A Theoretical Framework to Represent Narrative Structures for Visual Storytelling

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Abstract

In this paper, we present a theoretical framework to represent and manipulate narrative structures for visual storytelling. This framework can be used in applications beyond visual storytelling, which includes formal representation of stories, emotional, social and even economical interactions among agents. Our framework significantly extends and formalizes classical narratology theories. In our framework, we represent narratological functions as interventions by employing an extension of causal inference theory, as directed graphs that provide cause and effect relationships among agents. Moreover, we categorize them as real, expressed and observed interventions. This differentiation allows us to represent beliefs, lies and misunderstandings. In our framework, any transformation in causality graph structure is called an event by providing a non-linear temporal dimension that can even allow time-travel. This approach provides a general framework to develop tools for modeling narration and can help to investigate social and economic interactions.

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1 Introduction

Visual storytelling is one of the areas in visual aesthetic that is not well understood and that still requires a lot of creativity and hard work. The major portion of any movie production process is spent for the development of stories and storyboards. To improve the visual story development process there is a need for new theoretical approaches as well as new tools and techniques.

This paper presents a theoretical framework for representation and modeling narrative structures such as emotional, social and economic interactions among agents. This framework is conceptually simple and intuitive and can be used for the development of tools and techniques for visual storytelling. Our framework significantly extends and formalizes classical narratology theories and it can be used in applications beyond storytelling, which includes formal representation of stories, emotional, social and even economical interactions among“irrational” agents.

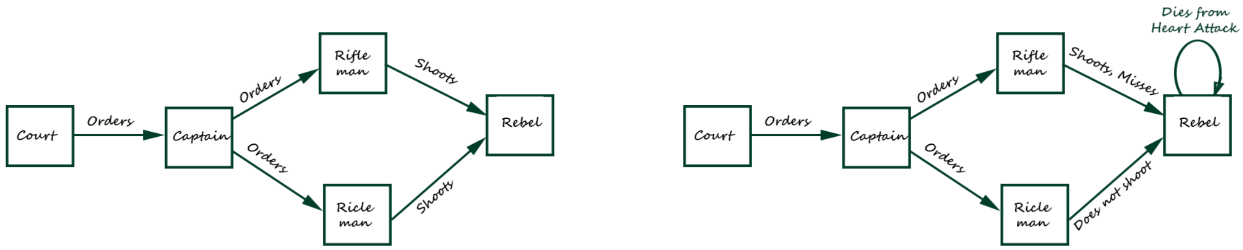
In our framework, we represent narratological functions as interventions by employing an extension of causal inference theory — using directed graphs that provide cause and effect relationships among agents and tasks [29, 28]. Moreover, we categorize them as real, expressed, and observed interventions. This differentiation allows us to represent beliefs, lies, and misunderstandings that can happen in any social interaction between irrational agents. This approach provides a general framework to develop models to investigate social and economic interactions.

2 Related Work

Narratological analysis was started in the 1920s by Vladimir Propp [34], who developed a grammar covering a restricted corpus of Russian folktales. Propp's analysis decomposed a candidate story into an initial state comprising a small collection of characters (*dramatis personae*) and a set of narrative functions over states. The application of a function to a state produces either the end state (the end of the story) or a new state. Propp showed that a small set of about 30 narrative functions plus a few constraints on function ordering could generate the whole chosen corpus of Russian folktales. Propp's analysis was used in some early story-telling programs in Artificial Intelligence ([26, 19, 20], with limited results. Propp's theory was substantially refined in the 1960s ([5, 11, 8]), when a distinct discipline called "narratology" emerged.

Greimas introduced the concept of "actant" in place of Propp's characters and showed that a generic story could be analyzed in terms of the circulation, which is regulated by strict rules, of valuable objects among a very limited number of actants[1]. Artificial Intelligence research in story-understanding and story-telling ignored post-Propp narratological

[1] In this paper, we use term "agent" instead of "actant".



(a) One version of Firing Squad: First, court orders captain to execute the rebel. Captain, then, orders two riflemen to shoot. Then, both riflemen shoot and hit the rebel. As a result, rebel is executed.

(b) Another version Firing Squad: One of the riflemen shoots, but misses the target. The second one does not shoot at all. Rebel dies from heart attack, so he is not really executed.

Figure 1: *A classic example of causal inference: Firing Squad. The drected graphs (a) and (b) provide clear representations of causal relationships among actions and provides all elements of basic task dependencies.*

research until very recently. Partly as a result of the work of Herman [15] and Ryan [36], computational approaches to narrative ([27]) have gained a renewed impetus and the computational representation of standard narratological models is one of explicit goals in the field ([37, 32, 35, 18]).

