Innovative Analysis Tools for After Action Review (AAR) Using AI and Modeling & Simulation

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ABSTRACT

During a training session using simulations, all information is recorded for replay, visualization and detailed analysis purposes. Classical After Action Review (AAR) tools offer many functionalities to zoom in on a specific moment or to give general feedback on the choices of the trainees. The materials trainers generally use are scores, videos and screenshots, which they have to enrich manually .

The STRATEGIC research project proposes innovative automated analysis tools, based on artificial intelligence and modelling & simulation. Our work focuses on three strategic pillars: :

- *a narrative reconstruction of the causality of the events using a graph model. This helps in understanding the consequences of the trainee's choices and highlights the key events of the session, thus facilitating communication during the debriefing session.*
- *an automatic generation of enriched operational diagrams offering smart synthesis of the tactical situation and its history: local force ratio, tactical lines, main effects of missions, contextual units capacities, ...*
- *interactive pictures for alternative solutions exploration*

Early results are so promising that the french land Army ordered many smart diagrams; not only for 3A and supervision of training sessions, but also for intelligence valuation. In the future it could be also used as a decision support & alert system at HQ.

1.0 TAKING AFTER ACTION REVIEW (AAR) TO THE NEXT LEVEL

1.1 Existing AAR tools for simulation-based training

Broadly speaking, a training session starts with a preparation phase, where the realistic operational environment is created, followed by an exercise phase where all the trainees take part in the simulation and, finally, a debriefing phase, also called After Action Review(AAR) where the stakeholders have an interactive discussion in order to understand what happened during the exercise and why, as well as how to improve or sustain performance in similar situations in the future. Duration and timing of the discussion are very important: too many details lead to a lack of concentration among the participants and inadequate timing tends to make the participants forget the real reasons that made them choose a specific course of action.

AAR refers to activities including verbal feedback, analysis of tactical situations, review of audio and video recording, and playback of the training session. Training can be prepared for an individual or group of individuals. The goal of the AAR is to provide feedback on performance during and after the exercise and to guide the trainees through the discovery of their strengths and weaknesses. The intention is for all those involved to discuss and learn from the information presented at the review.

Just as there is no one correct way to conduct an AAR, there is also no one correct way to automate an AAR. There are common requirements to be met in all types of training and AAR. Interviews with army observers/controllers at various combat training centers (Dyer, 2005) (Salter, 2007) clearly indicate that automation that improves training recall and diagnosis is desirable. Dyer et al (Dyer, 2005) noted that "AAR aids should assist the trainer, and should be used when they are "value added". The statement indicates that automated AAR should be geared toward assisting the trainer and not as a replacement for the trainer. According to (C.L Johnson, 2008), one of the biggest flaws of automated AAR tools is inability to determine cause and effect relationships and connections between events. Available AAR automations easily list events, but do not assist the trainer in linking these events to the mission plan.

Indeed, an effective AAR relies on accurate perception of the training events. As often happens when humans are involved, perceptions can be quite diverse among people viewing the same thing. Because computers and software are available to track or simulate battle participants, it is possible to present the ground truth of the situation in addition to the perceived truth during the AAR session. By allowing the trainee and the trainer to see the ground truth of the event rather than just their own perceived truth, the first steps of the learning process are begun.

1.2 Linear Logic(LL) and Planning for storytelling

In Artificial Intelligence, task planning is the problem of selecting an ordered list of *actions*, starting with a set of possible *initial states*, to achieve a particular *goal state*. It has numerous applications in robotics, scheduling, resource planning and even automated programming.

Physical behavior of a particular system associated with an action is summarized through a list of *preconditions* and a list of *effects* for the action, providing a discrete abstraction of system behavior. When an action is triggered, the environment is effectively modified in accordance with the described effects, eventually rendering other actions operationalizable depending on whether preconditions are now matched in the environment. Task plans based on such representation of action and change achieves a coherent sequence of actions with regards to causality, and has thus featured among popular techniques in the field of narrative generation and interactive storytelling: from a baseline representation of *narrative actions* or events (encompassing narrative material such as characters, objects, or even their knowledge or emotional states), stories can be represented, generated, and studied as a partially ordered plan of actions.

Among languages for representing actions for the use of planners are STRIPS, or PDDL. Using such standardised languages permits the use of a variety of planners, one example being for the generation of stories from raw material. In (Bosser 2010), Linear Logic (LL) has been proposed as an alternative to planning-based languages for the representation of baseline narrative actions and plot specification, based on the establishment of a strong connection between proofs in Linear Logic and action plans (Masseron Tollu Vauzeilles).

In LL, an action *a* can be encoded by means of the linear implication $\multimap$

$$a\colon q0 \otimes \cdot \cdot \cdot \otimes qi \multimap r0 \otimes \cdot \cdot \cdot \otimes rj \text{ , where qk and rk are resources of the simulation.}$$

This expression means that all of qk will be consumed after performing action *a*, while all of r0 will be produced. For *a* to be performed, all of qk must be available.

While this may not be an off-the-shelf solution for the real-time generation of original plots using baseline descriptions such as in AI planning, it has the advantage of relying on a strongly grounded logical framework founded on a low level resource-based description, which on its emergence opened the door to establishing and verifying properties of stories represented as Linear Logic proofs (Bosser ITP 2011). Analyzing the flow of resources throughout the sequence of unfolding action also allows the automatic construction of fine-grained diagrams that display the network of contributing causes, and the relationships between actions in a story (Martens 2013).

1.3 Narrative debriefing for simulation-based training

The large amount of data generated during training using simulation may complicate the AAR. To remedy this, we propose to develop a narrative creation toolkit that will assist human explanations, in terms of a story (or narrative) describing a given simulation session, for all participants. The idea is to provide a semi-automated analysis of the session based on a narrative reconstruction of the (potential) causal links that exist between events that occurred in the simulation, and to include tools to support their structured presentation.

