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Bridging the Gap Between Computational Narrative and Natural Language Processing

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Abstract

This paper motivates the importance of narrative in computer games and proposes the use of natural language processing (NLP) for computational narrative (CN) systems. We discuss some of the problems to address in order to bridge the gap between NLP and CN.

Motivation

Narrative is an important part of computer games. From early games like *Zork*, to the text-based interactive Victorian dramas generated by Versu (Evans and Short 2014) to 3D RPG games like *Skyrim* (Ruch 2011), the quality of the stories play a crucial role in engaging the player and the overall quality of the gameplay experience. To increase the computer's ability to generate engaging stories, a large body of research in AI and computational narrative (CN) has focused on story generation (Meehan 1976; Turner 1994; Riedl and Young 2004; Zhu and Ontañón 2014), and experience management (Weyhrauch and Bates 1997; Nelson and Mateas 2005; Sharma et al. 2010).

A well-known problem in computational narrative is the authorial bottleneck (Gervás 2009; Bateman 1997). Currently, CN systems rely on either large amounts of annotated data or handcrafted models in some knowledge representation formalism. Producing these models and annotations is time-consuming and requires specialized technical skills.

Future story generation systems can benefit significantly from combining natural language processing (NLP) and information extraction (IE), to automatically extract narrative content from natural language text. The extracted content can then be formalized in representations that story generation and experience managemnent algorithms can use. Recent few isolated pieces of work have focused on extracting narrative information such as characters (Calix et al. 2013; Valls-Vargas, Ontañón, and Zhu 2014), narrative structure (Chambers and Jurafsky 2008; Goyal, Riloff, and Daumé 2010), emotional arcs (Reagan et al. 2016), and character relationships (Roth and Yih 2004; Chaturvedi et al. 2015; Srivastava, Chaturvedi, and Mitchell 2015). We argue that this is an important research direction, which could enable CN systems to exploit vast amounts of existing content in natural language (e.g., existing literary canons) and enable content creation by non-technical writers.

Open Problems

To achieve this long-term vision, however, several open challenges need to be addressed.

Models of Computational Narrative: Despite a long history of work: from Propp (Propp 1973), to AI-based representations such as plans (Meehan 1977; Riedl and Young 2010), frames (Zhu and Ontañón 2014), plotpoints (Weyhrauch and Bates 1997; Nelson and Mateas 2005; Sharma et al. 2010) or social models (McCoy et al. 2011), the problem of how to computationally model narratives and story spaces remains open. Aspects such as authorial intent, conflict, or character subjectivity are not properly captured by existing models. Therefore, even if we could extract narrative knowledge from natural language text, it is unclear which representation formalism to use to represent it in and reason about it.

Narrative Information Extraction: Recent efforts in the NLP and IE communities have seen great progress. However, when dealing with complex narrative content, higher error rates have been reported than more constrained content domain (Valls-Vargas, Ontañón, and Zhu 2015). We attribute this phenomena to the specific complexities in fiction or drama (e.g., uncommon rhetorical figures, fantastic situations or anthropomorphic characters) which differs vastly from to the prose in standard corpora used for common NLP research and applications. Therefore, to fully bridge the gap between NLP and story generation, further research on how to automatically extract narrative information from unannotated text is needed.

Evaluation of Information Extraction Pipelines: Information extraction systems usually integrate several modules into a pipeline. Individual modules have been analyzed extensively (e.g., coreference resolution systems at the CoNLL shared tasks (Pradhan et al. 2011)). However, when the information extracted by the system is not accurate, it is hard to pinpoint which is the module responsible, since there is a lack of a general methodology that can be applied to arbitrary pipelined information extraction systems to evaluate the interplay of the errors introduced by each module.

Conclusions

Solving the previous problems can lead to significant progress in computational narrative systems for computer games. It would allow story generation and experience managers to automatically extract information from the large body of existing literature written in natural language, directly addressing the authorial bottleneck. Imagine, for example, an experience manager trying to adapt the current story line of an interactive game after the player performed an action that invalidated the author-provided set of plot points. This experience manager could tap into the literature looking for potential storylines, events or even new characters that could be incorporated in the current story, to achieve the desired authorial goals, and keep the story interesting.

