Towards Analogy-Based Story Generation

Jichen Zhu[1] and Santiago Ontañón[2]

[1] Department of Digital Media, University of Central Florida
12461 Research Parkway Suite 500
Orlando, FL, USA 32826-3241
jzh@mail.ucf.edu
[2] IIIA, Artificial Intelligence Research Institute
CSIC, Spanish Council for Scientific Research
Campus UAB, 08193 Bellaterra, Spain
santi@iiia.csic.es

Abstract. Narrative is one of the oldest creative forms, capable of depicting a wide spectrum of human conditions. However, many existing stories generated by planning-based computational narrative systems are confined to the goal-driven, problem-solving aesthetics. This paper focuses on analogy-based story generation. Informed by narratology and computational analogy, we present an analytical framework to survey this area in order to identify trends and areas that have not received sufficient attention. Finally, we introduce the new developments of the Riu project as a case study for possible new narrative aesthetics supported by analogy.

1 Introduction

Computational narrative explores the age-old creative form of storytelling by algorithmically analyzing, understanding, and most importantly, generating stories. Despite the progress in the area, current computer-generated stories are still aesthetically limited compared to traditional narratives. In both plot-centric and character-centric approaches for story generation, the widely used planning paradigm has a strong impact on these stories' goal-driven, problem-solving aesthetics.

In order to broaden the range of computer generated narratives, this paper analyzes the relatively under-explored area of story generation using computational analogy. Recent developments in cognitive science demonstrate the importance of analogy as a powerful cognitive faculty to make sense of the world [5, 10] as well as an effective literary tool to enhance such understandings through narratives [30]. Compared to the large body of planning-based work, significantly fewer endeavors have been spent on analogy. We argue that analogy is a promising direction towards novel narrative forms and aesthetics that planning-based approaches cannot provide. More broadly, our focus on analogy is aligned with Gelernter's account on computational creativity, in which analogy functions as the crucial link between "high focus" analytical cognitive activities and "low focus" ones connected through shared emotions [9].

Drawn from narratology and computational analogy, we propose an analytical framework to identify different key aspects of analogy-based story generation and systematically classify existing systems accordingly. We will also discuss the impact of these aspects (e.g. representation formalism) on the aesthetics of potential analogy-generated stories. The purpose of our overview is to recognize existing trends and the unexplored areas in this relatively new area of research. In this paper, we adopt a broad definition of analogy to include not only classic computational analogy techniques, but also other related areas, such as case-based reasoning (CBR) [1], conceptual blending theory [5, 6], and metaphor theory [18]. Finally, we will introduce the primary results of our *Riu* project as a case study for analogy-based computational narrative systems.

In the remainder of this paper, Section 2 describes our motivation from the vantage point of aesthetics and narratology. Section 3 presents a brief introduction of computational analogy. Based on Chatman's narratology, Section 4 presents our framework of three dimensions of analgy-based story generation and classifies existing systems. Section 5 illustrates our approach through a case study of the new developments of the Riu project. Finally, Section 6 summarizes the paper and future research directions.

2 Aesthetics and Computer-Generated Narrative

Interactive narratives carry the prospect of a fully fledged medium with similar levels of breath and depth as traditional media of storytelling [24, 27]. However, the current state of computer-generated stories, a crucial component of interactive narrative, is still far from this goal. In spite of the accomplishments of planning-based approaches, the stories they generate often fall into a very small range of narrative aesthetics. We are not simply referring to how polished the final writing style is. Instead, our primary concern is the built-in narrative affordances and constraints of specific architectures in relation to the type of stories they generate.

On the one hand, planning's ability to specify the desired final state gives authors tremendous amount of control over the story. On the other hand, its intrinsic goal-driven, problem-solving operations place an unmistakable stamp on the generated stories. One of the most salient examples of such planning-based aesthetics is Meehan's 1976 system Tale-Spin, whose style is still influential among many recent systems. Below is an excerpt of a story generated by Tale-Spin:

> Joe Bear was hungry. He asked Irving Bird where some honey was. Irving refused to tell him, so Joe offered to bring him a worm if he'd tell him where some honey was. Irving agreed. But Joe didn't know where any worms were, so he asked Irving, who refused to say. So Joe offered to bring him a worm if he'd tell him where a worm was...[22, p.129]