In the field of education or serious games, *storification* (Akkerman, 2009) is used to describe the creation of a causal structure by establishing links between narrative events. One of the challenges in these areas is the realization of systems to automate or semi-automate this activity in order to educate various user profiles. Conversely, studies in psychology of story understanding have also shown the importance of the perception of causal relationships between narrative events (Trabasso, 1985). While modeling causality occupies a central place in Artificial Intelligence (AI) (Pearl, 2009), Narrative Intelligence's point of view is closer to *commonsense reasoning*: the narrator must select the events to be recounted, express the causal links among them, and select a level of granularity of such connections in order to make the final story meaningful. Contrary to classical approaches from AI, narrative intelligence tends to provide an explanation in a form that is assumed to be more accessible for a human user (Riedl, 2016).

Our aim was not to provide a fully automated story construction system, such as in recent machine learning approaches: our system must support the confrontation of different points of view during debriefing and cooperative learning activities. As such, it should help each user to construct, and explain their own subjective narrative, depending on the information they had access to (depending on the roles of the participants, this may vary widely) and their decision rationale. The tutor in charge will have access to all information, and their constructed narrative will also differ.

Narrative refers to the presentation of a coherent sequence of events that combine to tell a story. According to (Mani, 2013), computational narratology is the study of narrative from the point of view of computation and information processing. It focuses on the algorithmic processes involved in creating and interpreting narratives, modeling narrative structure in terms of formal, computable representations. Its scope includes the approaches to storytelling in artificial intelligence systems and computer games, the automatic interpretation and generation of stories, and the exploration and testing of literary hypotheses through the mining of narrative structure from corpora.

Narrative structures are an important field of research in Artificial Intelligence, and have been for a long time. This is due to their ability to make knowledge explicit (Schank 1995, Reiter 2000). Technologies resulting from Interactive Narration have created a lot of interest in the fields of simulation or serious games (Cavazza,2016). By allowing the representation of scenarios and their progression, while preserving the coherence of a story and propagating the consequences of user actions, they permit the exploration of the knowledge represented by these stories. Thus, the formalization of a narration is a structure of knowledge which extends the logic of actions, providing a framework to represent the causal and temporal aspects relating to a given situation.

The narrative representation obtained provided by these technologies offers an innovative support for the discussion between trainees and trainers. It offers a contextual view of events and the ability to understand the causes and the consequences of each event or choice made by the trainee.

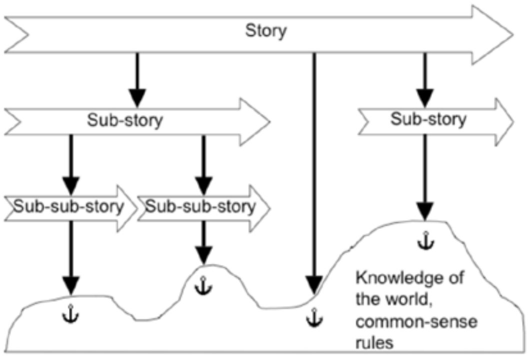

Figure 1 Verheij's visualization of hierarchical narrative grounded in common-sense

According to (Whitman Richards, 2009) the figure on the left embodies what might be considered the kernel of all narrative representations. At the top, the large arrow represents the main progression of the story: a linear set of events that proceeds, one after another, from start to finish. Beneath that are smaller arrows, representing smaller portions of the story that could be considered as stories in their own right. This nesting can continue, becoming relatively elaborate, until reaching a point where the stories represent a common-sense knowledge of the world, suggesting connections between argumentative and narrative elements (Bex, 2007).

Hence, to first order, there are three common denominators amongst representations considered: (1) narratives have to do with sequences of events, (2) narratives have hierarchical structure, and (3) they are (eventually) grounded in a common sense knowledge of the world.

2.0 THE STRATEGIC PROJECT

2.1 Objectives of the STRATEGIC project

As explained earlier, during a training session using simulations, all information is recorded for replay, visualization and detailed analysis purposes. Classical After Action Review (AAR) tools offer many functionalities to zoom in on a specific moment or to understand and give general feedback on the choices made by trainees. The material usually available to communicate with trainees are numerical indicators, videos and screenshots, all of which have to be manually enriched.

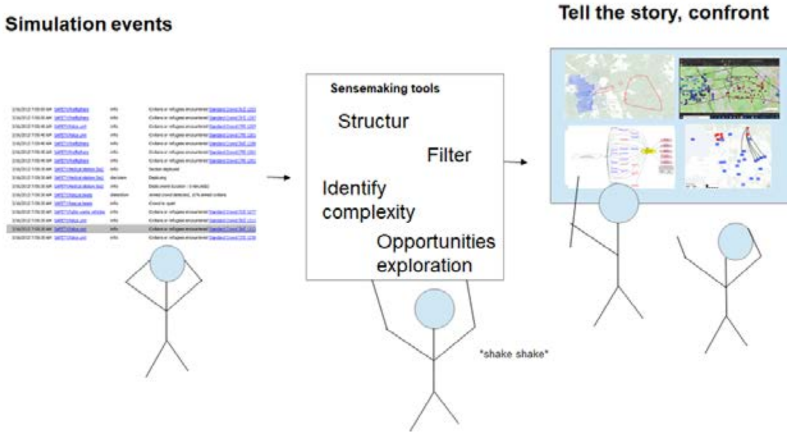

Figure 2 Use Case

The STRATEGIC research project proposed innovative automated analysis tools, based on artificial intelligence and modelling & simulation :

- a narrative reconstruction of the event's causality in the form of a graph of events. This facilitates the understanding of the consequences of the trainee's choices and highlights the key events of the session and thus supports the communication during the debriefing session.

- an automatic generation of enriched operational pictures offering a smart synthesis of the tactical situation and its history: local force ratio, tactical lines, main effects of missions, contextual units capacities, ...
- interactive diagrams supporting the exploration of alternative solutions

2.2 SWORD, a constructive simulation for military training

The training software we used, SWORD, relies on a constructive simulation which allows brigade and division command staff to become immersed in large-scale conflict scenarios such as stabilization operations, terrorist threats or natural disasters. It simulates a diverse range of situations in realistic environments and lets trainees lead thousands of autonomous subordinate units (at platoon and company levels) on the virtual field. Agents can receive operation orders and execute them without additional input from the players, while adapting their behavior accordingly as the situation evolves.

