. In all experiments, we set the temperature parameter to 0, and the stopping sequence

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2 Both authors are fluent in English.
3 These authors had no access to any language model during the labelling process and did not modify their labels in any way.
4 Note that several game bug taxonomies exist, however, they are not detailed enough to showcase the capabilities of LLM. The purpose of our paper is not to create a new bug taxonomy, but instead to demonstrate these capabilities.

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3 https://blog.eleuther.ai/gpt3-model-sizes/
to “Q:” to prevent repetition. We set max_tokens to 256 in the first stage and 32 in the answer extraction stage. For the InstructGPT models, we used the OpenAI API, and for the OPT models, we used the official implementation⁶, which provides a similar API to what OpenAI offers. We hosted our OPT models on an NVIDIA DGX System with 8xA100 GPUs (80GB) and 2 TB of system memory.

**Trigger Sentences:** We tested a total of seven trigger sentences, including two top-performing ones from prior work (Kojima et al. 2022). In particular, we included the trigger sentence “Let’s think step by step,” because it has been shown to boost the performance of the davinci variant of InstructGPT across many tasks (Kojima et al. 2022). We also included “First,” as a simple baseline (Ahn et al. 2022). We added five new trigger sentences to dictate different viewpoints and enforce the game’s rules to the language model. The complete list of trigger sentences can be seen in Table 1.

**Bug Type Classification:** In the bug type classification task, we only fed the question and expect the model to choose the correct bug types without the use of any triggering sentences.

**Evaluating the Experiments:** For the buggy event identification task, we calculated the accuracy for each set of descriptions separately, and report the average for all combinations of language models and trigger sentences. We also calculated the accuracy per game for the top performing model. To estimate the robustness of the buggy event identification under different descriptions of the same sequence of events, we used the Wilcoxon signed-rank test (Woolson 2007) to determine if there was a statistically significant difference between accuracies for each set of descriptions with the top performing model. For the bug type classification task, we determined accuracy both per bug type and on the entire dataset. We discuss the correctness of the reasoning of the models in the Discussion section.

**Results**

**Task 1: Buggy Event Identification**

LLMs show promising zero-shot performance for buggy event identification on our dataset. Although the accuracy varies depending on the model size and trigger sentence, our results suggest that LLMs can be utilized for game bug detection tasks. Table 3 shows the accuracy of the models across the various trigger sentences and descriptions.

The davinci model delivers the best performance, and it can achieve up to 70.66% accuracy using the first set of descriptions (Descr1) and the trigger sentence “Let’s reason the events according to the reference game”. The accuracy averages 65.27% across the entire dataset.

We find there are no consistent trends among different models. For example, for the OPT-66 model, the trigger sentence “According to the rules of the game” leads to the best average performance (40.12%).

**Robustness of Bug Detection:** The top performing model for buggy event identification is the davinci model, hence we focus on this model while analyzing the robustness of bug detection. The Wilcoxon signed rank test shows that only trigger sentence #1 leads to statistically significant differences between the different sets of descriptions. Therefore, the model is fairly robust with buggy event identification under most trigger sentences. However, sometimes the chosen set of descriptions can affect the accuracy.

**Task 2: Bug Type Classification**

We only report the performance of the davinci model for the bug type classification task, as it was the best-performing model in the buggy event identification task. Table 2 shows the bug classification accuracy per bug type. Our results show that the davinci model can correctly predict the bug type (44.01%) of the time for our set of labelled videos. The main source of misclassification is the *Irregular force* bug type, which is also the most frequent bug type in our dataset. This type of bug is most often confused with the *Collision*, *Graphics*, *Animation*, and *Teleportation* bug types, which are all game physics bugs (with the exception of Graphics).

The accuracy of the model also varies considerably across games. Table 4 shows the bug type classification accuracy per game. The davinci model performs best on the *Fallout 4* game. The model performs worst on the *Red Dead Redemption 2* game, and this poor performance correlates with the high proportion of *Irregular force* bugs (32 out of 52) for this game in our dataset.