References

Bateman, J. A. 1997. Enabling technology for multilingual natural language generation: the kpml development environment. *Natural Language Engineering* 3(1):15–55.

Calix, R. A.; Javadpour, L.; Khazaeli, M.; and Knapp, G. M. 2013. Automatic Detection of Nominal Entities in Speech for Enriched Content Search. *The Twenty-Sixth International FLAIRS Conference* 190–195.

Chambers, N., and Jurafsky, D. 2008. Unsupervised learning of narrative event chains. In *Proceedings of the 2008 Anniversary Meeting of the Association for Computational Linguistics*, volume 94305, 789–797.

Chaturvedi, S.; Srivastava, S.; Daume III, H.; and Dyer, C. 2015. Modeling dynamic relationships between characters in literary novels. *arXiv preprint arXiv:1511.09376*.

Evans, R., and Short, E. 2014. Versua simulationist storytelling system. *IEEE Transactions on Computational Intelligence and AI in Games* 6(2):113–130.

Gervás, P. 2009. Computational Approaches to Storytelling and Creativity. *AI Magazine* 49–62.

Goyal, A.; Riloff, E.; and Daumé, III, H. 2010. Automatically producing plot unit representations for narrative text. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, EMNLP '10, 77–86.

McCoy, J.; Treanor, M.; Samuel, B.; Wardrip-Fruin, N.; and Mateas, M. 2011. Comme il faut: A system for authoring playable social models. In *AIIDE*.

Meehan, J. 1976. *The Metanovel: Writing Stories by Computer*. Ph.d., Yale University.

Meehan, J. R. 1977. Tale-spin, an interactive program that writes stories. In *IJCAI*, volume 77, 91–98.

Nelson, M. J., and Mateas, M. 2005. Search-based drama management in the interactive fiction anchorhead. In *AIIDE*, 99–104.

Pradhan, S.; Ramshaw, L.; Marcus, M.; Palmer, M.; Weischedel, R.; and Xue, N. 2011. Conll-2011 shared task: Modeling unrestricted coreference in ontonotes. In *Proceedings of the Fifteenth Conference on Computational Natural Language Learning: Shared Task*, 1–27. Association for Computational Linguistics.

Propp, V. 1973. *Morphology of the Folktale*. University of Texas Press.

Reagan, A. J.; Mitchell, L.; Kiley, D.; Danforth, C. M.; and Dodds, P. S. 2016. The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Science* 5(1):31.

Riedl, M. O., and Young, M. R. 2004. An intent-driven planner for multi-agent story generation. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 1*, 186–193. IEEE Computer Society.

Riedl, M. O., and Young, R. M. 2010. Narrative planning: balancing plot and character. *Journal of Artificial Intelligence Research* 39(1):217–268.

Roth, D., and Yih, W.-t. 2004. A linear programming formulation for global inference in natural language tasks. Technical report, DTIC Document.

Ruch, A. 2011. The elder scrolls v: Skyrim radiant quest system, will customise your game as you play. *On-line, GameSpy*.

Sharma, M.; Ontañón, S.; Mehta, M.; and Ram, A. 2010. Drama management and player modeling for interactive fiction games. *Computational Intelligence* 26(2):183–211.

Srivastava, S.; Chaturvedi, S.; and Mitchell, T. 2015. Inferring interpersonal relations in narrative summaries. *arXiv preprint arXiv:1512.00112*.

Turner, S. R. 1994. A model of creativity. In *The Creative Process: A Computer Model of Storytelling and Creativity*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Valls-Vargas, J.; Ontañón, S.; and Zhu, J. 2014. Toward automatic character identification in unannotated narrative text. In *Proceedings of the Seventh Workshop in Intelligent Narrative Technologies*.

Valls-Vargas, J.; Ontañón, S.; and Zhu, J. 2015. Narrative hermeneutic circle: Improving character role identification from natural language text via feedback loops. In *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2517–2523.

Weyhrauch, P., and Bates, J. 1997. *Guiding interactive drama*. Carnegie Mellon University Pittsburgh, PA.

Zhu, J., and Ontañón, S. 2014. Shall i compare thee to another story? - an empirical study of analogy-based story generation. *IEEE Transactions on Computational Intelligence and AI in Games* 6(2):216–227.