Models capturing such behaviors comprise two components: algorithms that make agents perceive, move, communicate and shoot, and the description of the capabilities of the underlying equipment. The simulation session database contains three different types of information:

- Data regarding the physical element: components of units are described here. Because the simulation is a constructive simulation most of the features of the equipment or units are described by their effects or their capacities. This facilitates their description in terms of action and change.
- Initialization data for the scenario contains the following information: terrain, order of battle, weather, data provided by the simulation such as events, knowledge obtained by the agents, etc.
- Data generated by the simulation describes the evolution of the situation: information describing the evolution of the game containing all events, knowledge about the environment, and all mission reports. All this information is presented to the participants as a set of messages exchanged among the agents during the simulation that contains all the information described above. An extract of the simulation is shown below:

  [07:29:47] - Report - ENG.Counter mobility platoon: Disembarkment started
  .....
  [07:30:17] - Report - INF.Mortar troop: Unit detected at ...
  .....
  [07:30:17] - Report - INF.Rifle platoon: Unit detected at ...

2.3 Functional architecture

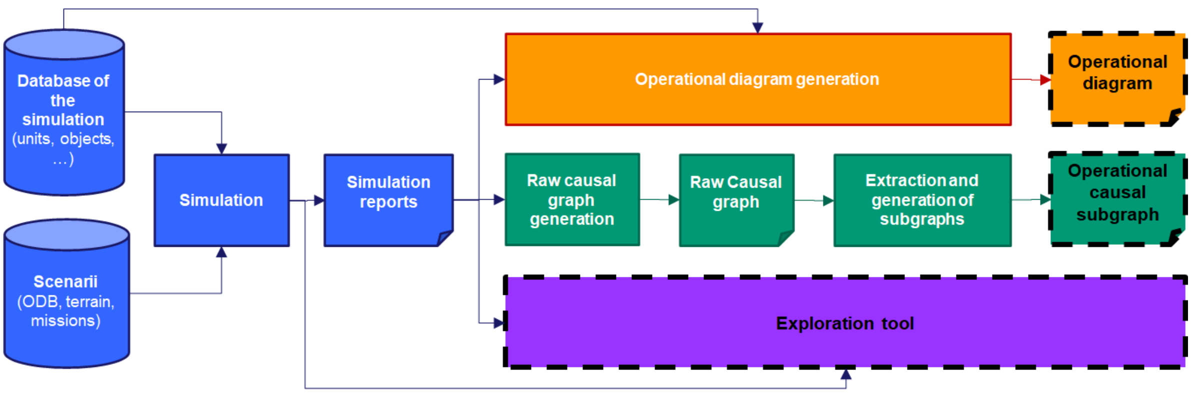

Figure 3 Functional architecture

Our work focuses on three main areas:

- an innovative and alternative conception of the representation of the tactical situation according to an operational focal point, exploiting the ontology of the simulation (effects of missions, role of units, ...) in a novel manner, and its models (ex: capacities of units, balance of power, ...), in order to allow the production of operational pictures illustrating the tactical situation at any moment in time.
- an analysis, interpretation and structuring of the reports of events resulting from the simulation in a form that allows for the employment of causal relationships: this work includes the reflection around the causality model to be adopted, as it had to be compatible with the information in the reports, and expressive enough to support an interactive construction of the explanation.
- careful consideration of the human-computer interface required to generate
  - relevant and actionable narrative subgraphs
  - intuitive and intelligible operational diagrams

2.4 Genericity of the solution for a variety of different scenarios

This work was based on different simulation scenarios with an increasing level of complexity: the first scenarios involved a very small number of units but still generated examples of reports allowing the implementation of the first version of the raw graph. We were thus able to program a first processing of the reports, enabling an elimination of superfluous information, retaining only the reports concerning resources and actions.

Next, we used other more operational scenarios*: Egypt, Sweden* and *Menil Anelle*. These three scenarios, ranked in order of size, made it possible to scale up the work carried out.

	Simple scenarii	*Egypt*	*Sweden*	*Menil Annelle*
Number of units	2-4	62	120	508
Size of the terrain (km)	SO	96*111	103*54	109*70
Duration (ticks= 10s)	SO	1807	3244	1662
Number of companies missions	0	91	325	670
Number of platoons missions	2-4	167	607	1620
Number of enemies detections	SO	121	191	488

Figure 4 Description of the scenarios

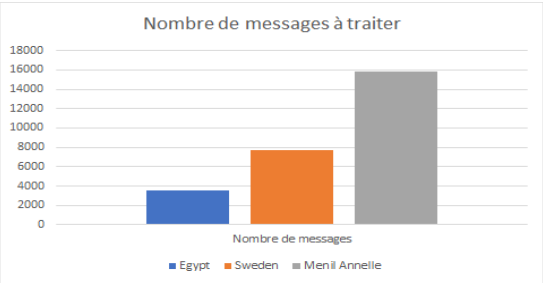

Figure 5 Number of events/reports to compute

The use of many different scenarios allowed us to validate the genericity of our technical and algorithmic solutions: different terrain, different units, different missions, …

3.0 NARRATIVE RECONSTRUCTION OF THE CAUSALITY OF EVENTS

The construction of the narrative support tool involves two steps: first, a raw causal graph is constructed by translating the simulation's reports into events linked by causal relationships, then subgraphs are extracted and automatically reworked in order to be readable.

3.1 Construction of the raw causal graph: a Linear-Logic based approach to story construction and analysis

The formalization of narratives is a problem that has often been approached in Artificial Intelligence from the perspective of representation and Reasoning about Action and Change (RAC), starting from the atomic modeling of a narrative action, and describing its impact on the environment. (Anne-Gwenn Bosser, 2010) & (Anne-Gwenn Bosser P. C., 2011) use Linear Logic (Girard, 1987) in modeling which has led to formal approaches to story analysis and property verification. Among other advantages, this approach allows for the modeling, in a declarative way, of each event, by describing its impact on the environment in terms of consumption and the production of resources. This has led to systems where stories generated from a linear-logic based declarative specification could be described by reconstructing causal relationships between events and displayed in the form of causal diagrams (Chris Martens, 2013), (Chris Martens J. F.-G., 2014).

