Chekhov’s Gun Recognition

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Abstract

Chekhov’s gun is a dramatic principle stating that every element in a story must be necessary, and irrelevant elements should be removed. This paper presents a new natural language processing task — Chekhov’s gun recognition or (CGR) — recognition of entities that are pivotal for the development of the plot. Though similar to classical Named Entity Recognition (NER) it has profound differences and is crucial for the tasks of narrative processing, since Chekhov’s guns have a profound impact on the causal relationship in a story. The paper presents a new benchmark dataset for the CGR task that includes 5550 descriptions with one or more Chekhov’s Gun in each and validates the task on two more datasets available in the natural language processing (NLP) literature.

"One must never place a loaded rifle on the stage if it isn’t going to go off. It’s wrong to make promises you don’t mean to keep."

Chekhov in his letter to Lazarev.

1 CGR Task

Chekhov’s Gun Recognition (CGR) is a subtask of information extraction that seeks to locate entities mentioned in unstructured text that will significantly affect the structure of the narrative as the story unfolds. Similarly to named entity recognition, CGR refers to the entities for which one or many strings, such as words or phrases, stand consistently for some referent in line with the so-called concept of rigid designators, see Kripke (1971) and Maxwell (1978). We understand the capacity of an entity to change the structure of narrative in terms of the philosophy of action, see Van Dijk (1976). The structural analysis of narrative first proposed in Shklovsky (1925) and revived in Propp (1968) is mostly focused on a characterization of the action and interaction sequences of ‘heroes’, the protagonists, and antagonists. Shklovsky (1925) introduces the concept of ‘actor’ as an entity that moves the story forward. CGR in these terms is understood as recognition of any ‘actor’ (no matter hero or not) in the unstructured text of the story.

It is important to note that we suggest understanding such actor-entity in the broadest possible terms. For example, if at some point a protagonist opens a window to air the room and the antagonist enters the building through this open window later as the story unfolds, such ‘window’ could be regarded as a perfect example of Chekhov’s Gun. Although there are several recent results in the areas of suspense generation Doust and Piwek (2017), narrative personalization Wang et al. (2017), and generation of short context-based narratives Womack and Freeman (2019), generating long stories is still a challenge van Stegeren and Theune (2019). We believe that CGR could provide deep insights into further computational research of narrative structure and is a vital component for the generation of longer entertaining stories.

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2 Data

Interactive Fiction games are text-based simulators where a player uses text commands to change the environment and navigate through the story. Such games represent a unique intersection of natural language processing and sequential decision making, which makes them extremely valuable in a machine learning context and draws the attention of various researchers. For example, in [Ryan et al. (2016)] the authors develop "expressionist", an authoring tool for in-game text generation and [Ammanabrolu et al. (2020)] generate interactive text-based worlds.

Navigating through interactive fiction the agent must often detect affordances: the set of behaviors enabled by a situation. Affordance detection is particularly helpful in domains with large action spaces, allowing the agent to prune its search space by avoiding futile behaviors. Fulda et al. (2017) present such an affordance detection mechanism and Haroush et al. (2018) develop the action-elimination architecture that solves quests in the text-based game of Zork, significantly outperforming the baseline agents.

In some sense, Chekhov’s gun recognition could be linked to affordance detection mentioned above, yet we argue that CGR is an isolated natural language processing (NLP) task due to its relevance to the structure of the narrative. We believe that further research of CGR as a stand-alone NLP task could shed light on fundamental properties of narrative generation, systematic principles of human attention, and structural conditions that these principles impose on story formation. Further in this paper, we illustrate CGR applicability to NLP tasks outside of the scope of interactive fiction, however, interactive text games are perfect playgrounds to test and benchmark CGR algorithms.

This paper presents a new dataset — Chekhov’s Guns from Interactive Fiction (CGIF). The dataset includes 5550 locations with one or more CG in each of them and is based on 995 games. Its’ total size is 1.5 megabytes. Every Chekhov’s Gun in the text is labeled as shown in Figure 1. We publish the resulting CGIF dataset with labeled CGs and suggest to it for CGR algorithms benchmarking.

![Figure 1: Text description of a location with highlighted items available for interaction. One can clearly see that CGR differs from NER though there is an overlap.](image)

The data consists of three different types of texts from interactive fiction games. The first part of the dataset is based on the Jericho introduced in [Hausknecht et al. 2020]. It includes 57 interactive fiction games with lists of all locations and all actionable entities. One could assume that every actionable entity in these descriptions was regarded by the authors of the game as something that could help

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1 Omitted to preserve the anonymity of the review
### Table 1

|                    | Accuracy | F1-score |
|--------------------|----------|----------|
| Pre-trained T-NER  | 0.05     | 0.00     |
| Fine-tuned T-NER   | 0.50     | 0.51     |

Table 1: Pre-trained XLN-RoBERTa T-NER hardly detects Chekhov’s Guns out of the box. Yet after fine-tuning on CGIF for entity span prediction the quality significantly improves.

the player moving forward. Iteratively searching all such actionable entities in every location with a script we get a list of Chekhov’s Guns.