Certainly, the stories generated by modern planning-based systems have become much more complex and other non-planning approaches have been developed, some of which will be discussed in Section 4.2. For example, the Visual-Daydreamer system explores very different non-verbal narrative aesthetics using animated abstract visual symbols whose actions are emotionally connected [25]. However, our intention here is to systematically survey this relatively unexplored area of computer analogy-based story generation and identify promising new directions that may broaden the aesthetic range of computational narratives. As one of such directions, our Riu system explores sequencing narrative elements by their associations with similar events, a literary technique famously experimented in stream of consciousness literature to depict human subjectivity [17].

3 Computational Analogy

Computational models of analogy operate by identifying similarities and transferring knowledge between a source domain S and a target domain T. This process is divided by Hall [12] into four stages: 1) *recognition* of a candidate analogous source, S, 2) *elaboration* of an analogical mapping between source domain S and target domain T, 3) *evaluation* of the mapping and inferences, and 4) *consolidation* of the outcome of the analogy for other contexts (i.e. learning). The intuitive assumption behind analogy is that if two domains are similar in certain key aspects, they are likely to be similar in other aspects.

Existing analogy systems can be classified into three classes based on their underlying architecture [8]. *Symbolic* models (e.g., ANALOGY [3] and the Structure Mapping Engine [4]), heavily rely on the concepts of symbols, logics, planning, search, means-ends analysis, etc. from the "symbolic AI paradigm." *Connectionist* models (e.g., ACME [15], LISA [16], and CAB [19]), on the other hand, adopt the connectionist framework of nodes, weights, spreading activations, etc. Finally, the hybrid models (e.g., COPYCAT [23], TABLETOP [7] and LETTER-SPIRIT [21]) blend elements from the previous two classes.

4 Analogy in Story Generation

Although several analogy-based systems have been developed to generate stories, there has not been any serious attempt to thoroughly and systematically identify different possibilities of analogy-based story generation. In order to better understand the area, this section presents a new analytical framework to classify different systems with the goal of presenting a clear picture of the current state and identify the areas that have not received sufficient attention.

4.1 Analytical Framework

In this section, we propose three dimensions to classify the landscape of analogy-based story generation: 1) the scope of analogy, 2) the specific technique of computational analogy, and 3) the story representation formalism.

The first dimension uses narratology theory to identify the *scope* of analogy — the level at which analogy is used in a narrative. In the widely accepted

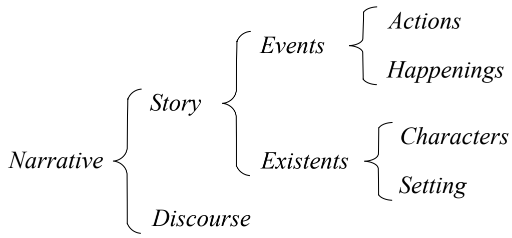

Fig. 1. Chatman's Taxonomy of Narrative Components [2, p.19].

theory of Chatman [2] (Figure 1), a narrative can be divided into two parts: the *story* and the *discourse*[3]. A story is composed of *events* and *existents*, each of which can be further divided into *actions* and *happenings*, and *characters* and *settings* respectively. Finally, discourse is the ways in which a story is narrated[4]. As the narrative progresses, these different elements may affect one another. For instance, events can affect existents.

Based on Chatman's taxonomy, we are able to locate the level at which analogy is performed, i.e. its scope. Our description below is organized from the local to the global scale:

Events: analogy can be used to map individual events (including character actions and happenings) from S to T. Analogy at this level focuses on transferring only events and/or the structure of multiple events, without taking existents into account.

Existents: existents can be fairly complicated structures. For instance, a character may have background, personality, and relations. If we partially specify a character in T, the rest of the character traits may be automatically defined by drawing analogy from another character in S, given that a strong analogical mapping can be found between them.

Story: analogy at the story level takes both events and existents into consideration as a whole. For instance, analogy at this level can map one complete scene (including existents and sequences of events) in S to another in T.

Discourse: analogy at the discourse level focuses on mapping discursive strategies, regardless of the story content.