We have produced a formal description of the translation of the traces of SWORD events into atomic actions, thereby building blocks of the raw graph. These actions represent exactly what, in the simulation, was changed by the triggering of the corresponding events. This component provides both a method for the translation of SWORD traces into actions in the raw graph, and the construction of a graph of contributing causes. The algorithm is based on the sequential processing of the state of the simulation over time, which in the future will allow it to build the above on-the-fly as the simulation progresses (through integration in SWORD rather than as a separate component). This state maintains at each moment of the simulation the entire operational status of the simulation units. as well as the knowledge units have about each other (visibility). The current implementation uses Go, and the process takes about 500ms on a mid-range computer for our most complex scenario. The graph produced is described in dot and json formats which facilitates their processing by standard tools (visualization, processing libraries).

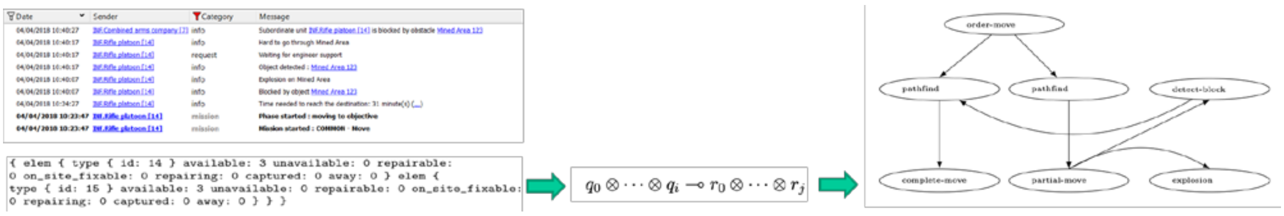

Figure 6 From the simulation events to the raw causal graph

The different kinds of events and reports produced by the simulation (position & state of the units, firefights, detection and move events, …) have been translated into linear logic formulas. The diagrams obtained retrace the contributing causes of the events. The diagram above shows an example of a graph computed using a simple scenario as a basis: a unit moves and encounters a mined area.

$$
\begin{array}{rl}
\texttt{order-move:} & location(Y) \multimap mission(id, move(Y));\\
\texttt{pathfind:} & mission(id, move(Y)) \otimes pos(id, X) \otimes Context(id, C) \multimap mission(id, move(Y)) \otimes pos(id, X) \otimes \\
& Context(id, C) \otimes path(X, Y);\\
\texttt{partial-movement:} & mission(id, move(Y)) \otimes path(X, Y) \otimes pos(id, Z) \otimes Y \neq Z \multimap Y \neq Z \otimes mission(id, move(Y)) \otimes \\
& path(Y) \otimes pos(id, Y);\\
\texttt{detect-block:} & path(X, Y) \otimes pos(id, Z) \otimes mine(Z) \multimap knowledge(id, block(mine(Z)));\\
\texttt{explosion:} & pos(id, Z) \otimes mine(Z) \otimes context(id, C) \multimap pos(id, Z) \otimes damages(context(id, C));\\
\texttt{pathfind:} & mission(id, move(Y)) \otimes pos(id, X) \otimes context(id, C) \multimap mission(id, move(Y)) \otimes context(id, C) \otimes \\
& pos(id, X) \otimes path(X, Y)\\
\texttt{complete-movement:} & mission(id, move(Y)) \otimes path(X, Y) \otimes pos(id, X) \multimap pos(id, Y)
\end{array}
$$

For example, a move can be caused by a mission, or damages can be caused by an explosion or firefights

Figure 7 Example of linear logic formulas

3.2 Construction of the narrative graph

The raw causal graph produced after the process described above is not directly usable as they are too big, even for small scenarios. One aim of the project was to provide a set of tools, based on generic or ad-hoc heuristics, to render it tractable for human understanding. Here are examples of heuristics we used for aggregating nodes of the raw graph into higher level narrative events or suggest entry-points for the analysis:

- The relationship between the number of causal relationships on a set of events and the importance of perceiving an event in a story has been discussed in (Mazlack, 2004). This was used as an heuristic to highlight events of interest .
- Spatio-temporal zones where events involve attrition were likely to correspond to exchange of fires, with many interactions between units and events. We used this as a heuristic to simplify and summarize a number of nodes into high-level ones.

The component thus offers a solution for the representation of the simulation's events in the form of a more streamlined causal graph in order to support the narration. It first applies ad-hoc simplification heuristics and clusterization algorithms on the raw causal graph. This allows us to obtain a higher level graph, called the "narrative graph" with a greatly reduced size that makes it computationally manageable in interactive time.

	Raw Causal Graph		Narrative Graph	
Test Scenario	# nodes	# links	# nodes	# links
Egypt	1902	4021	326	503
Sweden	5760	12620	973	1429

Figure 8 Size of the computed graphs

Smart filters are then applied, and offer partial views of the narrative graph. For example, one can ask for the history of a specific unit or the inventory of events that results in getting a specific event of the simulation. The result details: the missions of the units, their moves, the enemies detected, firefight events and damages… Views can also be enriched with their temporal and spatial extensions.

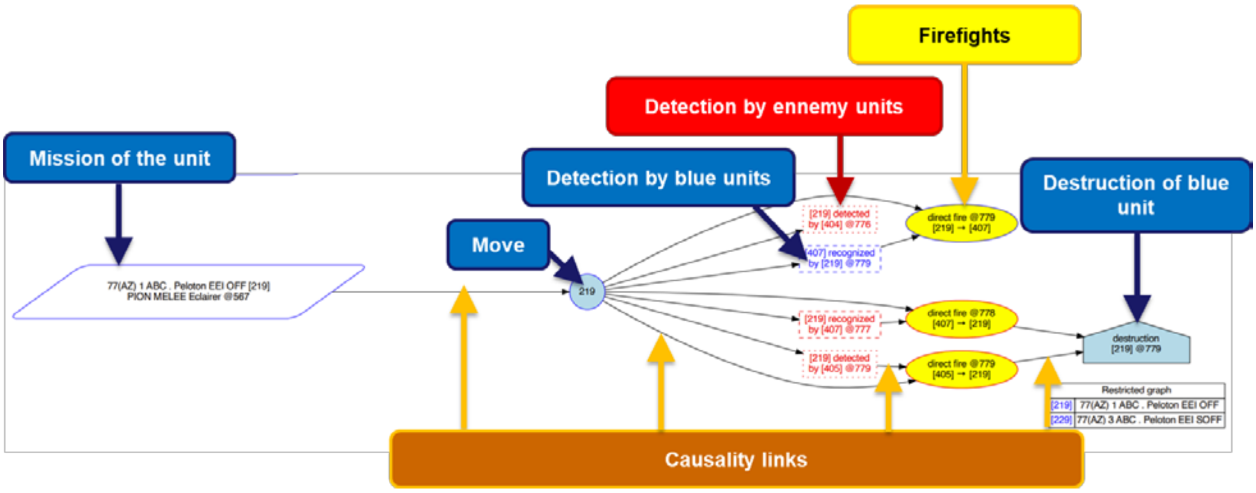

Figure 9 Narrative graph representation example : a focus on the history of a unit

