

Reader-Model-Based Story Generation

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Introduction

My research project consists of building a story generator which will explore the use of reader modelling for plot generation. The project will make use of an emerging body of work at the intersection of literature and psychology that investigates reader engagement. Although there are existing systems that use formal reader models in a narrative generation context, most of them are built for creating interactive narrative, and those that work with fixed narratives have focused on discourse generation from a fixed sequence of story events rather than plot generation. Making practical use of recent theories in the psychology of reading should also give a new perspective on those theories.

Related Work

Story Generation

Computational approaches to story generation have been the subject of research since the classic period of AI research, with key early systems such as Klein's *Automatic Novel Writer*, Meehan's *Tale-Spin*, and Lebowitz's *Universe* dating from the '70s and '80s (Klein 1973; Meehan 1976; Lebowitz 1984). More recently the field has diversified and systems based on techniques such as planning (Riedl 2004), intelligent agents (Theune et al. 2003), case-based reasoning (Pérez y Pérez and Sharples 2001; Gervas et al. 2005), computational analogy (Zhu and Ontanón 2010), and even genetic algorithms (Bui, Abbass, and Bender 2010) have been created. Each of these systems approaches the problem in a different way, both at the algorithmic level and in terms of what processes they enact.

Systems such as *Tale-Spin* focus on character simulation as a means of creating stories (recent agent-based work continues in this vein). Other systems (starting with Dehn's *Author* (Dehn 1981)) simulate at the author level, generating events not based on the actions of simulated characters but in response to the dictates of a simulated author. These author-level systems often include subsystems that work at the character level, but their main control flow takes an author's perspective. Most modern story generators work this way, approximating one way or another an agent that reasons about the plot of the story in an author-like way.

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A third approach, suggested since at least 1999, would incorporate reader-level simulation (Bailey 1999). Rather than just reasoning about narrative from an authorial viewpoint, a computer could incorporate theories about reading in order to reason about how the audience will perceive the story it generates, and revise the story based on this reasoning. Unfortunately, Bailey's 1999 reader-model-based system was never completed, and since then few systems have tried to incorporate such a mechanism. Pérez y Pérez's work on *Mexica* is one notable exception: *Mexica*'s reflection mode is very similar to my proposed use of a reader model (Pérez y Pérez and Sharples 2001). However, *Mexica*'s reflection mode simulates an author reflecting on their own work, and it doesn't make use of theories of reading.

Several interactive narrative systems have used formal models of their users to evaluate narrative possibilities, including Mott and Lester's work on *U-Director* and Szilas' work on *IDtension* (Mott and Lester 2006; Szilas 2007). *IDtension* in particular has a formal model that addresses the user's perceptions of ethical consistency, motivation, relevance, complexity, progress, and conflict. However, these interactive narrative systems necessarily operate incrementally, constructing a story from beginning to end while accounting for external input; these detailed reader models have not been applied to the generation of fixed narratives.

For non-interactive story generation, several authors have applied reader modelling to planning-based story generators (Cheong and Young 2006; Bae and Young 2008; Niehaus 2009). However, these systems have focused on the discourse generation task: given a fixed underlying sequence of story events, select and order them for presentation as a story. This means that their reader models are not involved at the plot generation stage, but instead are used afterwards to optimize presentation. This approach helps isolate the effect of a reader model and has been able to demonstrate several applications, but it doesn't fully address the potential of reader modelling for plot generation. Presumably, if the quality of a discourse can be improved by the use of a reader model, manipulating the underlying story events for better synergy with the reader model might be helpful. My proposed work will continue this direction of research: I plan to build a reader-model-based story generator which uses critiques from a simulated reader to drive an iterative story generation and refinement process at the plot level.

Modelling Readers

The inspiration to use a reader model to drive story generation comes not only from a perceived opportunity to extend existing story generation literature but also from recent work in both literature and psychology on why people read and what they think when they're reading. Scholars such as Lisa Zunshine, Keith Oatley, and Raymond Mar have published work that not only implicates human social reasoning as an important factor in why and how we read, but also begins to pin down exactly how we engage with fiction (Zunshine 2006; Mar and Oatley 2008). These new theories are grounded in cognitive science, and complement classical narrative theory by filling in some of the details of reader engagement. Whereas a narrative theorist like Greimas might theorize about the overall structure of a plot (Greimas 1988), a psychologist like Oatley is interested in what emotional responses readers will have to a text (Oatley 1995). These emerging cognitive theories of reading, combined with both classical narratology and reader-response theory represent a rich source of semi-formal knowledge about how readers respond to texts. In building my reader model, I will focus on Lisa Zunshine's work on intentionality and Oatley & Mar's work on emotional identification.