We have also collected 24 additional interactive fiction games that have published solutions and are not included in Jericho. For every game, we have created a script that can execute the commands described in the solution and controls the location where the command is executed. As an output of this script, we obtain a list of locations on the critical path that leads to the completion of the game. For every location, we also store a prefix of commands that leads the character to this particular location. Then we brute force the labels of CGs in the following manner. For every location, we reset the game and enter the prefix that brings us into this location. We store the description of the location and start iterating over all objects in this description using the command `examine <obj>`.

If interaction with one of the entities gives a non-trivial reaction from the game we label this entity as a CG.

Finally, we include 1500 other interactive fiction games for which we found no working solution. Instead of a solution-based strategy, we implemented a random walk for labeling Chekhov’s Guns in these games. In every game, we did 2500 random steps and implemented the same logic that we used for the solution but on a limited number of locations that we were lucky to obtain.

### 3 Task validation

We propose several ways in which one can approach the CGR problem using the CGIF dataset as well as other datasets available in the literature.

#### 3.1 Contrasting Chekhov’s Guns and Named Entities

Let us discuss how CGR differs from NER. To do that we use a recent T-NER model developed by Ushio and Camacho-Collados (2021). The pre-trained T-NER realization of the XLM-RoBERTa works in the entity span prediction regime marking the beginning and the end of a named entity in the text. Table 1 shows the results of the pre-trained T-NER of the CGIF dataset along with results after fine-tuning.

Table 1 illustrates that Chekhov’s Guns profoundly differ from Named Entities. Fine-tuning a pre-trained T-NER model on the CGIF dataset boosts the F-1 score from virtually zero to something around one-half, yet there is room for progress. It is important to note that CGIF is far smaller than the NER datasets that are commonly used in the literature. This experiment allows us to conclude that CGs form a distinct category of entities that is out of the scope of current NER: some of the named entities are Chekhov’s Guns yet a lot of Chekhov’s Guns are NOT named entities.

Table 2 provides some qualitative understanding of the contrast between named entities and CGs. T-NER classifies detected entities into several categories. After fine-tuning XLM-RoBERTa-based T-NER on CGIF dataset, we apply T-NER and our CGR model to four different datasets and look for the T-NER categories that are dominated by CGs. The CGIF column stands for the validation part of CGIF. There are only three T-NER categories, in which Chekhov’s guns happen to be a majority here. These are "product" with only one NER that is not a CG per every 18 CGs, "person" with one NER that is not a CG per 2.6 CGs, and "work of art" with one NER that is not a CG per 2.6 CGs. Yao et al. (2020) present a ClubFloyd dataset that is crawled from the ClubFloyd website and contains 426 human gameplay transcripts, which cover 590 text-based games of diverse genres and styles. The data consists of 223,527 context-action pairs in the format `[CLS] observation [SEP]`.

1https://huggingface.co/asahi417/tner-xlm-roberta-large-all-english
2http://www.allthingsjacq.com/interactive_fiction.html
Every context entry is accompanied with variants of human attempts to interact with objects and characters in the given context. Table 2 shows that for these context description T-NER categories “product”, “person” and “work of art” are dominated by CGs as well as in CGIF. However, there are other CG-dominated categories, such as “chemical”, for example.

Malysheva et al. (2021) present the TVMAZE4 dataset. The dataset consists of 13 000 texts that describe plots of TV series split into short episode annotations. WikiPlots5 is a collection of 112,936 story plots extracted from English language Wikipedia. These two datasets are significantly larger than datasets of interactive fiction. Table 2 demonstrates that once again categories “person” and “product” are dominated by CGs, but such categories as “corporation”, “organization” and “group” add up themselves to the picture.

Table 2: Lists of T-NER categories in which Chekhov’s guns tend to have higher relative frequencies across four different datasets. For every T-NER category, the number of Chekhov’s Guns the fall into this category is divided over T-NER recognized entities that are not Chekhov’s guns (provided this number is not zero). Table shows five categories in which Chekhov’s guns have the highest relative frequency.