Some heuristics that we considered as promising, such as the use of force ratio shifts, ultimately proved to be ineffective and redundant in spotting and factoring landmark events regarding the analysis of the causal centrality of certain nodes. On the other hand, simple mechanisms based on their spatio-temporal proximity for bringing together complex actions have proved to be very effective. They also naturally offer the highlighting of the salience of certain events from an operational point of view. From a performance point of view, the generation of the complete narrative graph may take a few minutes on the larger scenario, but once generated, the requests receive rapid responses.

4.0 AUTOMATIC GENERATION OF ENRICHED OPERATIONAL DIAGRAMS

In order to better understand the tactical context at a specific moment in time, to support the discussion and to offer a shared comprehension, we decided to propose smart diagrams based on the doctrinal decision parameters or directly inspired by operational synthesis generated at HQ for debriefing purposes.

4.1 Occupying The Terrain

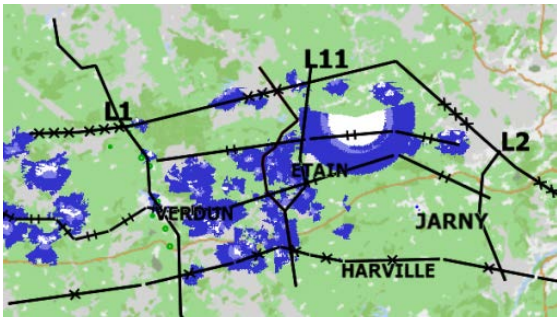

Figure 10 Contextual perception capacities

The system calculates the total area occupied by all units, the entire perception zone based on available equipment, the current missions of units, and the potential area covered by fire. These calculations can be performed on the basis of the hierarchical level of units, their equipment capacities, current missions, and positions. We directly used the capacities module of the SWORD simulation in charge of the calculation of the potential effects of the equipment of the units. Moreover, to provide an indication of the global force deployed at a glance, calculations of the density of forces could be added.

4.2 Local Force Ratio

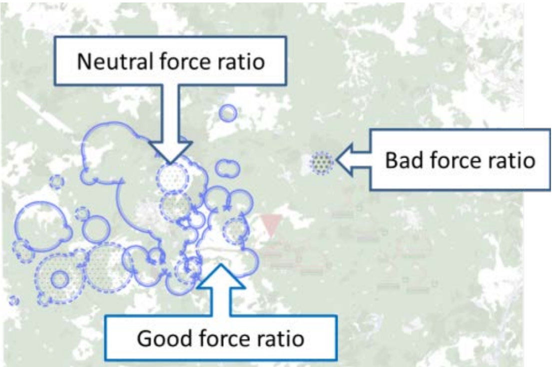

Figure 11 Local Force Ratio

The simulation calculates the force ratio of each agent based on its knowledge of the tactical situation. This is used as a decision-making parameter by autonomous units to help them determine whether they are likely to be able to accomplish their mission, or whether the situation is considered to be too dangerous (as written in the use of the force doctrine). It is therefore possible to offer a dedicated view of the local force ratios, which provides an insight into which forces, or area, may have required reinforcements.

4.3 Common Offensive and Defensive Control Measures

Commanders use common offensive and defensive control measures to synchronize the effects of combat power. Understanding and using commonly understood control measures enables commanders and staff to develop and publish clear and concise mission orders, as well as direct tactical actions quickly, with minimal communication during execution. Based on current missions, knowledge of enemies, and combat capacities of units, we are able to generate on the fly a global maneuver summary, which includes a calculation of tactical lines, such as the :

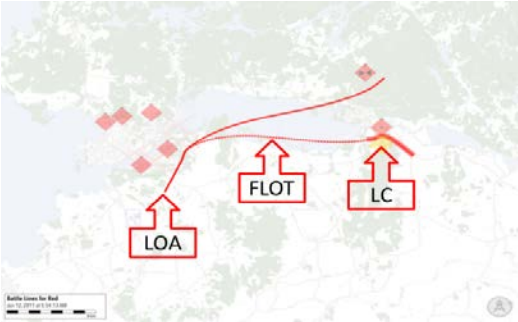

Figure 12 Tactical lines

- *Forward Line of Own Troops* (FLOT) that indicates the most forward position of the forces. The FLOT normally identifies the forward location of covering or screening forces.
- *Limit Of Advance* (LOA) is a phase line used to control the forward progress of the attack.
- *Line of Contact* (LC) is a general trace delineating the location where friendly and enemy forces are engaged.
- *Forward edge of the battle area* (FEBA) is the foremost limit of a series of areas in which ground combat units are deployed.

4.4 Current Effect Applied Layer

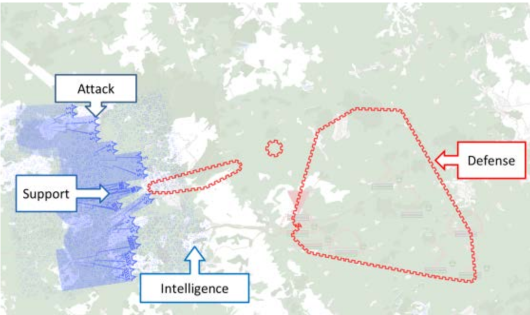

Figure 13 Effect applied

According to the past and current missions of the units, it is possible to provide a view of the main effects exerted by units on the field. For this purpose, the missions have been classified according to their main goal effect on the field and on enemies. In this first version we focused on four main effects: the intelligence, the offensive effect (attack), the defense effect (including engineering defense works) and the support. The result is an interactive layer that offers a way to choose the effect and the side. Naturally, the line of the front with an indication of the available support, the defense positions, and the scouted zones, all appear.