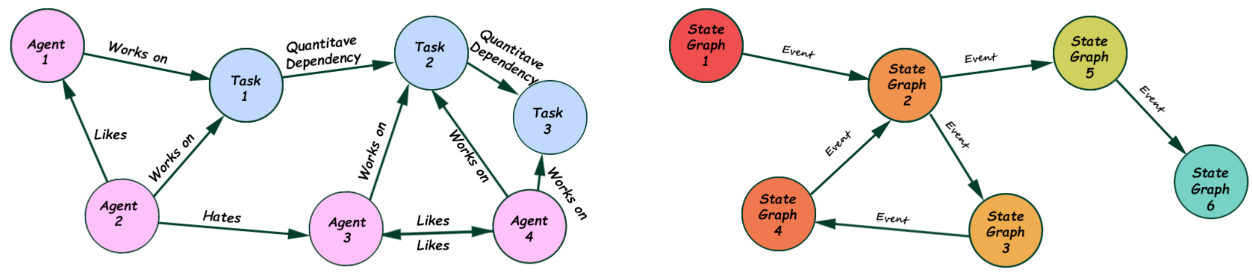
Theories of narratology is especially important for storytelling, which is one of the areas that is not well understood and that still requires a lot of creativity and hard work. The major portion of any movie production process is spent for the development of stories and storyboards. To improve the story development process there is a need for new theoretical approaches as well as new tools and techniques. There is, therefore, a strong interest in storytelling [25, 38, 16]. Mateas and Stern developed one of the first interactive storytelling software called Facade [24]. Two interactive storytelling systems that are based on a Markov Model have also been developed [9, 22].

Narrative theoreticians agree that there are at least two levels in any narration: Some events happen and these events are related in a certain way. Although there exist various terminologies used by different researchers, these two levels of a text can be identified by two questions : (1) What is told and (2) How is it told? In the most widely used structuralist terminology, the answer to the "what" question is called a *story* and the answer to the "how" question is called a *discourse* [10].

The causal inference theory introduced by Judea Pearl [31] provides a formalized approach to represent narratological functions, social and economic interactions using directed graphs. Figure 1 provides a classical example of causal inference theory: Firing Squad. As shown in this figure, not only task dependencies, but also actual events can be encoded by adding a description to each edge. Using that information, it is possible to differentiate two possible implementation of the same process as shown in Figure 1(a) and (b). This is a significant advantage for studying social and economic interactions, since it is possible to randomly create many possible implementations of the same process and evaluate the possibility of their occurrences. For instance, less experienced riflemen are more likely to miss the target. The rebel may not necessarily die. Even when rebel dies, it may not mean that riflemen actually executed the order correctly as demonstrated in Figure 1(b). The causal inference theory [30, 31] is successfully used in representing social [29, 28] and economical interactions [7, 1]. In this work, we present an extension of causal inference theory to provide narrative functions, which will be essential in the representation of stories as interactions and task completions by irrational agents.

3 Extended Causal Inference Theory

Classical causal inference theory can only represent factual information. It does not allow irrational behaviors that are frequently caused by emotional responses and/or impossible events, which are important in representing story narratives. In this paper, we demonstrate that an extended version of directed graphs that define causal inferences can also be used to describe such irrational behaviors and impossible events by providing all narrative functions. The new framework is based on two types of extensions to the standard directed graph representations of causal inference theory: (1) We introduced a temporal dimension that is triggered by events that creates qualitative changes in the universe; and (2) We introduced three layers to provide precise answers to both "what" and "how" questions. The first extension provides a way to differentiate among qualitative and quantitative changes in the story. In our framework, any qualitative change in causality graph structure is called an event. The second extension provides a way to differentiate



(a) Conceptual structure of a state graph, where each blue colored vertex is an agent and purple colored vertex is a task. In a state graph only continuous changes are allowed. For instance, the hate felt by Agent 2 against Agent 3 can only be given by a continuous function. Similarly, the change of the percentage of completion of a task can only be by continuous functions. Quantitative dependencies are described using inequalities.

(b) Conceptual structure of an event graph, where each colored vertex is actually a directed graph. Each of these state graphs is qualitatively different from each other. In other words, the number of vertices and edges can be different in each state graph. That is, events are discrete changes that cannot be expressed by using a continuous function.