Narrative: analogy at the complete narrative level considers story and discourse as a whole. Analogy at this global level is useful to identify global structural similarities, such as "explaining past experiences using flash-backs," which can only be captured when considering story and discourse together.

It is worthwhile to stress that certain analogies at a more global narrative level cannot be achieved by performing analogy at its child levels separately. For

[3] Some authors also use the terms of *fable* and *sjuzet* to represent a similar division.

[4] In Chatman's terminology, what we conventionally call *story generation* is actually *narrative generation* as it includes both story and dicourse.

System	*Scope*	*Technique*	*Representation*
Riedl & León's [26]	story	CAB - generation	planning-based
PRINCE [14]	existents	analogy - identification	WordNet
GRIOT [13] / MRM [35]	existents	Conceptual Blending	logical clauses
Minstrel [31]	story	CBR	Rhapsody
ProtoPropp [11]	story	CBR	OWL
Virtual Storyteller [28]	story	CBR	planning-based
MEXICA [33]	existents	engagement/reflection	relationship graphs

Table 1. Classification of Existing Analogy-Based Story Generation Systems.

instance, analogies at the entire story level may not be found at either the events or existents levels alone.

The second dimension is the computational analogy method used by a system. As mentioned before, we also include related areas such as CBR, conceptual blending and metaphor theory in our definition of analogy. We further differentiate the purpose of analogy as *identification* from *generation*. Identification involves only generating an analogical mapping for identifying similarities among two domains. Such similarities can be exploited later for story generation by other techniques, as shown in Section 4.2. By contrast, generation involves transferring inferences (knowledge) from S to T after completing the analogical mapping, i.e. analogy itself is used for story generation. From our survey of existing systems, most CBR-based systems only create mappings between S and T to assess similarity, and use other techniques for story generation. Hence, they fall into the identification category. This is because traditionally CBR techniques separate case *retrieval* (where similarity is used) from case *reuse* (where solutions are generated).

The third dimension is the system's story representation formalism. Different story representation formalisms afford analogical transfers at different levels, and hence allow different computational analogy methods to be applied. Magerko [20] distinguishes three types of approaches to represent stories: planning languages (which emphasize causality and structure), modular languages (which emphasize the content of the story without focusing on the temporal relations among the elements), and finally hybrid languages. If someone is interested in analogy-based generation at the story level, then modular languages (such as plot points, beats) will not be adequate, since those languages do not specify a story structure. On the contrary, such languages represent the useful information to work at the individual events and the existents level.

4.2 Classification of Existing Systems

The above framework can help us to classify existing analogy-based story generation systems, and more importantly, identify trends and unexplored areas. Table 1 shows the analysis of various systems using the above three dimensions. The first column is the name of the system, if any; the second column shows the level at which analogy is made (notice that this might be different from the level at which the system generates narrative components); next is the particular analogy technique used; finally, the last column shows the particular story representation formalism used for analogy.

Among the systems that adopt classic computational analogy, Riedl and León's system [26] combines analogy and planning. It uses analogy as the main generative method and uses planning to fill in the gaps in the analogy-generated content. The system performs analogy at the story level using the CAB algorithm [19] and uses a representation consisting of planning operators. The PRINCE system [14] uses analogy to generate metaphors and enrich the story by explaining a story existent in the domain T using its equivalent in S. In this case, analogy is used for identification, and a secondary method for generating local metaphors for the overall narration.

GRIOT [13] and the Memory, Reverie Machine (MRM) system [35], the latter is built on GRIOT, use the ALLOY conceptual blending algorithm to generate affective blends in the generated output, poetry in the case of GRIOT and narrative text in the case of MRM.

Several systems use a case-based reasoning (CBR) approach, including Minstrel [31], ProtoPropp [11] and the Virtual Storyteller [28]. All of these three systems perform mappings at the story level for story generation. These CBR systems possess a case base of previously authored stories. When a system needs to generate a story satisfying certain constraints, one of the stories in the case base satisfying the maximum number of such constraints is retrieved, and later adapted if necessary through some adaptation mechanism. Reminiscent of CBR, MEXICA [33] performs mapping at the existents level in order to generate stories using an engagement/reflection cycle (also used in the Visual Daydreamer [25]). In particular, MEXICA represents the current state of the story as a graph, where each node is a character and each link represents their relation (e.g., "love" and "hate"). MEXICA maps the current state to the states in the pre-authored memories and retrieves the most similar one for the next action.

