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A Force Dynamic Model of Narrative Agents

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Abstract

Emergent narratives are dependent on the behaviour modelling of agents in the storyworld. Typical approaches to behaviour modelling, however, overly encourage individual goals and needs, ignoring the dynamic interpersonal relations needed to create rising and falling conflicts. In this paper, we present a force dynamic agent model, in which relations and goals are modelled as forces, with the state of an agent treated as a physical object within an abstract space representing narrative tension. Building off previous work, we implement a test-bed and scenario in the Unity Game Engine. We show, through experimentation, that the dynamic force-based model causes the emergence of conflict curves mirroring traditional narrative perspectives. We conclude that an abstract physical modelling of narrative agents is able to embed several desirable properties for emergent narratives, namely, continuous conflict, dynamic interpersonal relations and temporal and strength modelling of the impact of individual actions.

Introduction

In an agent-based simulationist emergent narrative (EN), the actual narrative in question is considered an emergent property of the agent behaviour, and the plot is constructed through the actions taken by agents in consideration of their relation with the world model and other agents. In many examples of EN, such as *The Sims* (Maxis 2000) or *Crusader Kings II* (Paradox Development Studio 2012), however, the focus is on behaving *internally* (i.e. maximizing the needs, desires or goals of the individual) or by implementing complex global systems to simulate weather, economy, politics, etc. Often, in spite of the internal system complexity, emergent narratives are dull or produce interesting results only insomuch as they highlight the limitations of the system (Sych 2020). This sense of EN's being both highly complex and costly to design, but also somewhat mysterious in their ability to create narratives, often makes them inaccessible or unreliable, and often artificial systems such as drama management are used to more reliably produce dramatic behaviour (Roberts and Isbell 2008).

In this paper we present a simple, reaction based behaviour model for narrative agents, designed to encourage the emergence of *conflict curves*, i.e. steady rises and falls in conflict, as well as simple rivalries and friendships, without the use of drama management, memory, or relationship modelling. We propose that an alternate approach to the challenge of EN design is by instead focusing on the intrinsic properties of a small set of behaviours acting as an immediate reaction to the state of the simulation. Examples of such simulations include flocking behaviours from (Reynolds 1987), and life simulations from (Schmickl, Stefanec, and Crailsheim 2016), which use a few simple rules to generate complex interesting behaviours. The behaviour in this model is based upon *force dynamics*, a semantic model of causation originally proposed by (Talmy 1988) and the resulting model is implemented as an extension in the existing EN system from (Kybartas, Verbrugge, and Lessard 2021) where ENs are modelled abstractly as agents in a physical space. The intent with this model is not to claim its better to traditional models or approaches to EN, but rather to explore how an alternate approach to EN modelling can create many of the ideal properties of a narrative in a simplified, extensible manner. We identify three main contributions in this paper:

- The development and definition of a force-based model of narrative agents.
- The implementation of the model, user interface, and a corresponding testbed in the Unity game engine.
- An evaluation to analyze the emergent properties of the behaviour model

Background and Related Work

The force dynamic system presented in the paper is inspired by previous work on modelling and analyzing a possible worlds model of narrative agents for EN (Kybartas, Verbrugge, and Lessard 2021). In the following a section, a brief introduction to the background of this research is provided, as well as the theory behind *force dynamics*, in which causation is modelled using a simplified physical force model. This section further reviews related work which overlap or reinforce the work presented in this paper.

The Possible Worlds Model

The foundational system which is used in this paper is based on the narratological theory of *possible worlds* (PW), particularly the work of (Ryan 1991). Ryan's work models characters as a set of possible worlds, representing ideal states of the narrative's actual world. Throughout the course of a narrative, characters attempt to take actions which align the actual world with each of their ideal worlds, leading to conflicts whenever one or more character's ideal worlds mismatch, preventing an overall "ideal" in which all characters are satisfied. (Kybartas, Verbrugge, and Lessard 2017) designed and implemented a possible worlds model based off of Ryan's, in which worlds are modelled by a vector of numerical values indicating the state of the world, with characters evaluating actions based on how much the action will reduce the distance (taken as the Manhattan distance) between the actual world and one or more ideal thematic worlds, with the overall goal of having the distance for each thematic world be equal to zero. (Kybartas, Verbrugge, and Lessard 2021) found, through further analysis of the system, that the emergent narrative could be modelled as a set of physical *tension spaces* for each character, with each axis representing one ideal world and its distance to the actual world. Thus taking an action involved a corresponding physical movement in this space, in how it reduced, or increased distance between each thematic world and the actual world.

