Advances in Cognitive Systems 4 (2016) Submitted 4/2016; published 6/2016

Augmenting Mundane Narratives With Crowd-Sourced Semantically Interesting Events

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Abstract

Stories could be thought of as the currency of our collective social memory. In particular, stories that we tell each other about our daily lives play a significant role in our socialization. To understand what is worth telling a story about, and how to find, model and retell interesting event sequences from an interaction or observation, we have taken a crowd-sourcing approach to collect interesting events that can augment a mundane event sequence in an abstract story. We conducted a two-phase user study, in which a group of participants first augmented 3 abstract stories generated by Plot Graphs of 3 different domains, with semantically interesting events. In the second phase, a new group of participants were asked to rate the social interestingness of events of both kinds, when presented as a story. Results show significant preference for augmented events overall, and in 2 of the 3 stories when studies separately. This finding highlights the importance of identifying semantically interesting events in generating social stories from interactions and observations, and can provide a new methodology for doing so. Moreover, we report our results of learning models of such social interestingness, in terms of both predicting subjective ratings, and classifying events in mundane and augmenting types, using natural language features.

1. Introduction

Stories are an integral part of our human experience. We grow up listening to stories, and create new ones of our own by living our lives. Many of our values, beliefs, goals and cultural norms come from and are reflected in our stories. They also provide us with perspectives and mindsets, upon which a society functions and evaluates itself. Over centuries, storytelling has taken as many shapes as human imagination can find it in; besides obvious literature examples, movies and theater performances, songs of different genres, and even music, are all potential mediums of storytelling which have only evolved and improved through many generations of cultural development.

1.1 Significance of Social Storytelling

Beyond the mediums introduced above, storytelling is also present in our daily socialization. This form of storytelling is incredibly natural and intuitive, and in fact, it is so natural that at times it might be hard for us to be consciously aware of its role and importance in our lives. These are the stories that we tell our family and friends about our lives every day. Stories that go beyond tales and fiction and become personal, entail the events we have experienced or observed, the way they make us feel, and how they impact us. Such stories are not only integral to the wellness of our social relationships, but they also regulate and shape them. The act of telling a story to someone, the way it is told, the contents, details, timing and even our choice of words are social carriers, sending social messages, and constantly redefining our relationships.

An important aspect of social storytelling is its roots in real world. Communicating and socializing through stories that are rooted in such reality is an integral part of the process through which we come to make sense of our own and others' experiences as humans [1]. More formally, stories are our cognitive tool for situated understanding, and using this tool is central to the cognitive processes employed in a range of experiences from entertainment to active learning [9, 20]. In a developmental perspective, there has been more specific research on how children create their world view through building stories of their own [7], a process that arguably has great effects on the development of their personalities and values. Such findings can highlight just how inherent, essential and impactful social storytelling – and listening – is to our psychological, social and sociological wellness. Stories are, in a way, the currency of our collective social memory, the currency of our personal perception of the outside and inside world, and a currency with which we might plan and operate in the world, with us or those we know, as the characters.

1.2 A New Player in Our Social Landscape

Socialization is one of the most interesting, natural and beneficial phenomenons in the nature, and among different animals, humans could be perhaps fairly summarized as a showcase of its significance. Socialization is a deep bedrock for culture, morality, art, discovery, civilization and perhaps ultimately, all we call humanity. We strive to socialize every single day, and as a species, we consider removing this privilege from someone to be a sentence or even torture. This alone should reveal the extent to which we depend on this prime inherent need of ours, and just how instinctive the tendency to satisfy it can be. Another observation which can demonstrate the importance of socialization is that we, as humans, extend this tendency to non-humans [26]. In fact, we even assume social affordances [16] for objects [5], and interestingly, we do so through a similar process described earlier on how we create stories to make sense of our experiences and observations. In [12], this exact principle is stated as follows;

"*An object is transformed from a piece of stuff definable independently of any story-line into a social object by its embedment in a narrative.*"