Figure 2: *The graph in (a) provides an example of a state graph. The state graph changes with time, but all the changes are described by continuous functions. In other words, the topology of a state graph never changes. On the other hand, any topology change is described by a meta-graph, called event graph, shown in (b). Each vertex of an event graph is a state graph and directed edges of the event graph are events. Note that the event graph in this example includes a cycle that can correspond to either a circular story or a time travel.*

among reality, expressed reality and observed reality.

3.1 First Extension: Temporal Dimension

For story representations one of the most important elements is to provide a temporal dimension to describe possible or impossible temporal dependencies. To include time into our framework, we differentiate between two types of directed graphs: **state** —pertaining to the representation of the qualitatively stable state in a given time period —and **event** —pertaining to the event-based qualitative transition from one state graph to another. These qualitative state changes can allow non-linear temporal transitions such as circular stories and time travel. Each of these event graphs define a unique narration.

State Graphs: In our framework, the state of story in any given time is described by a state graph (see Figure 2a). In a state graph, the agents and tasks are placed in the vertices of the graph; the relationships, emotions, and causal interventions among agents tasks are placed in the directed edges of the graph. Edges and vertices of this graph carry three layers of information that can provide physical, expressional, and observational states. Self-loop edges in the state graph correspond to internal states and other edges provide relational states among agents.

Event Graphs: These are really directed graphs of directed graphs. In other words, each vertex of the event graph is a state graph and each directed edge of the graph is an event, which corresponds to a transformation from one static state graph to another static state graph (see Figure 2b). In other words, any modification of a static state graph is considered to be an event. For instance, introduction of a new agent is an event since it requires the creation of a new vertex in state graph. Similarly, changes in emotions or interventions are also events since they require changes in information provided in edges. Most importantly, such jumps in temporal space allow circular story lines such as in the recent movie “Live Die Repeat: Edge of Tomorrow or time travels which is very coming device in storytelling.

3.2 Second Extension: Irrationality

Our second extension is based on the observation that“humans” are not rational agents that act“only” to minimize certain cost functions. On the other hand, we posit that“humans” do not act arbitrarily. Their actions are results of imperfect knowledge that is accompanied by personal, social and behavioral threads. Thus, in our general framework we consider humans to be narrative characters, which are called agents who may act irrationally, but their actions are not arbitrary and still governed by some rules.

To achieve this we represent “physical human,” who can never been fully observed and known, just one of the layers of “agent” who has narratological existence and can act based on limited knowledge. This layering allows us to develop a general framework that can consider both rational and irrational behaviors. Our framework consists of three layers

–physical, expressional and observational, which are connected with **causality relationships**. These three layers that can help us to differentiate among real, expressed, and observed interventions, emotions, relationships, and events (See Figure 3). The framework can also allow us to visualize story processes from any point of view. Visualization depends on both expression and observation layers. The expression layer provides information about shapes and materials of characters. The observation layer can also provide information about cameras and shots. In what follows, we provide detailed information of each layer.

Physical Layer: This is the lowest layer in our framework. It provides the precise description of real events and real states such as interactions among agents and emotions of agents. This is the layer where all agents physically exist and interact. We assume that in any given time a physical layer has a well-defined state, which is given as the collection of all the states of all agents in the physical layer. In other words, the physical versions of agents are nothing but "boxes" or "containers" that carry states. Physical versions of agents can have either *internal* or *relational* versions of physical states. Internal states are the ones about the agents and tasks themselves. For instance, being dead is a possible internal state for an agent. However, that actant's "container" does not cease to exist by being dead. Its container still exists but its state is "not-living." Internal states can also be an emotional type such as "angry" or "happy," or physical type such as "tired or "sleepy." Similarly, being completed can be a possible state of a task. Relational states are the ones that define one agent's or task's "real" relation and "real" feelings towards another agent and task. For instance, one agent can be a daughter of another agent, or one agent may hate another agent. Note that relational states are not necessarily reciprocal. The relational states are represented as directed edges of the physical layers of the state graphs.