World and worldview models have been explored elsewhere in the interactive narrative community. (Harrell 2013) proposes using worldview models to represent different cultures and ideologies, which can then be explored and critiqued through a variety of interactive digital media. In work by (Harrell et al. 2018), ideological models were represented as a worldview using a numerical vector model, and where the distance between a certain ideology and a specific individual could represent how the individual is identified, or chooses to identify. (Sgouros 2015) similarly used a model in which each character's point of view and beliefs are entirely independent to that character. (McCoy et al. 2014) also model different social groups with internal rules and worldviews, as part of a large *social physics engine* to be used within EN games.

Force Dynamics

Force dynamics, as introduced by (Talmy 1988), modelled causation in linguistics as an interaction between forces, in which a protagonist object is assisted or hindered by an antagonizing force, and the result of this interaction. As an example "The wind stopped the ball rolling down the hill" involved a protagonist force, the ball's movement, being hindered by the antagonist force, the wind, which halts the ball's movement. Further examples explored how the same force dynamic model could apply to abstract situations, such as in the phrase "He found it hard to get out of bed", where the protagonist force is a desire to get up, and the antagonist force being whatever mental or physical state is hindering the subject of the phrase. Experimentation from (Wolff 2007) found that participants were easily able to determine the force dynamics occurring in computational physical and social simulations. (Wolff and Zettergren 2018) later formalized force dynamics into a computational vector model, again showing participant's interpretations of a physical scene closely represented what was predicted through the vector model.

Being able to read the causal forces between abstract objects was also linked to narrative in the work of (Heider and Simmel 1944), who found that participants were able to identify and retell similar stories from a highly abstract animation of moving shapes. Using crowd-sourced results from an online animation creator in the style of Heider and Simmel's work, (Roemmele et al. 2016) attempted to use machine learning to predict which "actions" were occurring based on the motions of specific shapes. The results, however, indicated that the motion trajectories were not enough to reliably predict the action occurring in the narrative. Contrastingly, Work from (Crick and Scassellati 2008) focused on identifying simple narratives occurring in abstract children's playground games, which was done by instead viewing the children's motion trajectories as the results of attractive and repulsive forces between children (who was escaping who, who was chasing who, etc.). Further research showed that robots were able to learn and participate in alongside the children in these games (Crick and Scassellati 2009). (Zhu and Ontanon 2010) explicitly used a force dynamic model in their work with the *Riu* system, in which narratives are generated by a conceptual blending process that aims to match different narrative's force dynamic structure to create analogies between them.

The Force Dynamic Model

In this section we formally present the force dynamic model of narrative agents, using and extending the existing the emergent narrative system of (Kybartas, Verbrugge, and Lessard 2021), and further discuss the implementation of the narrative testbed in Unity.

The Force Dynamic Model

In its simplest form the force dynamic model can be described according to four behaviours:

1. **Gravitational Force** - A narrative agent will always wish to move to a point of zero personal conflict. This desire grows the more conflicted an agent is.
2. **Interpersonal Forces** - An agent will react to any change in personal conflict caused by other agents by attempting to cause the same change back to the other agent. This reaction will be added to any existing interpersonal force acting against the other agent.
3. **Witness Scale** - If an agent witnesses an action, but is not directly involved in it, the impact of this action is reduced as is the resulting interpersonal force.
4. **Friction Coefficient** The gravitational force is constant, interpersonal forces decay per time step according to a friction coefficient.