To take this analysis further, we could provide a maneuver view that relies on the major expected effects regarding the enemy and terrain. For example one could produce a layer that differentiates between zones that must be recognized, conquered, controlled, etc., or enemies that must be eliminated or stopped. This could be achieved through the interpretation of the advancement of current missions, and the nature of planned missions.

5.0 ALTERNATIVE SOLUTION EXPLORATION TOOL

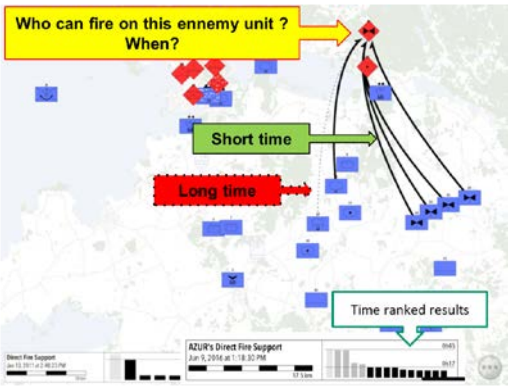

Figure 14 Delay to support calculation

The idea here is to offer an easy way to explore possible alternatives when managing the tactical situation and in this way propose the foundation for counterfactual analysis. For each unit on the battlefield, we provide a calculation of the time taken to reach a position to support a unit facing an enemy. To achieve this, the simulation calculates the best route for each unit. This calculation takes into account all equipment capable of direct or indirect fire, known enemy positions, the terrain, friendly and enemy engineering works, tactical limits, etc..

Thanks to the simulation, it is possible to easily identify who could support a unit or fire at an enemy and within which timeframe, considering the terrain and the capabilities of the units

6.0 EXPLOITATION OF THE RESULTS

6.1 Example of an operational use case

6.1.1 Simulation scenario

Figure 15 Blue mission

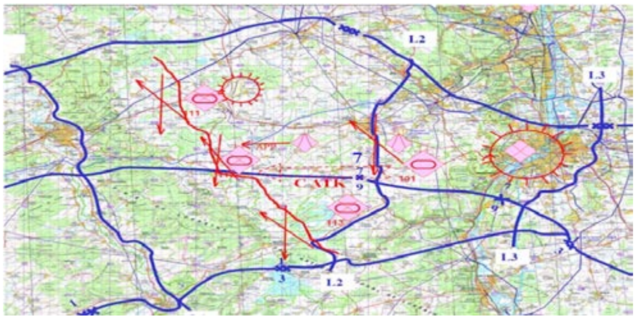

Figure 16 Ennemy mission

Blue objectives:

- Conquer the zone between lines L1 and L2 by overpowering each encountered enemy.
- Conquer the L2 line before June 17th.

Enemy objectives :

- Install two battalions on the defense line.
- Create large connected mined obstacle zones between the river and the defense line.
- Render the west of Metz a no-go zone, and retain control of the Etain airport.

The blue operation is a success, despite heavy losses. It appears that the bulk of the blue losses are made up of platoons from a reconnaissance battalion. It would therefore appear beneficial to identify the causes of these losses, and determine whether they could have been avoided.

6.1.2 Understanding the cause of heavy losses

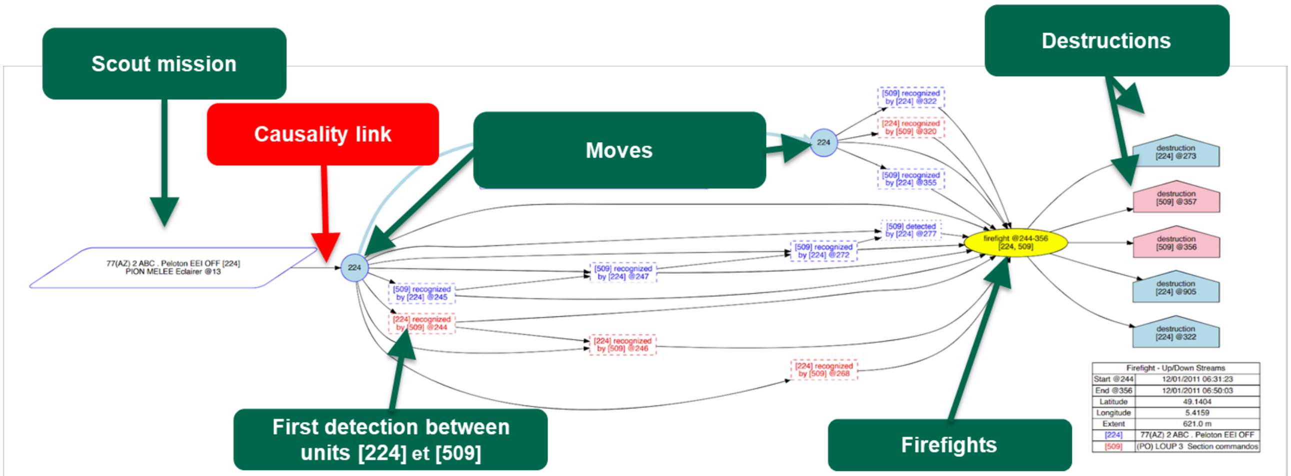

Figure 17 Narrative graph focused on unit 224

To this end, we generated a narrative graph focused on one of the destroyed scout platoons, the [224] unit. This option makes it easy to understand and recount the unit's story: it received a scout mission at 11h35 (tick 224), at which point it moved, and two minutes later encountered the enemy unit [509]. The two units detected each other, exchanged fire, and inflicted damage on each other between 11h43 (tick 273) and 12h21 (tick 500).