Zunshine talks about the cognitive science concept of "theory of mind" or intentionality as important to how we understand and enjoy fiction (Zunshine 2006). For example, she hypothesizes that one reason Virginia Woolf's work is often considered difficult to read is that Woolf frequently makes use of situations which require more than four levels of intentionality to be unraveled to be understood. This makes sense because humans are much worse at questions involving five or more levels of intentionality than those involving fewer (Kinderman, Dunbar, and Bental 1998). More broadly, Zunshine argues that one reason that we enjoy reading is that it provides exercise for our "theory of mind module": that it's pleasurable to be forced to guess and infer what characters are thinking. She also discusses the concept of "tagging" information: building a mental model of the story world that includes meta-information about the source of various assertions and how trustworthy those sources are. To support this, my narrative representation will keep track of different character viewpoints and my reader model will predict reader inferences about the character's mental states. Given such a model, my system will be able to exploit opportunities to create situations of reversal (where the reader's assumptions are overturned) and tension (where the reader has evidence for multiple conflicting assumptions).

In fact, the *IDtension* system mentioned previously includes similar functionality in the complexity portion of its reader model (Szilas 2007). However, *IDtension* uses authored "process" objects that represent generic sequences of events to model reader expectations, and it doesn't deal with intentionality. Niehaus' work on reader modelling is also quite relevant here: his discourse-level system includes an intentional inference subsystem (Niehaus 2009). However, Niehaus' use of the word "intentional" refers to character intentions, i.e., plans. Although inferring a character's plan based on their actions does involve theory-of-mind intentionality, this is just one specific instance of a broader

phenomenon that encompasses all of the ways in which the reader projects mental states onto characters. Although I plan to make intentional reasoning the core of my reader model, the works of Szilas and Niehaus contain a wealth of information and empirical data about the use of reader models for story generation. Where possible, I'll incorporate their ideas into my reader model as well.

Besides dealing with intentionality, my reader model will also reason about character emotions and the reader's identification with characters, informed by the work of Oatley and Mar (Oatley 1995; Mar and Oatley 2008). Through psychological experiments, Oatley and Mar have shown that both sympathetic and empathetic responses to the emotions of characters in fiction are an important part of reader engagement. If we take seriously the hypothesis that fiction serves to simulate social experience, in part through the emotions it evokes, then when generating fiction we should generate social situations involving the characters and make sure that their emotional responses are made visible to the reader. The emotion-handling part of my reader model will try to predict the sympathetic and empathetic emotions felt by the reader at different points in the story, and it will manage the story events to control these emotions. It will also try to use hints where appropriate to disambiguate or emphasize the emotional responses of the characters.

Story Understanding

Although my focus is on intentional reasoning and emotional identification as the foundation of a reader model, other sources also offer useful perspectives, including research on automated story understanding. The story understanding literature is relevant here because it represents stories from the perspective of the reader. Systems like Lehnert et al.'s, *Boris*, Elson & McKeown's *Scheherazade*, and Goyal et al.'s *AESOP* advance theories of how humans represent stories and which parts of the story are most important for comprehension (Lehnert et al. 1983; Goyal et al. 2010; Elson and McKeown 2007). These theories, especially when experiments compare them directly to human comprehension performance, bear directly on the construction of a reader model. Also, because these theories are developed for use in text analysis, they're designed with automatic processing in mind. Story understanding techniques cannot simply be used as a reader model, however, because they focus almost exclusively on comprehension, whereas my reader model will have to support aesthetic goals.

Computational Approach

The idea of creating a story generation system based on a model of reading seems worthy of investigation, and recent theories about the psychology of reading form a solid basis from which to create such a model. But using a reader model to drive a story generation system is not a straightforward task. I plan to use an incremental story generator based on an author-simulation approach as the base of my system.

Each step of the generator will correspond to an author goal, such as "create a plot outline" or "fill in the climax scene." This author-level generator will be augmented by

the reader model, which will give feedback as the story is being created. The reader model will point out both flaws in the current story as well as opportunities for improvement; this feedback will then be translated into additional goals.

While the implementation of the incremental generator will use normal imperative code, the reader model and plot framework will be implemented in first-order predicate logic. Because the reader model is mainly responsible for taking low-level properties of a narrative (such as the sequence of actions taken by a character) and outputting high-level properties of the story (such as whether the “reader’s” theory of mind is exercised in a certain scene), a logic-based implementation is a natural fit. Another reason for this choice is the modularity it affords: predicate-logic versions of different constraints can be easily decomposed, which will permit ablation testing of the system as a whole.