Based on Table 1, we can see that despite of their uses of different analogy methods and story representations, all systems perform analogy at the story or existents level. No attempts to date have been spent on performing analogy solely at the events level, solely at the discourse level, or at the complete narrative level. These are some promising lines of future research, even though analogy at the narrative level may require considerably large structures to represent it. Moreover, the systems discussed in this section extend the range of aesthetic possibilities by generating stories beyond what is achievable by planning approaches.

5 A Case Study: Riu

Riu is a text-based interactive system that explores the same story-world as Memory, Reverie Machine (MRM) [34, 35]. Compared to MRM which was developed on the framework of Harrell's conceptual-blending-based GRIOT system

[13], Riu uses computational analogy to influence the narratives being generated. The goal of the Riu system is to recreate the intricate interplay between the subjective inner life of the main character and the material world through computational narrative. The system produces stories about a robot character Ales, who initially lost his memories, and who constantly oscillates between his gradually recovering memory world and reality[5]. Compared to planning-based systems, Riu generates narratives without a strong sense of an end goal. Instead, the events and existents in the memory world and reality trigger and influence one another. This theme of Riu, inspired by stream of consciousness literature such as *Mrs. Dalloway* [32], requires novel uses of analogy and is difficult to achieve by planning. The representation formalism of both the story and the memory episodes is influenced by Talmy's *force dynamics* model [29]. It is composed of a sequence of *phases*, each of which is specified in a frame-based representation for every particular point in time containing all the existents.

The protagonist Ales starts without any memories of the past, and gradually recollects them during the story through a two-staged analogical identification process: surface similarity and structural similarity. Triggers in the real world may cause the system to retrieve memories from Riu's pre-authored library of memories based on surface similarities. For instance, an opening door may cause the retrieval of a memory of the oil change tests because they are both tagged as producing squeaky noises. Among the set of memories retrieved by surface similarity, the one(s) sharing deep structural similarities with real world events and existents will be recalled. An example of structural similarity can be between Ales playing with a cat and him playing with a pet bird, because the same structure of *(play Ales X), (animal X)*. Such structural similarity is identified by using SME [4] as part of the Riu system.

The Riu system also uses analogy for generation by bringing knowledge from the memories to the real world and vice versa. For example, when given multiple choices for action, Ales will "imagine" the consequence of each action A. First, a clause representing A is incorporated into the current state of the story, forming phase T_0. Then, the system tries to find analogical mappings with the recollected memories. In particular, the system maps T_0 to the first phase of each of the recollected memories. If for any memory M, composed of a sequence of phases S_0, ..., S_n, and if a strong enough mapping is found between T_0 and S_0, then the system generates a collection of phases T_1, ..., T_n by drawing analogy from M (i.e., what Ales "imagines" as the consequence of action A).

Figure 2 shows a sample interaction with Riu. The story starts when Ales finds a cat in the street. This encounter triggers one of his memories of a past pet bird. Three choices are scribed at this point — the user can decide whether Ales will "play," "feed," or "ignore' the cat. The user first chooses to "play" with the cat. However, the strong analogy between "playing with the cat" and "playing with his bird" leads to the inference (generated by analogy) that "if Ales plays with the cat, the cat will die and he will be very sad." In this case,

[5] We hereinafter use *reality* to refer to the main story world in contrast with the memory world.

Ales was walking on the street.
when he saw a cat in front of him.
When he was young, Ales used to have a bird.
Ales was so fond of it that he played with it day after day.
One day the bird died, leaving ALES very sad.
Ales hesitated for what to do with the cat.
(FEED IGNORE PLAY)
> play
No, I do not want the cat to die..., Ales thought.
(FEED IGNORE)
> feed
Ales took some food from his bag and gave it to the cat.

Fig. 2. An excerpt of User Interaction with Riu.

the "cat" in T_0 is mapped to "bird" in S_0, and all appearances of "bird" are substituted by "cat" in the generation of T_1 from S_1. Such mappings are applied not only to individual existents such as "cat," but also to relations and actions. In the resulting T_1, the cat is dead and ales is sad, and hence Ales refuses to play with the cat. The story then continues after the user selects "feed" for the second time. This simplistic imagination of Ales would be hard to generate using a rational planning approach.