The goals of the four behaviours are as follows. The gravitational force provides a continuous motivation to characters, meaning even in the absence of other forces the character's will still move towards an internal goal. The interpersonal forces provide the immediate, reactive forces to changes in the simulation. Since interpersonal forces would grow unbounded with Behaviour 2, a friction force models

Figure 1: The emergent narrative test bed, with each different panel labelled from one to six. The panels of the UI are roughly as follows: (1) are tweakable parameters representing the coefficient of friction as well as the falloff of action intensity when witnessed. (2) provides details of the current interrelations between a selected character. (3) provides detailed information about low level performance of the system. (4) is one of the major panels, it provides the controls for the simulation as well as a real time rendering of the current level of satisfaction/conflict in the system or a selected character. (5) is a text window showing a rough textual output of the "story" being created by the system. (6) displays detailed information about each character, their perceived actual world, avg. satisfaction, etc.

the falloff of interpersonal force over time. A friction coefficient of 1 means that interpersonal forces essentially reset every time-step, while 0 allows for unbounded growth. The witness scale defines the impact an action has on those who witness it. A scale of 1 means the witness receives the full impact of the action, and 0 means there is no impact. The witness scale also creates a reaction following the rules of Behaviour 2. In the current model, we make no assumptions about how an agent witnesses an action, as such all characters behave as witnesses for every action. Future work aims to explore the impact of different witness models, eg. proximity, visual, auditory, etc.

Formally, the force dynamic model is defined as a narrative N, where $N = \langle P, T, C, A, \sigma, \alpha \rangle$ where P is a set of *propositions*, T is a set of *themes*, C is a set of *characters*, A is a set of *actions*, σ is the *friction coefficient* between zero and one, and α is the *witness scale*, also between zero and one.

A character c is defined as $c = \langle w_p, W_t \rangle$ where w_p is the *perceived actual world* and W_t is a set of *thematic worlds*, one for each theme. The w_p is a vector of length $|P|$ with each value w_{p_i} corresponding to the perceived current value of the proposition p_i according to c.

A thematic world w_t is defined as $w_t = \langle w_s, w_c, \delta_s, f_g, F_i \rangle$ where w_s is the *satisfaction world*, w_c is the *conflict world*, δ_s is the *satisfaction filter*, f_g is the *gravitational force*, and F_i is the set of *interpersonal forces*, one for each of the others character in C.

The satisfaction world, w_s is a vector of length $|P|$ with each value w_{s_i} corresponding to the current satisfaction (between 0 to 1) of proposition p_i according to $c.t_w$. The satisfaction filter δ_s is a vector of *functions*, of size $|P|$ where each function δ_{s_i}, when passed p_i as a parameter, gives the corresponding value in the satisfaction world w_{s_i}. Essentially, the satisfaction world can always be calculated by applying the satisfaction filter to the perceived actual world $\delta_s(c.w_p) = w_{s_i}$. For each satisfaction world, a *conflict world*, w_c, is calculable by taking a vector of ones of size $|w_s|$ and subtracting w_s from it. This instead gives the amount of conflict for each proposition. At any given time the gravitational force is the distance from the conflict world to the zero origin, i.e. $f_g = -w_c$. Each interpersonal force f_i is the direction character c wishes character c_i to move, according to thematic world w_t.

Since a character is a collection of thematic worlds, each differently satisfied, we say that a character's position φ_c is a matrix of size $|W_t| \times |P|$ where $\varphi_{c_{i,j}} = c.w_{t_i}.w_{c_j}$. Essentially, the character's position is their overall conflict for each thematic world. Similarly the overall gravitational force ψ_c is a matrix of size $|W_t| \times |P|$ where $\psi_{c_{i,j}} = c.w_{t_i}.f_{g_j}$ and the interpersonal force of character c_i to character c_j is ϕ_{c_1,c_2}, a matrix of size $|W_t| \times |P|$ where $\phi_{c_1,c_{2_{i,j}}} = c_1.w_{t_i}.f_{i_{c_2}j}$.