With such perspective in mind on how we, as humans, show social tendencies toward a wide range of things and beings, and how we assume social affordances as we narrate our own world to ourselves, it should be clear how effectively socially engaging an intelligent agent sending social cues can be. As interactive things, intelligent agents are already subject to socialization by humans, but what truly boosts the potential for such agents is the fact that through natural language, voice, face, body, gestures and so many other properties and behaviors, we are constantly trying to make them be and behave like humans; causing an unmistakably intentional anthropomorphism. Adding the anthropomorphism effect to our already existing tendency to assume social affordances, introduces a unique arena for artificial intelligence.

The effectiveness of socially interactive intelligent agents has been demonstrated in numerous contexts and under various scenarios. It should come as no surprise that harvesting socialization, as a powerful tendency of humans, would result in significant effects. However, it is particularly the ever increasing list of applications and proven benefits of such interactive agents that has increased research in the related fields [11, 8], and has already commercialized simple forms of such social interactivity in the technology products of today (e.g., Apple Inc.'s "Siri", Alphabet Inc.'s "Google Now", Facebook Inc.'s "M" and Amazon.com Inc.'s "Alexa").

The attractiveness and benefits of such intelligent agents has made them a hallmark of modern artificial intelligence in both research and popular culture. In fact, this dependency of AI on social interaction might suggest an even deeper relation. As pointed out in [6], The Machiavellian Intelligence Hypothesis [4] suggests that primate intelligence was originally developed for solving social problems, and was only later extended to other domains. This is suggestive of a possible breakthrough in AI through attempts to create sociable agents, especially if we were to believe that what we call "Artificial Intelligence" can be recreated in similar ways in which cognition and intelligence evolved in primates and ultimately humans (more discussions in [27]).

1.3 Social Storytelling for Intelligent Agents

With such perspectives in mind, it seems very logical and rewarding to enable sociable agents - of any kind and form - to tell social stories about their possible interactions and observations. In fact, so much of our daily socialization and relations depend on such behavior that it might not be effective for such agents to socially engage humans without social storytelling capabilities.

Hence, to enable such behavior for sociable agents, we need to ask and answer many questions about finding the events, building the stories, telling the story, the social goals and effects in various situations, and more. However, perhaps most importantly, we have to ask the following;

What is an event sequence in an interaction or observation that could be regarded as an interesting social story if narrated?

In this paper, we focus on mundane event sequences generated by Plot Graphs [14], and attempt to augment them with new events that could potentially make the overall social story more worthy of telling. We then verify the assumption that such augmentations make the overall story more socially interesting, through a second phase of the user study. Lastly, we report our results of attempting to model such social interestingness – in terms of both predicting subjective ratings and classifying mundane and augmenting events – using natural language features.

2. Related Work

Story Generation is the process of selecting or creating a sequence of events that when narrated as natural language, visual graphics or sounds, will meet certain criteria of a narrative. Selecting or creating the sequence of events is usually done at the level of *fabula*, where each event is individually modeled (for instance using Plot Units [13]). The common criteria for evaluating a sequence as a narrative, is an outcome state, or is estimated using a dramatic arc [17, 21, 19]. Case-based reasoning [10, 25] and agent-based story generation [3] are also other approaches in generating narrative.

Most of the approaches explored in narrative generation, including the ones mentioned above, require an *a priori* knowledge of the domain. Story Intention Graphs [22] are one of the most comprehensive attempts in creating models of a domain, characters, their goals and beliefs. While having domain knowledge might be necessary or helpful in creating new stories about a specific scenario, it is not easy to create, learn or expand models about new domains.