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### Table 1: The used trigger sentences.

| # | Trigger Sentence |
|---|------------------|
| 1 | “Let’s reason the events according to the reference game” |
| 2 | “Let’s think step by step.” |
| 3 | “According to the rules of the game” |
| 4 | “The reference game is” |
| 5 | “Let’s think like a game tester” |
| 6 | “First,” |
| 7 | “Let’s think like a game designer.” |

### Table 2: Breakdown of bug type classification accuracy of the davinci model (in %)

| Bug Type         | Count | Accuracy  |
|------------------|-------|-----------|
| Player Animation | 28    | 96.43     |
| Teleportation    | 8     | 75.00     |
| Graphics         | 10    | 70.00     |
| (De)Spawning     | 9     | 70.00     |
| Collision        | 66    | 69.70     |
| Spinning objects | 10    | 50.00     |
| Sliding objects  | 18    | 33.33     |
| Irregular force  | 160   | 24.38     |
| Logic            | 24    | 16.67     |
| **Average (total)** | 334 | 44.01     |

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*https://github.com/facebookresearch/metaseq/*
Discussion of Failure Cases

Here, we discuss cases in which the davinci model failed to identify or reason about the buggy event correctly. In each sample box, the ground truth label is red, shows the model’s wrong prediction, and the bold text shows the trigger sentence and answer extraction prompt.

Wrong Reasoning and Wrong Prediction: For some questions, the model fails to complete the intermediate reasoning steps, with outputs being vague or wrong, leading to wrong answers that lack justification. Sample 1 shows such a case of wrong reasoning leading to a wrong prediction for a bug in the 

Wrong Reasoning Does Not Match the Prediction: Sometimes, the model’s prediction is correct, but the reasoning does not match the prediction. The model follows (some) proper steps toward the (correct) answer, but fails to justify it. In Sample 2 for the GTA V game, the model follows the events and explains the ragdoll state correctly. The problem is that the model does not justify its prediction, as it does not explain why the predicted event is the bug.

Wrong Assumptions: In a few cases, the steps outputted by the model are correct, but one or some assumptions about video games are incorrect. For example, in Sample 3 for the Far Cry 5 game the davinci model attributes a bug event to a possible earthquake that is not present in the game.

Problem with Reference Game: We use the “The reference game is” trigger sentence to force the model to compare the events within the context of the desired game. Surprisingly, in some cases, this leads to the model complaining about the absence of reference games. Sample 4 for the GTA V game shows an example of the model failing to recognize the provided reference game.
### Future Research Directions

**Improving the Poor Performance of OPT-175B:** The biggest model in the OPT family achieves a low accuracy, even compared to a smaller model of the same family, OPT-66B. Manual review of the output shows that the answer extraction prompt is not suitable for this model. Often the intermediate outputs of the model are correct, but in the second stage, the model outputs a wrong choice as the final answer. Sample 5 demonstrates that the model has correct reasoning for a bug in the Skyrim game, but fails in the answer extraction stage. Future studies should investigate how to resolve such issues with answer extraction.

**Automating the Description of Event Sequences:** Our primary focus is reasoning about the events in a video game to detect bugs, regardless of the source of the events’ descriptions. While it is possible to incorporate a vision model to summarize the events in the video game, this information could also be obtained directly from a game engine. A game engine can be modified to produce both graphical and textual output, which can then be used for bug detection. However, during a preliminary study, we tested CLIP-Cap (Mokady, Hertz, and Bermano 2021), ZeroCap (Tewel et al. 2022) and OFA (Wang et al. 2022) to create descriptions of videos, and found that none of them can describe frames from video games properly. Future studies should investigate how the description of event sequences can be automated.

**Searching for an Optimal Q:** In our dataset, it is possible to adapt the question template Q as long as the sequence S is not changed (in contrast to other Q&A datasets which come with a predefined question template). Future studies should search for optimal Q formats that lead to higher accuracy. This process requires a held-out set for validating the results to avoid possible biases. As we are interested in assessing the inherent properties of language models in bug detection, we did not fine-tune Q in our experiments, but instead designed a general format for all queries and video games.

**Consideration Regarding Inference’s Speed:** As the number of parameters in a model increases, its memory requirement and inference time also grow. Traditional techniques like layer removal (Anwar, Hwang, and Sung 2017; Zandigohar, Erdoğan, and Schirner 2021) and distillation (Hinton et al. 2015) could handle this problem, but the performance may suffer. That said, Dettmers et al. (2022) showed using a two-step quantization method, it is possible to reduce the memory footprint of a large model by 2x without performance degradation.

**Conclusion**

In this study, we demonstrated the promising capabilities of language models as video game bug detectors. We introduced a novel dataset of 334 question-answer pairs to exten-
sively evaluate large language models across the OPT and InstructGPT families. Our results are promising but indicate there are challenges in incorporating language models for video game bug detection. In summary, we have provided a new out-of-distribution task for benchmarking large language models, and we hope to motivate researchers from both the AI and software engineering communities to further explore this promising and exciting new direction of automated video game testing.

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