An action a is defined as $a = \langle i, R \rangle$ where R is a set *roles* and i is a required role, called the *instigator*, which will be mapped to the character taking the action. A role r is defined

Algorithm 1 One Timestep in the Narrative

function STEP(Narrative n)
  for $\forall c \in n.C$ **do**
    for $\forall f_i \in n.C.w_p.F_i$ **do**
      $f_i = f_i - (n.\sigma * f_i)$
  $c_i \leftarrow$ SelectCharacter($\in n.C$)
  $M, a \leftarrow$ ACT(c_i, n)
  for $\forall c \in n.C$ **do**
    APPLY(c, a, M, c_i)

as $r = \langle \delta_c, \delta_e \rangle$ where δ_c is a *condition filter* and δ_e is an *effect filter*. Given a perceived actual world of some character, the condition filter will return a vector where each value will be 0 if the condition is not met, and 1 if it is. The condition for an action is said to be *met* for a character c if each value of $\delta_c(c.w_p)$ is equal to 1. Common examples of condition filters would be to check if a value in the w_p is greater than a certain amount, or equal to it, etc. The effect filter, when applied to a character's perceived actual world, will set the world to new values according to each function. Common examples here might be increasing or reducing a particular value in w_p or setting it to something entirely different. An action is said to be *valid* if there exists at least one unique character that meets the condition for each role, and false otherwise. If an action is valid then there exists a mapping $M(C) \to R$ which maps a set of characters C onto the set of roles R (including the instigator i). If an action is taken, each role will apply the effect filter to the character mapped to that role.

If a character's perceived actual world is modified either directly by an action, or indirectly by witnessing an action, both φ_c and ψ_c will be updated between the time t_1 before the action, and the time t_2 after the effect filter is applied. Formally, given an action a and character c in role r then, we say the *movement* of c in role r of a is equal to the change in position, ω, i.e. $\omega_{c,a,r} = \Delta\varphi_c = \varphi_{c_{t_2}} - \varphi_{c_{t_1}}$. If a character *witnesses* an action, then they receive the equivalent of the effect filter, however the impact is scaled by α the witness scale. Essentially for a witness c_w the change in position is equal to $\omega_{c_w,a,i} = \alpha \times \omega_{c,a,i}$. Currently the witnesses are not impacted by the effects for other roles, but this remains interesting future work.

The functioning of the system is summarized using pseudocode, and occurs in a simple loop structure, where each loop performs one STEP, as shown in Algorithm 1.

Algorithm 2 Action selection procedure

function ACT(Character c, Narrative n)
  $score \leftarrow$ List of scores
  for $\forall$ valid M for $n.A : M(c) = n.A.i$ **do**
    $score.Add($SCORE$(M, n.A.i, C))$
  if $|score| > 0 \wedge max(score) >= 0$ **then**
    return $(M, n.A)[max(score)]$
  else
    return $null$

Algorithm 3 Action scoring function

function SCORE(Mapping M, Action a, Character c)
  $score \leftarrow 0$
  $score = score +$ SIMILARITY$(c.f_g, \omega_{c,a,i})$
  for $\forall c_r \in M(C) : c_r \neq c$ **do**
    $score = score +$ SIMILARITY$(c.f_{i_{c_r}}, \omega_{c_r,a,M(c_r)})$
  return $score$

Algorithm 4 Similarity function

function SIMILARITY((Desired) Matrix m_d, (Actual) Matrix m_a)
  $m_s \leftarrow$ Empty matrix the size of m_d
  for $\forall (i,j) \in |m_s|$ **do**
    if $Sign(m_{d_{i,j}}) \neq Sign(m_{a_{i,j}})$ **then**
      $m_{s_{i,j}} \leftarrow -(|m_{d_{i,j}}| + m_{a_{i,j}})$
    else if $m_{d_{i,j}} = 0$ **then**
      $m_{s_{i,j}} \leftarrow -|m_{a_{i,j}}|$
    else if $|m_{a_{i,j}}| > |m_{d_{i,j}}|$ **then**
      $m_{s_{i,j}} \leftarrow |m_{d_{i,j}}| - |m_{a_{i,j}}|$
    else
      $m_{s_{i,j}} \leftarrow |m_{a_{i,j}}|$
  return $Avg(m_s)$

Essentially at each step characters apply the coefficient of friction for Behaviour 4. Following this a character is optionally selected to act, we purposefully leave this ambiguous as many valid character selection procedures are possible. If a character is selected, they try to find a valid action and mapping using Algorithm 2, using a scoring method to maximize the best action choice.

