Untangling Complex Narrative with Narrative Cognition

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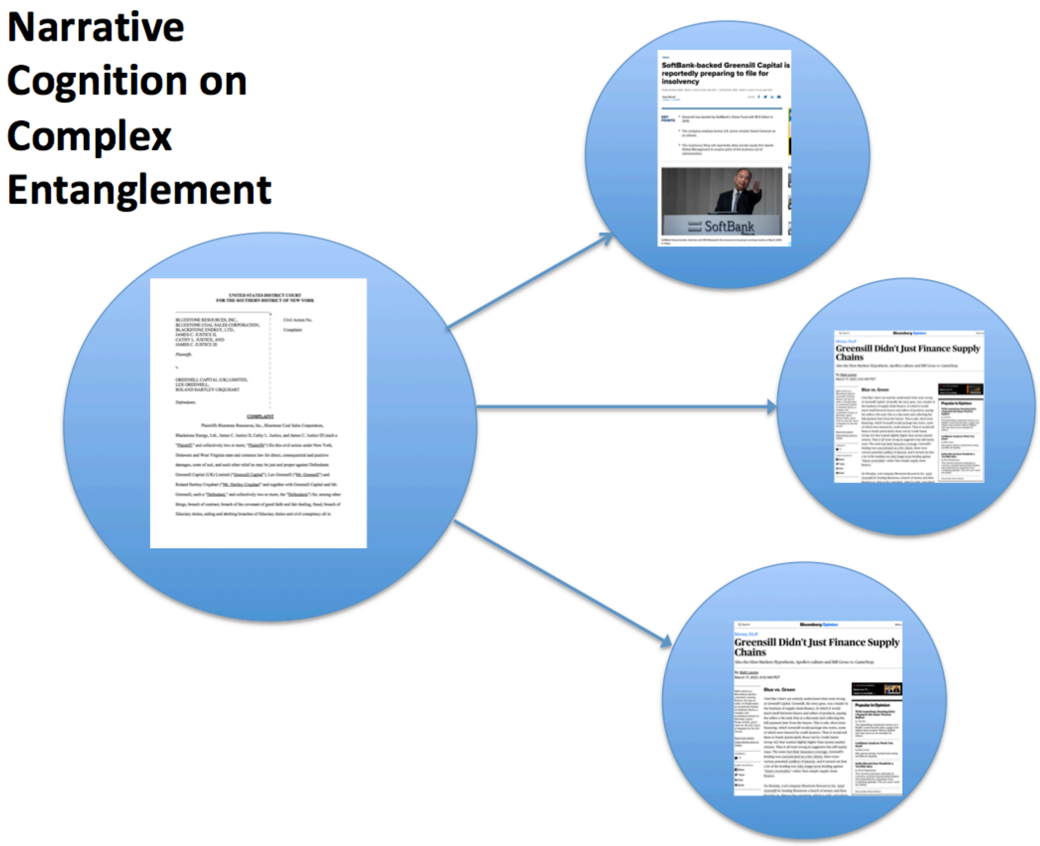


Introduction

Narrative cognition contributes to goal reasoning – an essential technique in problem solving. Making decisions is easy when connected stories in a narrative are detected, and key terms and relationships that form the dots and connections are identified. However, perform due diligent on complex narratives manually is time consuming and not scalable.

Building a platform that automates the due diligence of complex narratives can save time and boost productivity. An automated narrative cognition platform can add efficacy to the decision making process - yielding better outcomes. Yet, many celebrated AI approaches are unable to deliver this functionality. A novel approach to narrative cognition is presented in this article. It offers real-time automated narrative cognition as a service to narratives from English corpus. It does not require data science skill and works across all problem domains.

What are the advantages?

- Transforms a written narrative into visual display
- Enhances information transparency across an organization
- Serves as the basis for strategic analysis on complex scenarios
- Citizen utility democratizes due diligence, eliminates bias, and counters falsity

Matching AI for narrative cognition

Prior to our implementation phase, we look at various technologies as potential candidates. There are several established technologies available for natural language processing. They fall under three major categories:

1. Textual analytics applying dictionary statistics to evaluate textual documents on words, word frequencies, distance between words. The primitive nature of this approach offers little value toward natural language understanding.

2. Pre-trained processing similar to Bidirectional Encoder Representation from Transformers (BERT) and similar versions thereof. These tools offered a method of pre-learned models that requires huge knowledge base to be trained ahead of time, making it practical to apply pipeline methodology on pre-trained model for a given task. Through this technique, solution can be implemented to handle a variety of NLP applications including:
    a. Sentiment analysis
    b. Text generation that provides generated text based on a prompt
    c. Name entity recognition (NER) in an input sentence; label each word with entity it represents.
    d. Question answering – provides answer from a given context and question
    e. Fill in the blank on sentence with missing words
    f. Summarization – generates a summary of a long text
    g. Translation – translates a text in another language
    h. Feature extraction – returns a tensor representation of the text

    Given the growing size of pre-trained samples, efficacy of these applications will continue to grow. However, the opaque nature of BERT is extremely difficult to apply output for goal reasoning.