A couple of exceptions that do attempt to generate stories without prior knowledge of the domain include the *SayAnything* [24] and *MakeBelieve* [15] systems. The former mines lines of text from a corpus of blogs scraped from the Web, and interactively generates a story initiated by a human. The latter extracts commonsense rules about action sequences from the Open Mind knowledge base. Both systems use open knowledge sources instead of modeling a domain. While this is an inspiration for our work, and a step in the direction we consider to be useful, it does not make attempts to close the loop of observing new events, and generating stories based on them; but rather, they merely replace the domain knowledge with open knowledge sources.

We believe that social stories do not happen in such vacuums of our choosing. Using the approaches developed thus far, story generation systems may not accomplish what humans accomplish every day, using social storytelling. Hence, we decided to focus on a different approach, where stories are not generated from a priori domain knowledge, simulations, models of characters, corpora or public knowledge sources; but rather, from social interactions and user studies.

3. Approach

In our efforts to generate social stories from interactions and observations, we have taken various approaches that each focus on a different aspect of social stories. In particular, we have focused on both Data Mining techniques, which are rather context-independent, and also semantic approaches, which attempt to learn and leverage the contextual importance of event sequences without assuming any prior knowledge about them.

In our context-independent efforts, we have particularly focused on using *Sequential Rule Mining* to find socially interesting event sequences based on heuristics such as frequency and novelty, and principles such as *expectation violation*. Early versions of our work in this domain can be found in [2]. We continue to enhance this branch of approaches and explore new algorithms to expand it.

We also believe that the semantics of frequent domains can compliment context-independent approaches. Semantically interesting event sequences are the ones that contribute to a social story, particularly because of a contextual property or relation. Such sequences might not be captured by context-independent algorithms at all, or may be highlighted or presented better after developing a semantic understanding. Although using a domain knowledge is extremely helpful in this respect, it can be also severely limiting from a generalization standpoint. Since we believe social storytelling to be important for sociable agents operating in numerous and sometimes unpredictable contexts, we decided to take a more expandable approach. To this end, and in this paper, we augment mundane event sequences, generated from Plot Graphs [14] with semantically interesting events.