The reader model will necessarily include many domain-specific pieces which bridge the gap between story events and low-level reader impressions. For example, in a sitcom domain a “reveal-secret” verb might be included, but none of the relevant psychological theories are likely to mention scenes about revealing secrets specifically. Instead, a theory might reference “harmful” interactions between characters, or the emotional responses of characters. Thus some domain-specific common-sense knowledge must be encoded such as “revealing someone’s secret is harmful to them” or “negative emotions towards another character can motivate revealing that character’s secret”. Using a predicate calculus encoding of this knowledge will make the psychological theory portion of the reader model separable from this domain-specific knowledge.

Without further research, the details of both the iterative generator and the reader model are still undecided. This is in part because one major component of my proposed research involves using semi-formal and informal bodies of knowledge about reader psychology to build the formal reader model. In fact, my research agenda is not based on a computational technique: my main claim is not that using first-order predicate calculus within an iterative generator will advance the state of story generation. Rather, I am proposing that the use of a reader model at the plot level will have an impact on story generation, and to confirm this thesis I’ll need to figure out how best to implement one. Although the core design of my system is decided – an iterative author-level generator informed by a logic-based reader model – most of the details will be worked out as my research progresses, informed by both aesthetic demands on the output of the system and formal theories of reader psychology.

Prior Work

The use of an iterative author-goal generator as the base of my system is a direct result of my recent work with the *Minstrel* storytelling system. Over the past two years I’ve worked with Brandon Tearse, Michael Mateas, and Noah Wardrip-Fruin to reconstruct Scott Turner’s 1993 *Minstrel* story generator, creating a modified version called *Skald* (Turner 1993; Tearse et al. 2011; 2012). *Minstrel* uses a blackboard system to track author-level goals, while relying on a unique ‘transform recall adapt method’ (TRAM)

system for most of its low-level story alterations. Although I don’t intend to use the TRAM system (and accompanying graph representation of stories) for my work, my author-level iterative generator borrows significantly from Turner’s ‘author-level plan’ (ALP) subsystem. Not only am I borrowing Turner’s ideas, but the experience of implementing a story generator has prepared me to undertake this task again.

Besides my work on *Skald*, I’ve also recently implemented an (unpublished) prototype logic-based story generator using answer-set programming. Answer-set programming is a programming paradigm supported by an automatic stable-model-finding process which converts first-order logic constructions into stable models – predicate truth-assignments which are consistent with the implication rules given (Gelfond and Lifschitz 1988; Brain and De Vos 2005; Gebser et al. 2011). Although my prototype generator is severely limited (for example it can’t generate stories longer than about five timesteps), it functions as a proof-of-concept for the application of answer set programming to story generation. Because this prototype reasons arbitrarily rather than following some intuitive algorithm for satisfying the constraints given to it, it is often able to come up with surprising solutions some of which turn out to be quite interesting scenes. This potential for complex interactions between rules, although difficult to control, is valuable for story generation, since one aesthetic goal of a story generator is to produce novel results (ideally it should be able to surprise even its creator).

Evaluation

Experimental evaluation should be able to demonstrate the effect of my reader model, and ideally pinpoint contributions from various constraints. By asking humans to evaluate specific qualities of short generated stories (such as “was character A angry”) it should be possible to test portions of the reader model dedicated to specific inferences (e.g. a portion of the reader model that attempts to mimic inferences about emotion). It may even be possible to evaluate more general story characteristics such as plot coherence or the presence of a theme, but these properties may be difficult to tease out.

Another way to measure the usefulness of a reader model is to run the model on existing stories. I will convert existing stories into the system’s logical representation, and then ask the reader model to point out flaws in both unaltered and edited versions. Ideally, the reader model’s predictions should agree with a human analysis of a fixed story, and it should also give credible suggestions for improving a story where a key event has been intentionally deleted. This experiment will serve as a sanity check and help direct further development of the system.

To measure the overall quality of the system output, I will use a survey tool designed to measure narrative engagement (Busselle and Bilandzic 2009). I will compare generated stories against human-authored stories based on generated plots and against fully human-authored stories. I don’t expect the generated stories to compete evenly with human-produced stories, but I think that actually including a realistic baseline is important.

I also plan to conduct qualitative evaluations, soliciting detailed feedback from a small number of participants. This qualitative feedback will primarily be used during system development to identify flaws in the generated stories. By publishing this qualitative feedback along with quantitative results, I hope to justify the reader-model-based approach not only by showing specific effects but also through the general quality of the system’s output.

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