Chekhov’s Gun is a type of entity that plays a causal role in the development of a narrative. Since some of such entities are named, modern NER models could detect some percentage of CGs in a text. These would typically be single characters (say, Thor), groups or some organizations (say, Asgard), or objects that are “branded” in some sense (i.e. Mjölnir, Obedience Potion or statue of Loki). Along with CGs that are named, there is a large portion of CGs that are not detected within the framework of NER. In this subsection, we have provided a basic benchmark for CGR via fine-tuning XLM-RoBERTa based T-NER model, and have shown that the model trained on CGIF does not have to be only used for interactive fiction but can be applied to other NLP datasets.

### 3.2 Chekhov’s Guns and Human World Knowledge

Humans tend to understand causal relations between entities in a given text intuitively. If a player wants to leave the location, she might try to use the door that was mentioned in the description. If the door is closed, to open it the player could look for a key, etc. This given understanding of the “world” is crucial for interactive fiction yet its importance is not limited to the textual game-play. Models endowed with such understanding would be far more usable across the board of NLP tasks. Let us show that CGR is a cornerstone for the acquisition of such knowledge.

In Subsection 3.1 we have already introduced the dataset presented in Yao et al. (2020) and have used the descriptions of the game context to explore differences between NER and CGR. Now let us focus on the actions that this dataset contains. These are actual attempts of human players to interact within the proposed environment. One action typically consists of a verb (i.e. go, take, open, etc.) that is followed by a description of an entity with which the player is trying to interact. We call these entities Action Targets (AT). Since the dataset contains gamelogs of several players some ATs could be mentioned several times. These would be the entities that are perceived by humans as more interesting to explore and use in the game. Table 3 summarizes what share of ATs could be labelled by a CGR model.

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4 https://www.tvmaze.com/
5 https://github.com/markriedl/WikiPlots
All payer action targets (AT) | Unique ATs
---|---
| p >0.5 | p >0.65 | p>0.8 | p>0.95 | p >0.5 | p >0.65 | p>0.8 | p>0.95
Share of CGs that occur in AT list | 0.38 | 0.43 | 0.48 | 0.57 | 0.22 | 0.25 | 0.29 | 0.36
Share of ATs labelled as CGs | **0.84** | 0.65 | 0.30 | 0.05 | **0.84** | 0.65 | 0.30 | 0.04

Table 3: XLN-RoBERTa T-NER fine-tuned on CGIF predicts which action targets from Club Floyd dataset would a player try to interact with. The entities with higher CG probability estimates almost surely end up in the list of action targets. If the entities with lower CG probability are included they cover up to 84% of all action targets used by the human players. Since the Club Floyd dataset contains raw interactive fiction data, there are entities with which several players try to interact. Table provides both the results for the full list of action targets, as well as for the list of unique action targets.

CGR model predicts if an entity is a CG with some probability. Varying this probability threshold would change the prediction of the model. With a higher threshold, the list of CGs would naturally be shorter. Table 3 shows that the share of CGs that overlap with some human action targets grows if the threshold is higher. At the same time, if the model has a lower threshold it predicts more than 80% of all the entities that humans try to interact with.

4 Chekhov’s Guns and the structure of narrative

Papalampidi et al. (2019) introduce a TRIPOD dataset that includes plot synopses with turning point annotation. The five turning points that Papalampidi et al. (2019) use are:

- Opportunity — the introductory event that occurs after the presentation of the setting and the background of the main characters;
- Change of Plans — the event where the main goal of the story is defined;
- Point of No Return — the event that pushes the main character(s) to fully commit to their goal;
- Major Setback — the event where everything falls apart;
- Climax — the final event of the main story.

Figure 2 shows how the average number of CGs per sentence varies in these turning points. Since we are interested in relative dynamics within a story, we calculate the average number of CGs per sentence and see its difference with an average number of CGs across all five turning points. Since the number of CGs per sentence might be higher for longer sentences we also calculate how the average number of words per sentence differs in every turning point.

Turning point number one — Opportunity — tends to have more words per sentence as well as more Chekhov’s Guns in them. As the plot thickens in Change of Plans and Point of No Return, sentencees get shorter, however, the number of Chekhov’s Guns per sentence gets lower as well. Rephrasing Chekhov’s quote one could say that some of the "loaded rifles" are already placed on the stage, and we are waiting for the shots. Indeed, in Major Setback number of CGs per sentence jumps, while the average number of words per sentence remains low. In the Climax the number of CGs drops to its lowest.

Table 4 shows how CGs first occur and reoccur in the story depending on the turning point. Indeed, almost one third of CGs first emerge in the Opportunity part of the story. In every later turning point five to seven percent of all CGs in a story are the once that we first meet in the Opportunity part. The percentage of first occurrences consistently drops from 32.2% in the first to 12.8% in the last turning point.