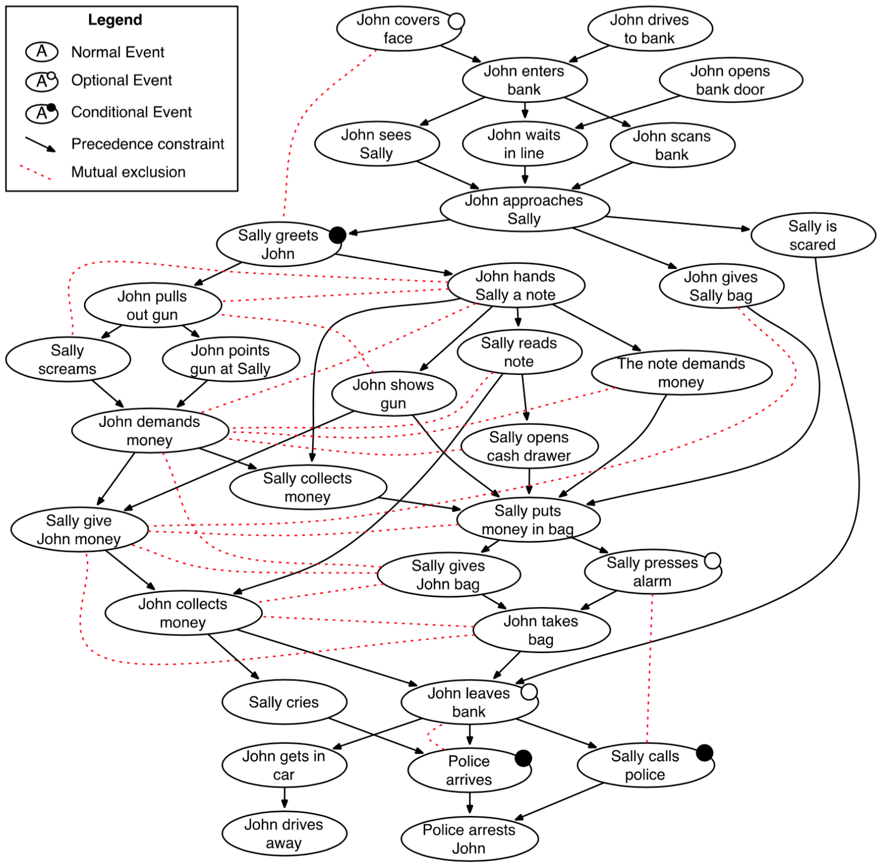

Figure 1: A sample Plot Graph capturing possible mundane event sequences in a bank robbery. Figure adopted from [14].

3.1 Plot Graphs

Plot Graphs capture various paths that event sequences in a given context could follow. While each Plot Graph is related to a specific context, there is no prior model that they depend on. Plot Graphs are purely generated from crowd-sourced events that human users have entered into the system, upon being asked to describe the high-level events in a certain context or scenario (e.g., eating at a restaurant). The system in [14] will then create nodes for those events on which many users have agreed, and after assigning precedence, the overall result is a graph which describes how different event sequences in the given context can proceed. Plot Graph nodes maintain a temporal partial ordering, and have different properties and relations with each other, such as being optional or mutually exclusive. A *path* in a Plot Graph is analogues to an *instance* of the story.

4. User study

Our user study consisted of two phases, a crowd-sourcing phase to collect the semantically interesting augmentations, and a second phase to verify the hypothesis that such augmentation are subjectively more interesting to a new audience, than the mundane (but critical) events generated from the Plot Graphs.

We used 3 stories instantiated from 3 different plot graphs. The stories were about a *bank robbery*, *dining at a restaurant*, and going on a *plane flight*. "Stories" here, as explained before, are generated paths in the respective Plot Graphs, and therefore translate into a *sequence of events*. Each event is a short sentence, usually containing less than 20 words. These 3 event sequences (set of sentences) were the input for our first phase. Tables 1, 2 and 3 list every event in the 3 stories.

For both phases, our participants were university students who did not research on story generation. The participation was made through online digital forms and questionnaires. Each participation, in both phases, took between 15 and 30 minutes.

4.1 Phase I: Crowd-Sourcing

During the first phase of the study, we provided each participant with one of the 3 stories, and asked them to add an event in between every two events in the original sequence. We did not specify what kind of event can be added, and the only limitation was to use short events, suggesting, but not enforcing, only one sentence. Original events could not be edited by participants, but they could use the opportunity of a "new event" to elaborate on the prior ones.

Moreover, all of the events in the story were available to a participant at all times. We chose this approach to allow our users to scan back and forth through the story while adding augmenting events, and to be able to use their imagination better accordingly. Furthermore, since Plot Graph nodes (events) are not editable, they limit the overall events of the story in a significant way. For instance, the plane can never "crash" during the Plane Flight story, since we have the event of landing as an original node. Hence, providing the entirety of the original events all at once can also assure us that the participants would not find conflicts between the original events and theirs.

We recruited 12 participants for this phase. We assigned every participant only to one story, and therefore 4 augmentations for each story, and a total of 12 augmentations was achieved.

Participants had the option to skip adding an event if they chose to do so. There were less than 5 skipped augmentation chances in all stories across the participants.

4.2 Phase II: Rating the Events

In order to verify the hypothesis that augmenting events make a mundane sequence of events ("a generic story") more semantically interesting, we conducted a second user study.

In this phase, we firstly generated augmented stories from the results of the first phase in the following way. For every story, and between every two mundane events, we randomly chose and inserted one augmenting event out of all augmenting events written by the participants of the first phase for the same position of the same story. This allowed us to make sure that the added events are merely "augmentations" to the semantics and context of the story, rather than a specific event sequence that any particular participant could have planted in between the events to create a new

Table 1: The bank robbery story used in the study, generated from the respective Plot Graph.