Having a view of the tactical situation at this moment consequently appears highly beneficial:

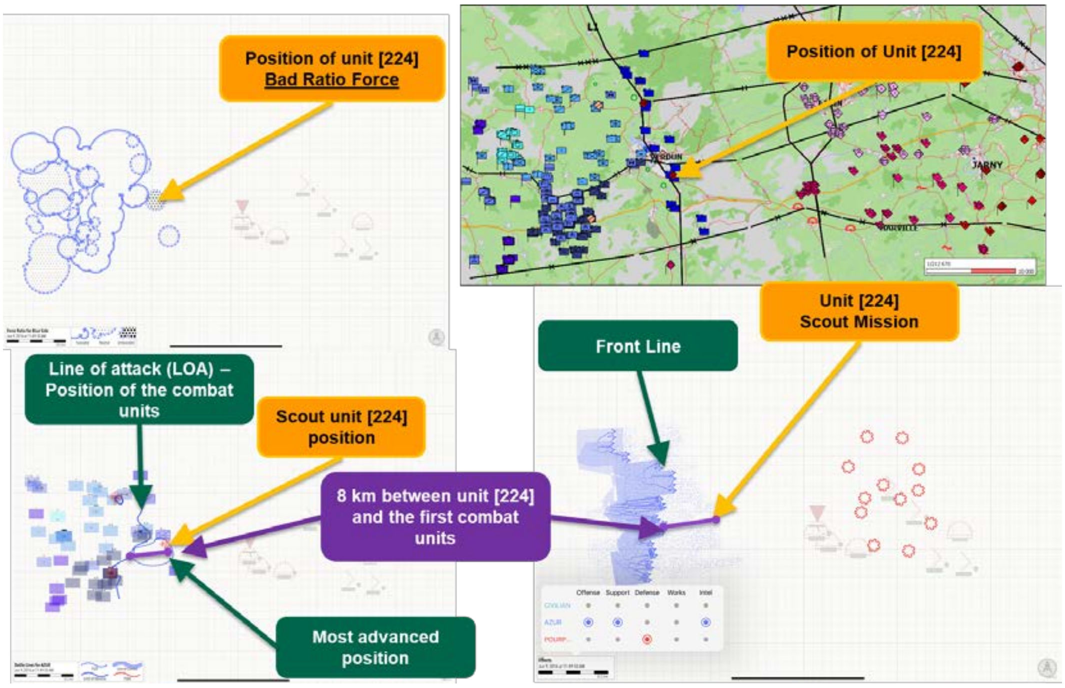

Figure 18 Tactical context of unit 224 during the firefight

These operational diagrams offer a view of the tactical context when the scout unit [224] is being shelled. The force ratio diagram indicates that it was isolated: the two other diagrams show that it was on a front more than 8 kilometers from the first combat units.

6.2 Immediate and further exploitation perspectives

Following multiple demonstrations and presentations of the project to operational and MOD staff, a variety of profiles were highly interested in the project. On one hand, the teams in charge of the SOULT training program have therefore ordered "smart diagrams" from MASA for mobile exercise supervision and AAR. On the other hand, the section of the Digital Office of the Land HQ(EMAT), in charge of analysis and operational research, also ordered smart diagrams related to the enhancement of intelligence. This section's mission is to analyze digital data, both organic and operational, to present objective and consolidated views. Two capabilities have been ordered: the display of the contextual detection capabilities of a camp and the interpolation of the future enemy positions.

To create his/her own version of the course of the simulation and give a point of view, rather than just building a narrative graph, the user could also receive automatically simplified portions, and combine them with the other views of the AAR tool: a map, smart pictures, indicators… Then, the exploration of counterfactual "*what if*" scenarios would also be possible from the simulation interface, thanks to the replay function that allows you to start the simulation again from a given timestamp. The trainee and trainers could then modify the course of action and evaluate the benefits of these changes. This counterfactual exploration offers the possibility to go beyond a simple understanding by identifying the contributing cause and events which "if they had happened in a different manner would have changed the outcome of the simulation": it is this type of simulative reasoning that underlies the human causal interpretation.

To conclude, the use of this set of tools for sensemaking purposes in the context of decision support is an avenue that needs to be explored. Not only are these tools naturally adapted to the needs of a command post, but it is also possible to think further ahead and dynamically process information from the battlefield to prioritize, alert, contextualize and calculate their consequences. Indeed, by creating a digital twin of the battlefield, and integrating these innovative tools, it would be possible to:

- Contextualize the information from the terrain: prioritization of information and automatic sending of alerts through intelligent information processing. Indeed, depending on its tactical context, the same information will not have the same meaning.
  For example, the report « *Enemy unit detected at XXX position* » may have totally different meanings according to the position and the context of this detection

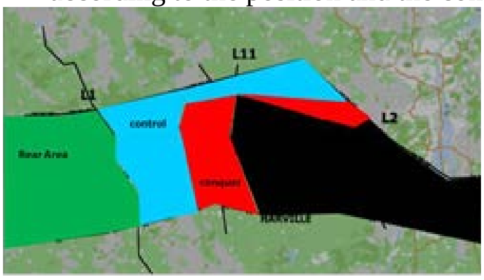

Figure 19 Context of the information

  - In the black zone, to reconnoiter, means that the scout missions are going well.
  - In the red zone, to conquer, an increase in the number of enemy units could mean the arrival of reinforcements and therefore a force ratio switchover.
  - In the blue zone, to be secured, new enemies should not remain in this area, it means that remaining enemy forces were not all evaluated.
  - In the green zone, that is secured, enemies in this area should result in a serious alert being sent.

- Calculate and alert on the consequences of events: automatic alert if a current (or planned) mission is compromised by the evolution of the tactical situation. For example, the destruction of a bridge can compromise medical support or require the preparation of a new logistical route.
- Calculate smart indicators for mission monitoring: as explained earlier, it would be possible to compare the current situation to the expected one or automatically compute the reports from the field to evaluate efficiency, the evolution of events, or the risks from a specific mission.
- Identify chain of events : a study has explored the use of classification techniques to format the raw graph on a data set test using machine learning methods. These methods would then not be used for the construction of the raw graph, but we propose to explore this avenue to perform manipulable "summaries" of the graph. The contribution of machine learning methods to facilitate the understanding of this graph could be deepened and in particular be used to:
  - Determine the probability of the occurrence of a sequence of actions
  - Detect unlikely sequences (threshold value)
  - Predict the rest of a sequence

  Many AI applications requiring trust start to turn to these methods, especially when the core of the technology remains based on symbolic methods and machine learning methods are applied to the processing of the raw graph.