This is a qualitative picture that illustrates the potential of CGR as a stand-alone NLP task: since Chekhov’s guns are the entities that affect causal relations within the narrative they could be useful for the overall analysis of the narrative structure.

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6 https://github.com/ppapalampidi/TRIPOD
Figure 2: Average number of CGs per sentence and the average number of words in a sentence differ in different turning points of the story. The axis shows the difference between these values calculated at the corresponding turning point and the story at large. The first turning point of a story has more words and more CGs per sentence than usual. Then the sentences tend to get shorter. The second and third turning points of the story have fewer Chekhov’s guns per sentence, while at the fourth turning point the number of CGs per sentence peaks.

| Turning Point # | 1   | 2   | 3   | 4   | 5   |
|----------------|-----|-----|-----|-----|-----|
| 1              | 32.2| 7.2 | 6.3 | 6.8 | 5.4 |
| 2              | 0.0 | 21.7| 4.0 | 4.0 | 3.3 |
| 3              | 0.0 | 0.0 | 17.3| 2.5 | 2.6 |
| 4              | 0.0 | 0.0 | 0.0 | 16.0| 2.8 |
| 5              | 0.0 | 0.0 | 0.0 | 0.0 | 12.8|

Table 4: Percentage of CGs in every turning point of a story. Every row represents CGs that first occurred in the corresponding turning point and then reoccurred in later parts of the story that stand in the corresponding column. The diagonal sums to 100% representing all first occurrences.

5 Discussion

In recent years we have seen various exciting results in the area of Natural Language Generation (NLG). One line of research addresses generation of semi-structured texts varying from dialogue responses, see Li et al. (2016, 2017, 2019), to Chinese traditional poetry, see Zhang and Lapata (2014); Wang et al. (2016). Another line of research addresses the generation of stylized texts, see Tikhonov and Yamshchikov (2018); Yang et al. (2018). There have been recent results that try to generate longer blocks of text, such as Kedziorski (2019) or Agafonova et al. (2020), yet the generation of longer texts is only possible under certain stylistic and topical constraints that exclude the problem of narrative generation altogether.

We believe that understanding narrative and its key principles are paramount to further advances in NLG. However, the narrative is fundamentally causal, thus deeper understanding of causality in NLP should provide new insights into the structure of the narrative. Currently, our understanding is lacking due to a variety of reasons:

- human cognition is often verbal and narrative-based which makes attempts to verbally conceptualize narrative implode on themselves;
- narration is not only a linguistic but a cultural act, that fundamentally affects humans as ‘cultural animals’, this influence of narrative hinders its conceptualization in rigorous mathematical terms;
- narrative is centered around long-term dependencies, that could be formally characterized as a critical behavior of language, see Lin and Tegmark (2017).

Each of these very general issues needs separate attention, but we believe the CGR is an exemplary step to address these problems. First of all, CGR allows addressing the notion of ‘actor’ in line with
Shklovsky (1925), broadening it from a person to any entity that interacts with a storyline. This
ability to personalize various entities could be regarded as a cornerstone associative mechanism that
might be a basis for creative cognition [Mednick, 1962]. Secondly, as with any NLP task, CGR could
be developed for every culture or language. Further development of CGR could provide general
cross-cultural insights into the process of story formation. Finally, CGs significantly contribute to
the criticality of language in line with ideas expressed in Lin and Tegmark (2017). CGs occur
in the story and understanding which object is pivotal for the narrative to unfold is one of the key
bottlenecks on the way to automated narrative generation. We believe that all these factors make
CGR an exemplary NLP task that could bring us further in the direction of narrative generation. We
also believe that the NLP community needs further NLP tasks that could be regarded as formalized
problems yet help with one or several challenges listed above.

6 Conclusion

This paper presents a new causal natural language processing task — Chekhov’s gun recognition
(CGR). It formalizes the notion of Chekhov’s gun as an entity that has a causal effect on the
development of the story in line with structuralist views. It provides a corpus of interactive fiction
games to introduce the benchmark for CGR. To illustrate the differences between CGR and NER, it
validates the proposed task on four different datasets. Using human player data the paper demonstrates
that the CGR model predicts human attempts to interact with entities within interactive fiction. Finally,
it shows how the CGR classifier could be applied to an external dataset to obtain insights into the
structure of the narrative.

References

Yana Agafonova, Alexey Tikhonov, and Ivan P Yamshchikov. 2020. Paranoid transformer: Reading
narrative of madness as computational approach to creativity. arXiv preprint arXiv:2007.06290.