1	Jack puts on a mask
2	Jack enters the bank
3	Jack pulls out a gun
4	Jack shoots gun in the air
5	Jack asks teller to put gold in bag
6	He also gets money from customers
7	Jack leaves the bank
8	Jack gets into car
9	Bank guards fire guns
10	Jack gets away

Table 2: The restaurant story used in the study, generated from the respective Plot Graph.

1	Sally calls a restaurant and makes a reservation for tonight
2	When it's time, she drives to the restaurant
3	She meets her friend by the door
4	They ask for a table
5	Sally and her friend are then seated
6	They look at the menu
7	Waiter comes and introduces self
8	They order drinks and food
9	Then the food arrives
10	And they eat they finish their dishes
11	Sally and her friends then pay for the food
12	They tip the waiter
13	They leave the restaurant

Table 3: The Plane Flight story used in the study, generated from the respective Plot Graph.

1	John walks through the airport door
2	He receive his boarding pass
3	And checks in his bags
4	He then waits in line for security check
5	John goes through security
6	After security, he then buys a sandwich
7	He waits in line to board
8	He boards the plane and looks for his seat
9	He finds the seat
10	John then places his luggage
11	He sits on his seat and fastens seat-belt
12	Plane takes off
13	John watches a movies
14	Plane lands
15	He picks up his luggage
16	And exits airport

parallel narrative. In other words, if one participant augmented the story with new events that are causally dependent on each other, then evaluating the resulting augmented story would arguably evaluate that specific augmentation, and not the phenomenon of a semantically augmented story. Hence, we tried to minimize such cases with the aforementioned strategy.

We generated 6 such augmented stories, and asked a group of new participants to rate, on a 5-point Likert scale, how much each event contributes to the overall social story being more interesting. This time, we provided participants with one event at a time, while they had access to all of the prior events at every given point. We recruited 6 participants for this phase, and each rated the events of 2 of our 6 augmented stories, resulting in 2 set of ratings for every story. An example of an augmented story provided to the users is seen in Fig. 4.

Table 4: An example of an augmented story provided to the users in phase 2 of our study. The lines on even numbered rows (also in *italic*) are augmented events, each randomly chosen among the augmentations of the phase 1 participants, for the same story and same position.

1	John walks through the airport door
2	*and stands in the check-in line*
3	He receive his boarding pass
4	*and seat assignment*
5	And checks in his bags
6	*and grabs a bite to eat*
7	He then waits in line for security check
8	*along with 40-50 other travelers; he wonders where each of them is headed*
9	John goes through security
10	*While going through security, his tummy begins to grumble*
11	After security, he then buys a sandwich
12	*and an apple from a deli catering to travelers on-the-go*
13	He waits in line to board
14	*and a baby throws up on him*
15	He boards the plane and looks for his seat
16	*the air hostess greets him*
17	He finds the seat
18	*he was looking for - aisle seat 23C - next to a mother and baby.*
19	John then places his luggage
20	*in the overhead compartments.*
21	He sits on his seat and fastens seatbelt
22	*taking a quite shot of courage*
23	Plane takes off
24	*and John watches the houses and cars below fade into tiny specks of nothingness.*
25	John watches a movies
26	*and falls asleep in the middle*
27	Plane lands
28	*in Cambodia, a place completely foreign to him.*
29	He picks up his luggage
30	*from the disorganized collection area*
31	And exits airport
32	*into a new world of sights and smells, eager to explore.*

4.3 Results

To investigate if there is a significant difference between the ratings in the phase II of the study, we used the Mann-Whitney U test between the augmented and mundane set of ratings of each story, and also overall. The results, along with a one-tailed p-value are provided in the Table 5 below.

Table 5: The results of the phase II of our user study. “m-mean” refers to the average rating of the Mundane events in the story, while “a-mean” refers to that of the Augmenting events. The p-value is the result of a one-tailed Mann-Whitney U test (the *U-value* of the Mann-Whitney test indicated an approximately normal distribution in all of our tests, and therefor *Z-value*s and the resulting p-values could be trusted).