All innovative solutions proposed here for decision support require two principal prerequisites:

1) a database containing all friendly equipment, plus presumed enemy equipment. Descriptions of all types of equipment must be accompanied by effect descriptions, to enable the simulation of the battlefield.
2) the integration of the command and control systems within the tools described above, with a view to importing all data into the simulation: unit positions, logistic states, enemy knowledge, engineering work, NRBC zones, available missions, etc. We then have to design a data representation that provides an easy-to-understand, intuitive display of processed information.

7.0 ACKNOWLEDGMENTS

This paper is based on the STRATEGIC research project funded by the Direction Générale de l'Armement (DGA) through the ASTRID Maturation program.

8.0 CONCLUSION

To conclude, narrative graphs used for simulation based training can be simple, or extremely complex. They let us :

- Explain the story of a unit
- Understand the role of all the units involved in a phase or firefight and its context
- Visualize the role of the units in the maneuver and assess their importance (a mission may or may not have multiple consequences)

So far we have focused on combat units and more specifically on the following events: mission, fire, movement, detection, damage. We need to add other types of units, missions and events: logistics, engineering, ... and offer an interactive graph path to obtain a global and detailed view. A learning algorithm could then propose automatic simplifications of the graph.

In addition, in order to understand the overall tactical context at an identified moment, we offer innovative and alternative views of the tactical situation, offering:

- A calculation of the capacities of the units on the ground according to the tactical context (current mission & speed of unit, weather, experience of the unit…)
- A calculation of the main effects applied on the terrain according to the missions assigned to the units
- A calculation of the force ratio (or units' local strengths) based on their knowledge of the enemy
- A calculation of the main tactical lines (FLOT, LC, LOA)

Some work has already been commissioned by the Army in a framework that goes far beyond the scope of the AAR.

9.0 BIBLIOGRAPHY

[1] Sanne Akkerman, Wilfried Admiraal, and Jantina Huizenga. Storification in *History education: A mobile game in and about medieval Amsterdam*. Computers & Education, 52(2):449–459, 2009

[2] Anne-Gwenn Bosser, M. C. (2010). Linear Logic for non-linear storytelling. Dans *Frontiers in Artificial Intelligence and Applications.* IOS Press.

[3] Anne-Gwenn Bosser, P. C. (2011). Structural analysis of narratives with the Coq proof assistant. Dans *Proceedings of Interactive Theorem Proving - Second International Conference (ITP-2011).*

[4] Bex, F. J. (2007). *"Sense-making software for crime investigation: how to combine stories and arguments?" Law, Probability, and Risk, 145-168.*

[5] C.L Johnson, A. G. (2008). Automated After Action Review: State-of-the-Art Review and Trends. *The Journal of Defense Modeling & Simulation*.

[6] Cavazza, M. &. (2006). Narratology for Interactive Storytelling: A Critical Introduction. *Technologies for Interactive Digital Storytelling and Entertainment. Third International Conference. Lecture Notes in Computer Science.* Berlin: Springer.

[7] Chris Martens, A.-G. B. (2013). Linear logic programming for narrative generation. Dans *International Conference on Logic Programming and Nonmonotonic Reasoning.* Springer.

[8] Chris Martens, J. F.-G. (2014). Generative story worlds as linear logic programs. Dans *Seventh Intelligent Narrative Technologies Workshop.*

[9] Dyer, J. W. (2005). *"After action reviews with the Ground Soldier System. (ARI Research Report 1840)".* Arlington: U.S. Army Research Institute for the Behavioral and Social Sciences.

[10] Girard, J.-Y. (1987). Linear logic. Dans *Theoretical Computer Science.*

[11] Girard, J.-Y. (1987). *Linear logic.* Theoretical Computer Science.

[12] Goguen, J. (2004). *CSE 87C Winter 2004 Freshman Seminar on Computational Narratology.* San Diego: Department of Computer Science and Engineering, University of California. Récupéré sur http://cseweb.ucsd.edu/~goguen/courses/87w04/

[13] Harrell, D. A. (2007). *Theory and Technology for Computational Narrative. PhD Thesis/.* San Diego: Departments of Computer Science and Cognitive Science, University of California.

[14] Headquarters, D. o. (2019). *ADP 3-90 OFFENSE AND DEFENSE* . Army Doctrine Publication.

[15] Mani, I. (2013, january 28). *Computational Narratology*. Récupéré sur The living handbook of narratology: lhn.uni-hamburg.de/node/43.html

[16] Lawrence J Mazlack. Granular causality speculations. In Fuzzy Information, 2004. Processing NAFIPS'04. IEEE Annual Meeting of the, volume 2, pages 690–695. IEEE, 2004.

[17] Meister, J. C. (2003). *Computing Action. A Narratological Approach.* Berlin: de Gruyter.

[18] Norvig, S. R. (2003). *Artificial Intelligence: A Modern Approach.* Prentice Hall.

[19] Judea Pearl. *Causality: Models, Reasoning and Inference*. Cambridge university press, 2009.

[20] Reiter, R. (1991). The frame problem in the situation calculus: A simple solution (sometimes) and a completeness result for goal regression. *Artificial intelligence and mathematical theory of computation: papers in honor of John McCarthy*, pp. 359–380.

[21] M. O. Riedl. Computational narrative intelligence: a human-centered goal for artificial intelligence. In Proceedings of the CHI 2016 Workshop on Human Centered Machine Learning, 2016.

[22] Salter, M. K. (2007). *After Action Reviews: Current Observations and Recommendations (ARI Research Report 1867).* Arlington: U.S. Army Research Institute for the Behavioral and Social Sciences.

[23] Simon, N. a. (1972). *Human problem solving.* Prentice-Hall, NJ.

[24] Tom Trabasso and Linda L Sperry. *Causal relatedness and importance of story events.* Journal of

Memory and Language, 24(5):595 – 611, 1985.

[25] Whitman Richards, M. A. (2009). *Advancing Computational Models of Narrative / MIT-CSAIL-TR-2009-063.* Computer Science and Artificial Intelligence Laboratory.