6 Conclusions and Future Directions

In this paper, we have systematically explored the idea of generating stories using computational analogy. Although planning-based techniques have been proven fruitful, analogy offers new narrative possibilities as a complement to the aesthetically goal-driven stories generated by planning.

Drawing from narratology and computational analogy, we have presented an analytical framework consisting of three dimensions — narrative scope, analogy technique, and story representation — and used it to classify existing systems of analogy-based story generation. As a result, we have identified the trends of existing work and, importantly, areas requiring more attention. For instance, analogy at the level of solely discourse, solely events, and the complete narrative level have not been explored. We have also seen that although the story representation formalism used plays a key role on enabling certain types of analogies, little effort is put into theorizing their effects on different story generation systems. Additionally, we have presented a case study of the Riu system. The project not only explores new techniques of integrating analogy, but also demonstrates the potential of a new kind of narrative aesthetics.

Based on our analysis, we propose several interesting future lines of research. First, most work on analogy has focused on the story and existents level. We believe that the reason is that these two narrative elements are relatively easy to represent using planning-based or frame-based representations. In addition, analogy may be applied to the unexplored scopes. Some potential theoretical problems is how to represent discourse in ways which are amenable to analogy.

Second, the impact of story representation formalisms (e.g., plot-point based, beat based, and planning-based) on analogy and essentially story aesthetics needs to be further studied. Different representations afford different uses of analogy, and imbue certain narrative aesthetics.

Third, analogy has been used for both generation purposes and identification purposes. Using analogy for identification purposes is interesting since it enables the development of hybrid story generation systems, which can combine analogy with planning or with other generative techniques. An exploration of the possibilities to create such hybrids and how such hybridizations affect the generative possibilities and the resulting aesthetics is also a promising future research line.

Finally, the goal-driven aesthetics of planning-generated stories is well known. Similarly, what is the complete range of aesthetic affordances of analogy? We believe the exploration of such questions may help us identify new generative techniques beyond planning and analogy.

References

[1] Agnar Aamodt and Enric Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Communications*, 7(1):39–59, 1994.

[2] Seymour Chatman. *Story and Discourse: Narrative Structure in Fiction and Film.* Cornell University Press, June 1978.

[3] Thomas G. Evans. A program for the solution of a class of geometric-analogy intelligence-test questions. In *Semantic Information Processing*. MIT Press, Cambridge, MA, 1968.

[4] Brian Falkenhainer, Kenneth D. Forbus, and Dedre Gentner. The structure-mapping engine: Algorithm and examples. *Artificial Intelligence*, 41:1–63, 1989.

[5] Gilles Fauconnier. Conceptual blending and analogy. In Dedre Gentner, Keith J. Holyoak, and Boicho N. Kokino, editors, *The Analogical Mind: Perspectives from Cognitive Science*. MIT Press, Cambridge, MA, 2001.

[6] Gilles Fauconnier and Mark Turner. *The Way We Think: Conceptual Blending and the Mind's Hidden Complexities*. Basic Books, New York, NY, 2002.

[7] Robert M. French. *The subtlety of sameness: a theory and computer model of analogy-making*. MIT Press, Cambridge, 1995.

[8] Robert M. French. The computational modeling of analogy-making. *Trends in Cognitive Sciences*, 6(5):200–205, 2002.

[9] David Gelernter. *The Muse in the Machine*. Free Press, New York, 1994.

[10] Dedre Gentner, Keith J. Holyoak, and Boicho N. Kokinov. *The Analogical Mind: Perspectives from Cognitive Science*. MIT Press, Cambridge, 2001.

[11] Pablo Gervás, Belén Díaz-Agudo, Federico Peinado, and Raquel Hervás. Story plot generation based on cbr. *Journal of Knowledge-Based Systems*, 18(4-5):235–242, 2005.

[12] Rogers P. Hall. Computational approaches to analogical reasoning: a comparative analysis. *Artif. Intell.*, 39(1):39–120, 1989.