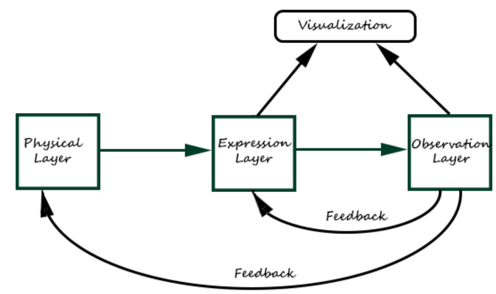


Figure 3: *Flowchart of the three layers and causality relationships among the layers.*

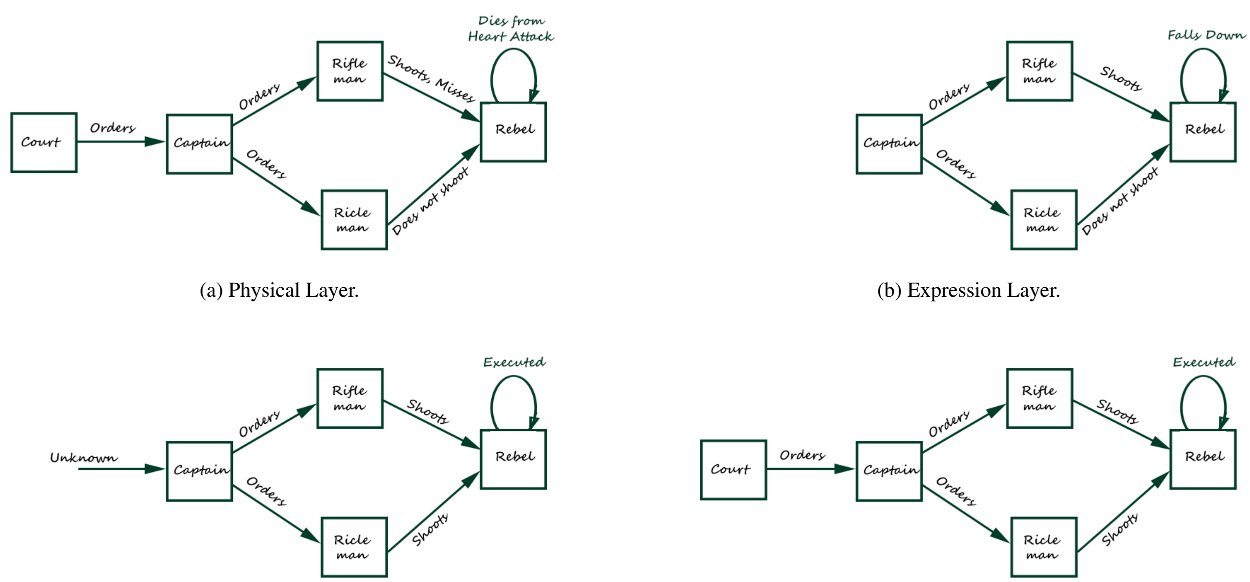
We call any change in the state of the physical layer as *a physical event*. For instance "dying" or "completing" are events that turn a physical version of an agent or a task from "alive state" to "non-living" state. Similarly "falling-in-love" is an event in which one of the physical states of an agent turns from "neutral" to "love." Each of these events can be caused by the agent or the task itself or another agent or another task. The causations of events are called interventions [31]. The interventions that cause physical events are represented by the directed edges of the physical layer of the event graphs (see Figure 4(a)).

Note that the physical events are all "factual." Physical versions of agents do not have capability to observe even themselves. They are just "boxes" or "containers" that carry states that are continually changing. Other layers turn these physical versions of agents into more complicated beings.

Expression Layer: This layer gives us a description how the agents express their emotions and internal states. Expression layer also provides a guidance how the events and states should be visualized. In other words, this is the layer in which some of the states of the physical layer are expressed. Expressions formally can be considered to be a transformation from a physical layer to an expression layer (see Figure 3). They can be in a wide variety of forms such as facial expressions, verbal expressions or postural expressions. Another problem with expressions is that small changes can cause widely different expressions. It is therefore hard to include expressions into a model. One of our contributions in this work can be that we do not consider all these forms and how the expressions are produced. Instead, we focus on the source of expressions. This approach simplifies the complexity that is inherent in expressions. In terms of sources, we consider expressions of *internal states* or *relational states.* An expressions of an internal state can be an expression of an emotion. Shouting and frowning are examples of expressions of angry emotion. But, fake expressions are also possible. For instance, smiling can hide the fact that the actant is angry internally. Note that fake expressions that hide internal states may not necessarily be intentional. The actants themselves may not know that they are, in fact, angry. Expressions of relational states are the directed edges of the expression layer of the state graphs. These are expressions of one agent's feeling or relationship towards another. For instance, one actant who hates another actant may say "I hate you" or simply look annoyed. On the other hand, another actant even can act as if as if s/he liked the other person by hiding his/her true feeling. Even a relationship between two people can be expressed. For instance, a father may tell to his son "You are not my son." Again, these misleading expressions may not necessarily be intentional. It may simply the case that the agent does not know that he is actually the father. But, expression itself does not change the fact that he is the father. Similarly, we can include expressions of tasks, which describe how their internal states can be visualized.