3. Symbolic logic – uses propositional calculus or predicate calculus to analyze textual documents. Relationships of words are drawn from the underlying

sentential logic and statement logic. A discovery process uses this technique to look for context boundary in natural language documents, detecting connecting stories, identifying symbols that link stories together that formed the narrative. This method does not rely on pre-trained data. Rather, it discovers symbols and relationships from documents.

Features comparison among established technologies available for natural language processing:

Common NLP Feature	Narrative Cognition Requirement	Text Statistics Provision	Bert or Similar Provision	Symbolic Logic Provision
Modal development	Optional	Y	Y	Y
ML, DL, or RL Model	Optional	Maybe	Y	N
Count word frequencies, distance between words	Optional	Y	Y	N
Pre-trained model	Optional	Y	Y	N
Bidirectional Encoder Representation	Optional	N	Y	N
Sentiment analysis	Optional	Y	Y	N
Generated text based on prompts	Optional	N	Y	N
Name entity recognition	Optional	N	Y	N
Question answering	Optional	N	Y	N
Fill in the blank on sentence with missing words	Optional	N	Y	N
Summarization	Optional	N	Y	N
Translates text to another language	Optional	N	Y	N
Feature extraction returns a tensor representation of the text	Optional	N	Y	N
Discover new scenario not previously known	Required	N	N	Y
Discover previously unknown stories	Required	N	N	Y
Depict nexus between stories	Required	N	N	Y
Work with unknown words or terms	Required	N	N	Y
Traceable reasoning for stories and casual linkages	Required	N	N	Y
Unbiased analysis	Required	N	N	Y
Relevancy ordering of events and concepts	Required	N	N	Y
Draw reference from original text to support stories	Required	N	N	Y
Consistent real-time experience	Required	N	N	Y
Time series comparison of developing narrative	Optional	Maybe	Maybe	Y
Aggregate multiple narratives for cognition	Required	N	N	Y
Evaluate doubts and uncertainties	Optional	N	N	Y
Labeled abstractions	Required	Maybe	Maybe	Y
Interactive analysis	Required	Y	Y	Y
Provide key context	Required	N	N	Y
Detect logic in data	Required	N	N	Y

A hybrid implementation based on symbolic logic

Narrative cognition requires traceable casual linkages of stories in a narrative. Being able to trace casual linkages enables the user to evaluate alternatives. Fletcher [(2)] argued that causal reasoning is not attainable by symbolic logic since synapse is missing. However, the process of narrative cognition is not about generating casual reasoning from a narrative. Instead, it is identifying casual reasoning offered by the narratives. Koo [(3-5)] suggested a fact-based model that used fuzzy logic in conjunction with confidence assessment to depict intents offered by the author thereby addressing the transitive properties between symbols; detecting top subjects down to the atomic supporting facts. By transforming a narrative with symbolic logic according to a fact-based model, it offers clear insight into connected stories in a narrative.

An example of narrative cognition (1)

For the purpose of discussion, we elicited an English Language AI Enablement (ELAINE) platform that uses symbolic logic to demonstrate the effectiveness of using narrative cognition to untangle complex narrative. The narrative used in this discussion is a filed complaint of a lawsuit between Bluestone Coal (Bluestone) and Greensill Capital (Greensill). The dispute is related to supply chain financing.

Bluestone vs. Greensill case background

"Supply chain financing" is a form of supplier finance. A middleman is inserted between the buyer and the seller. The middleman buys the receivable from the seller at a discount, and earns a fee and the discount when the buyer pays the receivable in full (like a payday loan). Such agreement is a known as "Receivable Purchase Agreement" or RPA in short.

Bluestone sells coal to customers for production of steel. Greensill is a financial company acting as a middleman that offers supply chain financing to Bluestone. An RPA was executed between Bluestone and Greensill. As part of the agreement, it contains an exception on the definition of receivable to include prospective receivable from potential customers of Bluestone. In addition, Bluestone pledged various assets as collateral. Greensill obtained financial resource from Credit Suisse group (a German bank). Greensill secured insurance as a protection against default.

All went well until Greensill faced challenges from its insurance underwriter. Greensill, hoping to launch an IPO, was unable to find a new auditor. Questions about the valuation of some of the assets kicked off a chain of events that led Credit Suisse to freeze $10 billion in investment funds that Greensill relied upon to fuel its business. Greensill filed for insolvency in the U.K.