The scoring procedure is shown in Algorithm 3 and consists of finding an action and mapping that best matches their personal gravitational force (Behaviour 1), and the desired impact of the action on the other characters in the mapping (Behaviour 2). The similarity score between a desired and actual force is shown in Algorithm 4 and scores forces based on how close they are to the desired force without exceeding it or moving in the opposite direction. Lastly, if an action is selected, each character applies the action to their perceived actual world and updates their interpersonal forces towards the instigator as needed (Behaviour 2 and 3), this is shown in Algorithm 5. It is notable that using discrete actions still limits the ability of the agent to move perfectly according to their desired forces. While discretized actions are easy to author and evaluate, future work aims to look at the creation of parameterizable actions, whose magnitude or even directions can be varied to more closely match the desired vector of the agent.

Implementation

As with the possible worlds model, the extended force dynamic model was implemented within the Unity game engine. At this stage, a testbed was also developed which allows the system to be run with any given content, allowing for tweaking of the simulation speed, live adjustment of dif-

Algorithm 5 Apply Action

function APPLY(Character c, Action a, Mapping M, Instigator c_i)
  if $c = c_i$ **then**
    $c.w_p = c.w_p + \omega_{c,a,i}$
  else if $\neg c \in M$ **then**
    $c.w_p = c.w_p + \alpha \times \omega_{c,a,i}$
    $c.f_{i_{c_i}} = c.f_{i_{c_i}} + \alpha \times \omega_{c,a,i}$
  else
    $c.w_p = c.w_p + \omega_{c,a,M(c)}$
    $c.f_{i_{c_i}} = c.f_{i_{c_i}} + \omega_{c,a,M(c)}$

ferent parameters and multiple forms of output. A screenshot of the resulting system can be seen in Figure 1. The implementation was designed as a simple way to observe multiple parameters of the system as it runs. Importantly, panel 4 charts the average level of satisfaction across all characters, or a specific character by selecting a character in the drop-down menu. Many of the behaviours we will want to observe during evaluation will be represented using this graph. These results are also dumped to a csv file for further evaluation as necessary.

The implementation also involved the creation of a number of simple scripts, allowing the majority of the narrative model to be authored using plain text, that can either be loaded as a file or written directly into the Unity editor. Using this model, a testbed was developed for evaluation and experimentation purposes. The testbed includes nine characters, three propositions, three themes and sixty actions. Using this testbed as an example, we can demonstrate the authoring process of the narrative model.

Propositions and themes are defined using simple text arrays. In the testbed the propositions and themes are as follows:

```
Propositions: [Severity, Energy, Aggressive]
Themes: [Personal, Elite, Populace]
```

The setting of the testbed world is a negotiation taking place in a fantasy world with elves, humans and dwarves. The propositions are used to describe the *mood* of the negotiations, i.e. are the agents being *severe* (0 = happy, 1 = serious), *energetic* (0 = peaceful, 1 = boisterous), or *aggressive* (0 = passive, 1 = aggressive). The themes related to the perspectives that each character has about how they should ideally behave during a negotiation, i.e. how do they *personally* want to behave, how do the *elites* want them to behave and how does the general *populace* behave.

A character is defined by providing a name, and a set of satisfaction filters for each theme. Currently, the perceived actual world and forces are initiated automatically. An example character definition is as follows:

```
Ophelia: Personal: [^0, ^0, ^0]
         Elite: [^0, ^0, ^1]
         Populace: [^0, ^0, ^1]
```

The character in this example is called "Ophelia" and has three thematic worlds for each of the themes listed above. The arrays use a simple *symbol*, to define which satisfaction filter is used, and an optional *value*, to provide a parameter to the filter if it is needed. In this demo, the satisfaction filter is always $\wedge$ and some value v. $\wedge$ refers to a *linear falloff* filter, defined as $\wedge(c.w_p, v) = |v - c.w_p|$. So, as an example, in Ophelia's personal world she ideally wants the negotiations to be happy, peaceful and passive, each being 0, resulting in $\wedge 0$.