Prithviraj Ammanabrolu, Wesley Cheung, Dan Tu, William Broniec, and Mark O Riedl. 2020.
Bringing stories alive: Generating interactive fiction worlds. arXiv preprint arXiv:2001.10161.

Richard Doust and Paul Piwek. 2017. A model of suspense for narrative generation. In Proceedings
of the 10th International Conference on Natural Language Generation, pages 178–187.

Nancy Fulda, Daniel Ricks, Ben Murdoch, and David Wingate. 2017. What can you do with a rock?
affordance extraction via word embeddings. arXiv preprint arXiv:1703.03429.

Matan Haroush, Tom Zahavy, Daniel J Mankowitz, and Shie Mannor. 2018. Learning how not to act
in text-based games.

Matthew J Hausknecht, Prithviraj Ammanabrolu, Marc-Alexandre Côté, and Xingdi Yuan. 2020.
Interactive fiction games: A colossal adventure. In AAAI, pages 7903–7910.

Richard Koncel Kedziorksi. 2019. Understanding and Generating Multi-Sentence Texts. Ph.D. thesis.

Saul Kripke. 1971. Identity and necessity. Identity and individuation, 1971:135–64.

Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016. Deep
reinforcement learning for dialogue generation. In Proceedings of the 2016 Conference on
Empirical Methods in Natural Language Processing, pages 1192–1202.

Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. 2017. Adversarial
learning for neural dialogue generation. In Proceedings of the 2017 Conference on Empirical
Methods in Natural Language Processing, pages 2157–2169.

Ziming Li, Julia Kiseleva, and Maarten de Rijke. 2019. Dialogue generation: From imitation learning
to inverse reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence,
volume 33, pages 6722–6729.

Henry W Lin and Max Tegmark. 2017. Critical behavior in physics and probabilistic formal languages.
Entropy, 19(7):299.
Anastasia Malysheva, Alexey Tikhonov, and Ivan P Yamshchikov. 2021. Dyplodoc: Dynamic plots for document classification. *arXiv preprint arXiv:2107.12226*.

Grover Maxwell. 1978. Rigid designators and mind-brain identity.

Sarnoff Mednick. 1962. The associative basis of the creative process. *Psychological review*, 69(3):220.

Pinelopi Papalampidi, Frank Keller, and Mirella Lapata. 2019. Movie plot analysis via turning point identification. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1707–1717.

Vladimir Propp. 1968. Morphology of the folktale, trans. *Louis Wagner*, 2d. ed.

James Ryan, Ethan Seither, Michael Mateas, and Noah Wardrip-Fruin. 2016. Expressionist: An authoring tool for in-game text generation. In *International Conference on Interactive Digital Storytelling*, pages 221–233. Springer.

Viktor Shklovsky. 1925. Theory of prose (b. sher, trans.). *Champaign, IL: Dalkey Archive Press. Original work published*.

Judith van Stegeren and Mariët Theune. 2019. Narrative generation in the wild: Methods from nanogenmo. In *Proceedings of the Second Workshop on Storytelling*, pages 65–74.

Alexey Tikhonov and Ivan P Yamshchikov. 2018. Guess who? multilingual approach for the automated generation of author-styitized poetry. In 2018 *IEEE Spoken Language Technology Workshop (SLT)*, pages 787–794. IEEE.

Asahi Ushio and Jose Camacho-Collados. 2021. T-ner: An all-round python library for transformer-based named entity recognition. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*, pages 53–62.

Teun A Van Dijk. 1976. Philosophy of action and theory of narrative. *Poetics*, 5(4):287–338.

Daisy Zhe Wang, Wei He, Hua Wu, Haiyang Wu, Wei Li, Haifeng Wang, and Enhong Chen. 2016. Chinese poetry generation with planning based neural network. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 1051–1060.

Pengcheng Wang, Jonathan P Rowe, Wookhee Min, Bradford W Mott, and James C Lester. 2017. Interactive narrative personalization with deep reinforcement learning. In *IJCAI*, pages 3852–3858.

Jon Womack and William Freeman. 2019. Interactive narrative generation using location and genre specific context. In *International Conference on Interactive Digital Storytelling*, pages 343–347. Springer.

Cheng Yang, Maosong Sun, Xiaoyuan Yi, and Wenhao Li. 2018. Stylistic chinese poetry generation via unsupervised style disentanglement. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3960–3969.

Shunyu Yao, Rohan Rao, Matthew Hausknecht, and Karthik Narasimhan. 2020. Keep calm and explore: Language models for action generation in text-based games. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8736–8754.

Xingxing Zhang and Mirella Lapata. 2014. Chinese poetry generation with recurrent neural networks. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 670–680.