Story	**m-mean**	**a-mean**	**p-value**
Bank Robbery	2.93	3.28	0.1
Plane Flight	1.28	1.75	**0.001**
Restaurant	1.87	2.83	$\ll$ **0.001**
Overall	1.89	2.5	$\ll$ **0.001**

4.4 Discussion

Overall, we see a strong confirmation that augmenting events contribute significantly more than mundane events, to the overall sequence being a better social story. While this might sound as expected, it is important to note that this finding is not necessarily obvious, since the main (mundane) events of the story shape the overall structure and the “arc” of the narrative. Moreover, this finding can suggest that the motivation for telling a social story is often not the mundane events, but rather the semantic details in between them, which may seem subjectively, socially and culturally more interesting.

We believe that the nature of the Bank Robbery story has made it a generally more interesting story (highest rating averages), however, the relatively short length of the story might have prevented the phase I participants from engaging with the context, and providing deeper and more semantically interesting augmentations. Moreover, we imagine that the higher mean ranking of the augmented events in Restaurant story, compared to the Plane Flight story, could have been the result of having an extra character (Sally’s friend) in the story. Theoretically, more characters could drive more imagination and result in more interesting augmenting events, and we intend to investigate the effects of such narrative level features on social interestingness of the stories in future.

5. Building Models of Social Interestingness

Learning about events that can contribute to building a social story, in a given context, is very valuable. As pointed out before, repeating contexts of interaction could be a target for semantic approaches, for which a sociable agent could use models of semantically interesting event sequences. In particular, we imagine such approach to be more generalizable than many alternatives.

To this end, we attempted to build models of interesting events, which can best contribute to a social story, using fairly simple natural language features. Such models are purely based on crowd-sourced mundane and augmenting events, and their subjective ratings by our users. We imagined two different learning tasks; 1) modeling the subjective ratings through regression, and 2) building a binary classifier for predicting event types (mundane vs. augmenting).

5.1 Features and Dataset

We selected our features based on a common subset of part-of-speech tags used in text classification tasks. The features used for both of our learning tasks can be found below. We normalized our features when using algorithms in which normalization could have an effect.

1. number of words
2. number of verbs
3. number of nouns
4. number of adverbs (e.g. *naturally*)
5. number of adjectives (e.g. *big*)
6. number of interjection (e.g. *haha*)
7. number of particles (e.g. give "*up*")
8. number of determiners (e.g. *the*)
9. number of propositions (e.g. *in*, *of*, *like*)
10. number of cardinal numbers (e.g. *1*, *third*)

Our user studies of previous sections resulted in a fairly small dataset of 106 unique instances. These instances are user ratings performed on every unique sentence, where the rating associated with every sentence is the average rating assigned to it by different participants.

5.2 Classification Results

Using the features above, we tried various learning algorithms to build a binary classifier that can predict the type of a new event as *mundane* or *augmenting*. Out of 106 instances, 67 were augmented and 39 were mundane. We used 5-fold cross-validation for testing the models.

We found that BayesNet algorithm yields the best results out of most common learning techniques, with only a Stacked approach [28] (when using both BayesNet and Neural Network) yielding slightly better precision and recall, Table 6.

Table 6: Binary classification results (weighted average for instance of both classes). The stacked method is using both BayesNet and Neural Network.

Algorithm	Precision	Recall	F-Measure	ROC Area
BayesNet	0.845	0.792	0.796	0.83
Stacked	0.85	0.802	0.805	0.843

5.3 Regression Results

In our regression task, we tried to use the same 10 features introduced earlier to predict the rating associated with every sentence. In this dataset, mundane sentences had 4 associated ratings each, and hence we used the average of ratings for each sentence. Augmenting sentences, however, had between 2 to 4 ratings each ($\sim$2.5 in average), and likewise, the average of these ratings was assigned to each augmenting sentence. The reason for having various numbers of ratings for augmenting events is the randomness introduced in second phase of our user study.