[13] D. Fox Harrell. *Theory and Technology for Computational Narrative: An Approach to Generative and Interactive Narrative with Bases in Algebraic Semiotics and Cognitive Linguistics*. Dissertation, University of California, San Diego, 2007.

[14] Raquel Hervás, Rui P. Costa, Hugo Costa, Pablo Gervás, and Francisco C. Pereira. Enrichment of automatically generated texts using metaphor. In *MICAI*, pages 944–954, 2007.

[15] Keith J. Holyoak and Paul Thagard. Analogical mapping by constraint satisfaction. *Cognitive Science*, 13:295–355, 1989.

[16] John E. Hummel and Keith J. Holyoak. Distributed representations of structure: A theory of analogical access and mapping. *Psychological Review*, 104:427–466, 1997.

[17] Robert Humphrey. *Stream of Consciousness in the Modern Novel*. Perspectives in Criticism. University of California Press, Berkeley and os Angeles, 1954.

[18] George Lakoff and Mark Johnson. *Metaphors We Live By*. University of Chicago Press, Chicago, 1980.

[19] Levi B. Larkey and Bradley C. Love. Cab: Connectionist analogy builder. *Cognitive Science*, 27(5):781–794, 2003.

[20] Brian Magerko. A comparative analysis of story representations for interactive narrative systems. In Jonathan Schaeffer and Michael Mateas, editors, *AIIDE*, pages 91–94. The AAAI Press, 2007.

[21] Gary E. McGraw, Jr. *Letter spirit (part one): emergent high-level perception of letters using fluid concepts*. PhD thesis, Indiana University, 1995.

[22] James Meehan. *The Metanovel: Writing Stories by Computer*. Ph.d., Yale University, 1976.

[23] Melanie Mitchell. *COPYCAT: A Computer Model of High-level Perception and Conceptual Slippage in Analogy-making*. PhD thesis, University of Michigan, 1990.

[24] Janet H. Murray. *Hamlet on the Holodeck: The Future of Narrative in Cyberspace*. The MIT Press, Cambridge, 1998.

[25] Rafael Pérez y Pérez, Ricardo Sosa, and Christian Lemaitre. A computer model for visual-daydreaming. In *AAAI Fall Symposium on Intelligent Narrative Technologies*, Washington D.C., 2007. AAAI Press.

[26] Mark Riedl and Carlos León. Generating story analogues. In *AIIDE 2009*. The AAAI Press, 2009.

[27] Marie-Laure Ryan. *Narrative as Virtual Reality: Immersion and Interactivity in Literature and Electronic Media*. Johns Hopkins University Press, Baltimore, 2003.

[28] I.M.T. Swartjes, J.A.F. Vromen, and N.E. Bloom. Narrative inspiration: Using case based problem solving for emergent story generation. In A. Cardoso and G.A. Wiggins, editors, *Proceedings of the Fourth International Joint Workshop on Computational Creativity*, pages 21–28, London, June 2007. Goldsmiths, University of London.

[29] Leonard Talmy. Force dynamics in language und cognition. *Cognitive Science*, 12(1):49–100, 1988.

[30] Mark Turner. *The Literary Mind: The Origins of Thought and Language*. Oxford UP, New York; Oxford, 1996.

[31] Scott R. Turner. *Minstrel: a computer model of creativity and storytelling*. PhD thesis, University of California at Los Angeles, Los Angeles, CA, USA, 1993.

[32] Virginia Woolf. *Mrs. Dalloway*. Harcourt, 2002 (1925).

[33] Rafael Pérez y Pérez and Mike Sharples. Mexica: A computer model of a cognitive account of creative writing. *J. Exp. Theor. Artif. Intell.*, 13(2):119–139, 2001.

[34] Jichen Zhu. *Intentional Systems and the Artificial Intelligence (AI) Hermeneutic Network: Agency and Intentionality in Expressive Computational Systems*. PhD thesis, Georgia Institute of Technology, 2009.

[35] Jichen Zhu and D. Fox Harrell. Daydreaming with intention: Scalable blending-based imagining and agency in generative interactive narrative. In *AAAI 2008 Spring Symposium on Creative Intelligent Systems*, pages 156–162, Stanford, CA, 2008. AAAI Press.