As can be seen from this discussion, expressions may unintentionally or intentionally hide or reveal facts, even for tasks. However, they do not change the facts about physical states. We call any change in the expression as *an expression event*. An expression event is usually a manifestation of physical event. On the other hand, without any change in physical states, an expression may change. The interventions that cause the expression events are represented by the directed edges of the event graphs (see Figure 4(b)).

Observation Layer: This is the layer where each agent's observations are kept. Each agent's observation can be different since every agent can observe a different subset of expression layer. Moreover, one agent can interpret the meaning of an expression different than another agent. Narration only exists in this layer. Narration comes from the limited knowledge of agents and trigger further events through feedback to physical layer. In our framework, a linear narrative is a path on a given event graph that provides sequences of "observational states." The transition from one "observed" state to the next is called a "narrative" event. Narrational events trigger and stimulate physical events (See Figure 3). Note that tasks cannot make observation, but, their observations can be different than truth. For instance, a task, which is not yet completed can be considered as completed by some agents. We consider *Self-observation or self-awareness*, *observations of expressions of others' internal states,* and *observations of expressions of relational states*. Note that self-awareness may affect the expression. Therefore, there is feedback from observation layer to expression layer in Figure 3. The effect can be two ways. An actant who is aware of its internal state can hide it or show it based on its role in the story. On the other hand, an actant who is not aware of its internal state cannot show it regardless of its role in the story. An extreme example is Bruce Willis' character from Sixth Sense, who does not know that he is dead until at the end of the movie.



(a) Physical Layer.

(b) Expression Layer.

(c) Observation Layer for an Outside Observer.

(d) Observation Layer for Captain or Rebel's Ghost.

Figure 4: *An example of three different layers of a simplified event graph: Firing squad. Note that although there is only one physical and expression layer, there can be more than one observation layer since every agent can have its own observation layer.*

Observations of others can always be misleading. Based on their roles in a story two agents may observe/interpret the same expression differently. For instance, an angry expression can be observed as tired by one agent and simply as an anger by another. Observations of expressions of relational states can also be misleading. For instance, an actant says "I love you" and one receiving actant can observe it as a manipulation, another receiving actant can observe it as a manifestation of a real love. Observation layers also provide information about cameras and shots [4, 17, 14, 21]. We can define a character called "audience," who can only observe events without effecting them.

We also have observational events, which will be defined as a change in observation. In such events, nothing in physical and expression layers has to change; however, at least one agent changes its observation. A far-fetched example is the movie 6th sense, in which the character of Bruce Willis was unaware of the fact that he was already dead. The ending of the movie was his realization of being dead. This new observation did not change any existing facts, but, we consider it an intervention since the observation changes. The interventions that cause observation events are represented by the observation layer of directed edges of the event graphs (see Figure 4(c) and (d)).

These layers allow us to represent a wide variety of aspects of real or fictional stories from misunderstandings to lies; from intentional lies to unintentional lies. Figure 4 provides an example of three different layers of a simplified event graph for Firing Squad. This figure demonstrates that it is possible to precisely tell the story using this representation. Although the rebel is not killed by firing squad, everybody can deduce that he was executed by the firing squad. Even the ghost of the death rebel may not know that bullets did not hit him. On the other hand, unlike an outside observer, both captain and rebel know that there was a court order. Assume two riflemen had never killed anybody before the event. Since they did not kill the rebel they continued not to be "a murderer" after the event. Therefore, in physical layer their state did not change. However, according to an outside observer, the Captain, the first rifleman and the ghost of the rebel, they both are turned into a murderer (or an executioner). On the other hand, the second rifleman knows that that he is still not a murderer since he did not shoot. As shown in this example, a storyteller can precisely describe what really happened in the scene using such a representation.

4 Conclusion and Future Work

This representation is mainly useful for representing existing stories in a precise form. It can also be used by storytellers to precisely define everything in their stories. Of course, the resulting structures can be very complicated to draw on paper. Therefore, there is a need for software that can allow storytellers "to design or to model" their stories. In this section, will demonstrate how "Extended Causal inference Theory" can be used for designing stories. We first motivate importance of Extended Theory for narration modeling — i.e. designing and modeling of stories — with an analogy with polygonal mesh surface modeling.