We found that Support Vector Regression (SVR) [23] yields considerably better results than linear regression. Here too, we used 5-fold cross-validation for testing the models. It is worth noting, for comparison purposes, that the mean standard deviation of all ratings was **1.07**. Table 7 contains the main results of our regression models.

Table 7: Regression results (weighted average for instance of both classes). RMSE denotes the Root Mean Squared Error. The data is normalized. Support vector regression used a sigmoid kernel. The mean standard deviation for all ratings is 1.07.

Algorithm	Correlation Coefficient	RMSE
Linear Regression	0.464	0.872
SVR	0.557	0.845

6. Conclusion and Future Work

In this paper, we have discussed an approach to augment a mundane sequence of events in a story, with semantically interesting events, through crowd-sourcing. We find that participants see augmented events to be significantly more interesting, in contributing to a social story, than the mundane ones. This is particularly important considering the ways in which we consider a sequence of events in our daily lives to be worthy of telling a social story about. Moreover, using natural language features, we have built models of such social interestingness for the aforementioned events. Specifically, we attempt to classify a new event as a semantic augmentations or a mundane event. We also try to estimate the subjective social interestingness rating for new instances through regression models.

Extending Plot Graphs. As an immediate future work, we are planning to use the crowd-sourced augmented events to *extend* Plot Graphs with new nodes that can capture possible semantically interesting events. Such new nodes can be created using the same techniques used for creating original Plot Graph nodes, through crowd-sourcing. Fig. 2 depicts such possible extension for a subset of a Plot Graph.

Furthermore, we plan to use features other than those from natural language in order to build models of socially interesting events. For instance, narrative level features, such as *the introduction of a new character* could be worth investigating. It would be also interesting to use a more powerful

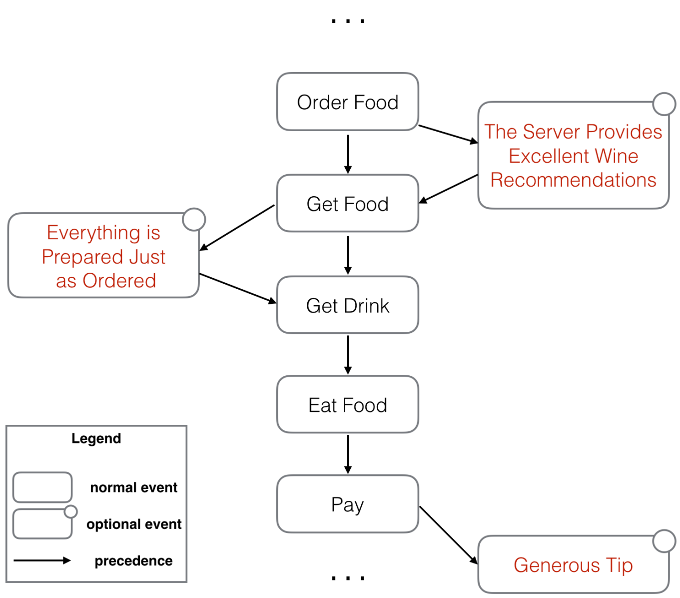

Figure 2: A subset of a Plot Graph extended with possible optional events which demonstrate socially interesting events. This simplified demonstration needs to be further refined in order to better capture the relationships between the extension nodes.

feature selection technique, for instance the one used in [18], in which for classifying *humor*, the authors have enforced classifiers to identify humor-specific features by supplying them with negative examples that do not introduce major differences in other aspects. This method is particularly interesting since we naturally have access to such positive and negative examples, as mundane and augmented events. Lastly, although gaining precision and significant results using limited data is desired when it comes to generalizing to other domains, we intend to perform larger scale studies with more story instances, and significantly more participants, when combining various branches of our work.

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