The action script uses a simple definition of action name and the action pre/post-conditions for each role. Below is an example for the definition of the "Insult" action:

```
Insult: (Agent;[x,x,x];[i,i,+0.4])
        (Recipient;[x,x,x];[i,i,+0.4])
```

In this example, an x condition filter is $x(c.w_p) = 1$, so the filter will always return true for any proposition. Therefore the $[x, x, x]$ precondition essentially means there are no preconditions for either role on the insult action. For the postcondition filters, i refers to the identity filter: $i(c.w_p) = c.w_p$, meaning the action does not change the proposition of the world as a result, and $+4$ means to use an addition filter $+$ with parameter 0.4, i.e. $+(c.w_p, 0.4) = c.w_p + 0.4$). In the testbed the third parameter refers to the Passive/Aggressive environment of the negotiations, meaning that the insult action will raise the perceived aggressiveness of the negotiation for both characters. The script compiler is easily extensible, meaning new filters can be added by defining new symbols in the compiler.

The output of the test world is rendered through text, with each action generating a line of text that is added to the overall "story output" of the emergent system. Each action's textual output is rendered using a custom *string grammar* system. The system allows both for basic string grammar functionality, but also includes functions to reference internal system values at the time the string is expanded, and also conditionals to only allow certain expansions if conditions within the system are met. The output for our insult example is defined as follows:

```
Insult: "What a [BadAdjectives] [BadNouns]
        you are, <Recipient.Name>!"
        mutters <Agent.Name>;
```

[BADADJECTIVES] and [BADNOUNS] both refer to symbols in the grammar (not shown here), and may be expanded to e.g. "foul peasant", "pitiful dog", etc. $<$ RECIPIENT.NAME $>$ and $<$ AGENT.NAME $>$ both tell the grammar to fetch the names of the recipient and agent to be inserted into the final rendered text. So if the recipient is Heliodor and the agent is Dracaena, the result would be something like *"What a pitiful dog you are, Heliodor!" mutters Dracaena.*

Evaluation

At this stage of development, our interest is in being able to create certain emergent properties which are linked to abstract narrative "qualities", namely varying relations and moments of tension. We evaluate this using the conflict curve results rendered in the Unity testbed. The desirable properties are as such:

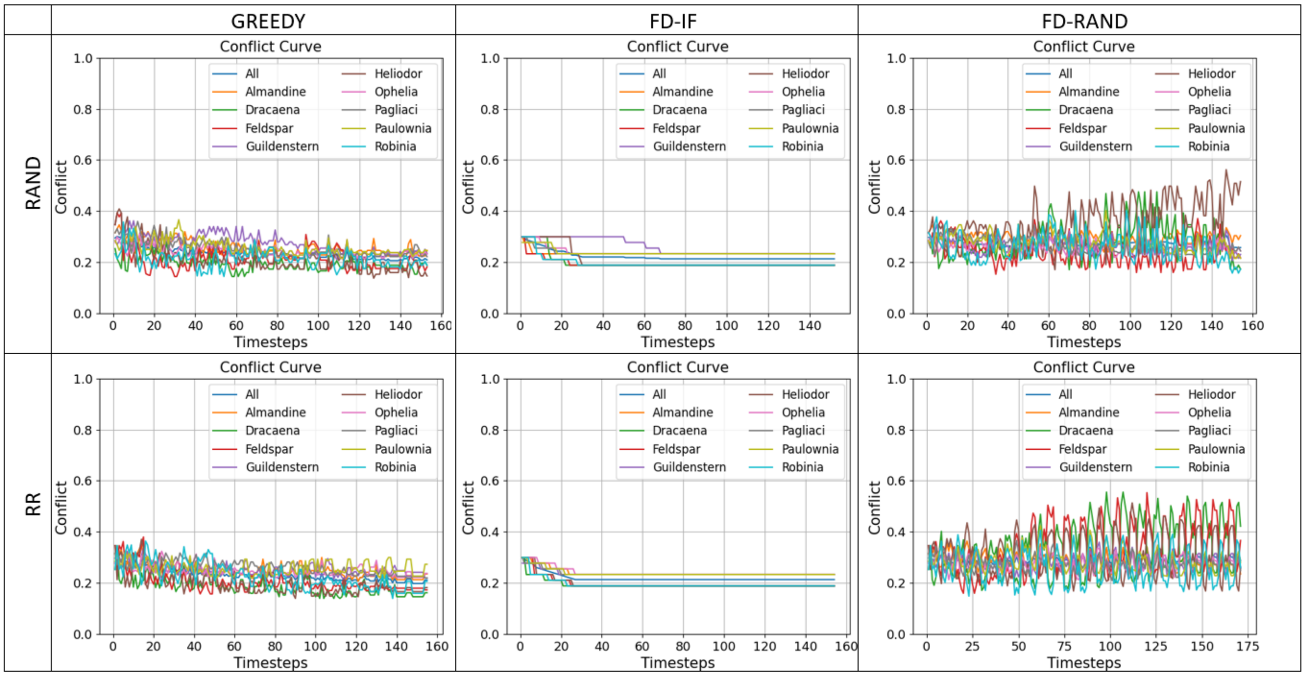


Figure 2: Experiment results, differing character selection procedures as well as action selection procedures

1. The push and pull of forces should create chronic peaks of conflict and valleys of satisfaction, similar to a “narrative curve”.
2. The tension between characters, and the evolution of the relationships should create situations of rivalry and allyship, (i.e. taking actions with the intent to help or hurt another based on their relationship) that should vary and fluctuate over time.
3. The system should avoid stagnancy, repetition, and high volumes of noise.

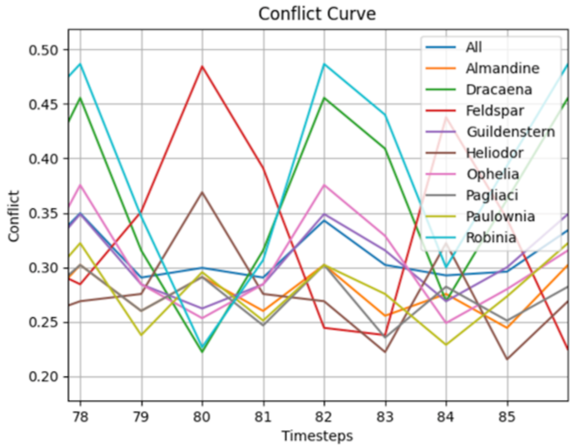
We evaluate each of these parameters in an exploratory manner, using multiple runthroughs of a sample emergent narrative world and utilizing the output of the test bed to as a means to evaluate the results. The sample emergent narrative is based on an eventual goal of a functional EN game about negotiations in a fantasy world, and currently contains the definitions of the characters and actions, with a simplistic canned text grammar to represent the actions textually. The sample world consists of an actual world with three propositions, three themes, nine characters, and a set of sixty actions. We compare three action selection procedures and two character selection procedures. For action procedures we use a baseline greedy action selection, where characters only score their own satisfaction as the instigator of the action. Second, we take the result when the friction force is set to 1, and witness score of 0, i.e. the interpersonal forces will always be set to zero, which we call (FD-IF). Lastly, we compare the results when using the force dynamic model with a small friction force 0.05, and a witness score of 0.7 (FD). Given that the action selection procedure is deterministic, we also test both a randomized (RAND) approach to selecting characters, as well as a deterministic round-robin (RR) cycle throughout each character.

Experiment Results

The experiment results are summarized in Figure 2, showing the results for each action selection procedure and the deterministic (round robin) and nondeterministic (random) character selection procedure. The experiment was run up to about 150 timesteps with a few examples having more to be able to emphasize certain notable results. Notably, the random character selection only presents one possible run of the system, whereas the round robin results are all discrete and repeatable.

Character Selection Procedures The major result of note with respect to character selection procedure is that in each case the RR model would eventually converge in a “cycle”, where characters would take the precise same actions, which can be seen by looking at the end of each of the three graphs, where the patterns start repeating past a point. The convergence can take some time depending on the action selection procedure but it still is an undesirable property. It is unlikely that a purely deterministic model would ever be used in an EN, and any form of interaction from a player would provide a source of randomness. Notably, the RAND model tended to follow a similar curve to the RR model, with the notable exception being the FD model.