For the development of modelers, the underlying theoretical frameworks always play a pivotal role. For instance, graphs embedded on surfaces, i.e., 2D Graph rotation systems (2D-GRS), provides an underlying theoretical framework for polygonal mesh modeling [12]. 2D-GRS has been used to represent all possible 2-manifold meshes and it has been implicitly used in the guise of various mesh data structures, such as half-edges [23], quad-edges [13] and doubly-linked face lists (DLFL) [2]. 2D-GRS with topology preserving operators such as SPLICE and TWIST [13], or Euler operators [23] or INSERTEDGE, CREATEVERTEX and TWIST [3] provide shape algebras for 2-manifolds. These operators allow users to create all and only 2-manifold meshes. Therefore, users can create any polygonal mesh by using these operators.

Similarly we need a theoretical framework for simulating narrative processes. We claim that the Extended Causal inference Theory provides a formal structure that can represent all possible fictional or non-fictional stories. In other words, any existing story from X-Men to Cinderella, from The Godfather to The Shawshank Redemption, from Psycho to Citizen Kane could be representing precisely in this formal structure. The problem is that it is impossible to formally prove that our structure can represent all cases. However, we can informally demonstrate that our structure can support many unusual structures that exist in various stories.

The key part of the design will be the development of directed graphs that fully describe social interactions and task completion processes. Again by using an analogy to polygonal modeling, it is better to provide operators that can help story designers to model their simulations efficiently. Since we are basically dealing with directed graphs, the basic graph manipulation operators INSERTEDGE and CREATEVERTEX are the only operators needed to manipulate the topological structure of event graphs. Of course, as in the surface modeling case, any higher level operator can be produced as a composite of these two operators.

Another important issue in narration modeling is to attach information to vertices and edges. Unlike surface modeling, which usually requires to attach only 3D position data to vertices, in the design of simulations we have to deal with very high dimensional data and some of this information is simply numbers. For instance, most of the information such as emotions are not necessarily numerical. Moreover, in some cases functions must be attached to vertices that represent tasks and inequalities must be attached to directed edges that define task dependencies. This can be very hard for designers in general, on the other hand, as soon as designer define the undirected graph that represent the process, it is possible to simplify the information. The information, then, could be very low dimensional and easy to describe for the designer.

The representation, can also be used in semi-automatic story creation. In this case, the structure of the plots [39] can be given by the pre-packaged directed graphs. The real challenge, then, lies in populating these graphs with high dimensional data about agent ability, behavior and personality. One of the main challenges will be to create realistic distributions based on designer specifications. In the semi-automatic story creation, not all agents must be virtual. By allowing real people replace the virtual agents, we actually can turn a system into a multiplayer game. Such games can be used for educational purposes, as we have discussed earlier.

Another issue is to create dynamically changing states of virtual agents, if the agents display personality. Recently, we have shown that discrete-time Markov processes can be used for this purpose. We demonstrated that, with Markov processes working on physical and expression layers of our extended framework, it is possible to create never-ending stories semi-automatically [22]. We expect Markov processes will be particularly useful in this case since they can provide random but predictable results in long term for given agent ability, behavior and personality.

We believe that this representation can be great tool to test and verify assumptions about in a wide variety of applications beyond storytelling. To turn the general framework into a research tool to construct different models, a modular system for the visualization, design, and construction of models is needed. Such a modular system can be used effectively in a broad range of social science and economic applications by providing significantly more power than any deterministic model. For the implementation of such a system, the key is to implement the underlying structure as a simple software kernel, which can then help design and construct specific models for specific problems. The implementation of such a basic kernel is not really difficult because of conceptual simplicity of the general framework. Using such a kernel, it can also be easy to design and construct simple models, in which the number of agents is small and the number of states is limited. On the other hand, the real challenge will be the construction of the models with a large number of agents and states. Thus, a significant amount of effort needs to go to development intuitive interfaces that can help researchers in social sciences and economics to design and construct their own complicated model.

To achieve this goal, the kernel must be simple, extensible and allow modular development and provide strong visualization tools. This extensibility and modularity will allow to build a variety of user interfaces based on the same kernel. We expect that the classical theory of narratology can provide useful approaches for the development of some user interface concepts. For instance, it can be possible to automatically construct a model with large number of actants and behaviors based on the type of the stories that might exist in the model. For instance, if we want to create a model in which there will be one or two quest plots, a few love plots and one rivalry plot, we can automatically create main heroes and heroines. It is also possible to automatically create supporting actants such as a best friend, confidant or charmer. Events may mainly come from the actions of the main actants and the others just react those events.

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