Action Selection Procedures In both the RAND and RR model, the greedy action selection approach produces variation in the levels of conflict for each character, but the overall trend is downward and converges to minor actions instead of dramatic actions. This is caused by each agent be-




```
[078]   Feldspar demostrates his ability to drink an
        entire tankard of ale in one gulp to Ophelia.
[079]   Paulownia and Feldspar lean forward and talk
        amongst peacefully themselves for some time.
[080]   "It is nice to speak calmly to one another,"
        Robinia says to Feldspar.
[081]   "Cheers, Paulownia!", Pagliaci says cheerfully.
[082]   Feldspar demostrates his ability to drink an
        entire tankard of ale in one gulp to Robinia.
[083]   Pagliaci quietly chats with Paulownia.
[084]   Ophelia and Feldspar lean forward and talk
        amongst peacefully themselves for some time.
[085]   "Cheers, Paulownia!", Heliodor says cheerfully.
```

Figure 3: A sample conflict curve, showing a small instance of how friendship and rivalries create consistent variations in the conflict curve

ing generally able to reach a satisfied state, meaning there is no need to take anything but minor actions to keep their satisfaction level. A more extreme version of this behaviour occurs in the FD-IF model, where the characters reach a local minimum of satisfaction extremely quickly and, having no actions to increase satisfaction, only take actions which maintain the same level of conflict. One reason for this is without interpersonal forces, the scoring procedure prioritizes actions with no impact on other characters, meaning there is little to no conflict gain at any point in the narrative. The FD model represents the system as intended, and it is notable that the behaviour is in contrast to the greedy and FD-IF graphs: conflict grows over time and more dramatic actions are taken. The FD-RR graph, however, still stabilizes around a certain level of conflict and ends up in the repetition pattern common to all of the RR graphs, whereas the FD-RAND graph maintains its randomness. The FD-RAND, therefore, seems to represent the ideal behaviour of the system. Though there are certain trends of growing or shrinking conflicts with some of the characters, these characters nonetheless also have the most dramatic variations in conflict, and don't achieve a point where they are stably conflicted or satisfied.

The FD-RAND model Many of the behaviours of the FD-RAND model occur as visible patterns which repeat over the course of the EN run. To better observe these, Figure 3 shows a small subsection of six timesteps from a separate run of the system, and we also provided the canned text to roughly give the "narrative" occurring during this section. Though not shown in the graphs, the system also keeps track of the biggest rivals and closest friends (in terms of interpersonal forces) during each timestep, which in this section the rivals were Robinia and Feldspar, and the friendships varied between Ophelia, Dracaena and Robinia. In this small section of the story, Feldspar, who's ideal world is a boistrous high-energy one, is interacting with a number of calm characters, mainly Ophelia, Robinia and Paulownia. There is a back and forth in the actions, with the characters specifically trying to speak calmly with Feldspar, who responds with cheers and more drinking. The conflicts occurring, though not well represented by the text (which makes the scene feel overly cheerful), make clear patterns on the conflict curve. Essentially, we can see that the rivals Feldspar and Robinia have roughly inverse conflict curves, with Feldspar's actions lowering his conflict always at the expense of Robinia, who is then pushed up to almost the same level of conflict. This is a direct result of the reactionary nature of the interpersonal forces, and similarly we see that the friends, Robinia, Dracaena and (to a lesser extent) Ophelia have curves that essentially match each other, since in this case the characters do not take any action at the expense of the other. Looking for inversions and mirroring reliably shows the different rivalries and friendships which are emerging from the behaviours within the system. And Figure 2 shows that the mirroring and inversions vary over the narrative, as new rivalries and friendships are created or forgotten. This is one of the benefits of the witness and friction forces, where slowly characters forget about their interpersonal forces over time if they don't directly interact with the character, but meanwhile they are also always judging the other characters for their actions, which leads to new relationships.

Conclusion

In this paper we presented and evaluated a force-dynamic model for narrative agents, focusing on the ability of the system to implicitly model narrative qualities. We found that, while the discrete nature of the system could lead to issues in very specific, discrete setups, force-dynamics overall creates a natural, consistent and varying conflict within the system. While in an early state, the FD model can already demonstrate sophisticated behaviour, that can be formally analyzed with a conflict graph. Future work aims to look further into the representation of these interpersonal forces, which can be expressed in a number of ways depending on the medium, such as better textual representation, facial expressions, etc. The simplicity of the model, coupled with the results, provides an interesting alternative to more traditional drama-management approaches to EN, one which provides the same features, but through a carefully constructed and simple set of behaviours.

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