Bluestone, dependent on Greensill for financing had to look for alternative lenders. Bluestone now sued Greensill for alleged fraud. Bluestone claimed that it has no prior knowledge of Greensill's problem and seeking for remedy.

From the surface, this looks like a run of the mill lawsuit. However, the effect has much deeper impact. Credit Suisse who is not part of the lawsuit could potentially lose billions over Greensill's collapse. In addition, law firms are preparing claims for Credit Suisse's Greensill investors.

Deploying Narrative Cognition – the process

The complaint is comprised of a forty-five pages court document. Getting a good understanding of a narrative like this with narrative cognition yields benefit depending on roles of the audience:

1. For educators, the narrative offers insights into subjects being learned
2. For plaintiff, the narrative offers strategies to reinforce the case in court
3. For defendant, any weakness in the narrative can offer a better defense
4. For management teams, it offers insights on risk mitigation
5. For general readers, it answers curiosities and serves as a case study, helping to prevent future mistakes

Following steps identifies a process of narrative analysis:

1. Identify actors
2. Identify facts
3. Discover connected stories based on context and semantics
4. Discover casual linkages and relationships
5. Create a narrative map to depict facts, actors, stories and linkages
6. Obtain insight through observation of the map

Automated narrative cognition has the advantage of unbiased precision and speed. *The time required for the automated narrative cognition on the forty-five pages of formal complaint took less than 10 seconds.* The interactive report provides a contextual view of this complex narrative.

Narrative Cognition Process with ELAINE

- ELAINE discovers key words as symbols using predicate calculus.

- Symbols are connected to form high-level abstractions (HLA).

- Behind each HLA is the context and semantics that made up the stories within a narrative.

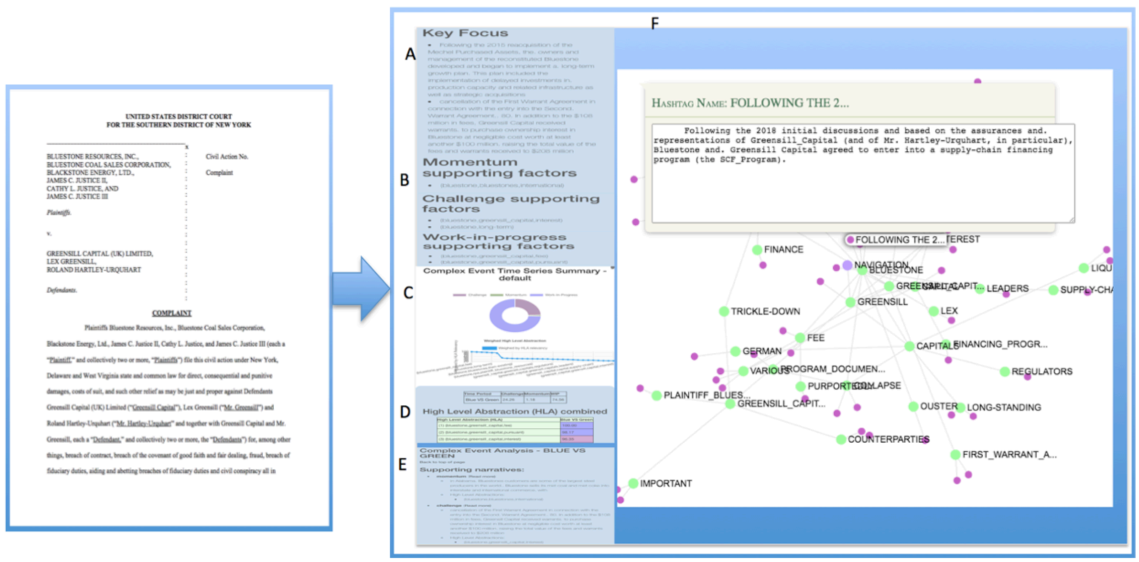
- An interactive topological diagram is rendered to show symbols connecting HLAs that it discovers. Hovering over each end node will trigger a pop-up text-box showing the corresponding semantic excerpt. Clicking on the node will open up a context sensitive display of the original document pin-pointing the relative context and location of the excerpt.

- Each HLA is ranked by relevancy according to its semantics posture. Semantics posture is determined by three components - momentum, challenge, and work-in-progress. HLA ranking is derived from the relative significance of semantics according to the author's composition style.

The qualitative benefit of automated narrative cognition on a legal complaint is the exposure of subtle insight that offers strategic values. By submitting the original complaint to ELAINE in verbatim, it gives back an interactive WEB report.

The following diagram explain the points of interest in the output report produced by ELAINE:

Automated Narrative Cognition

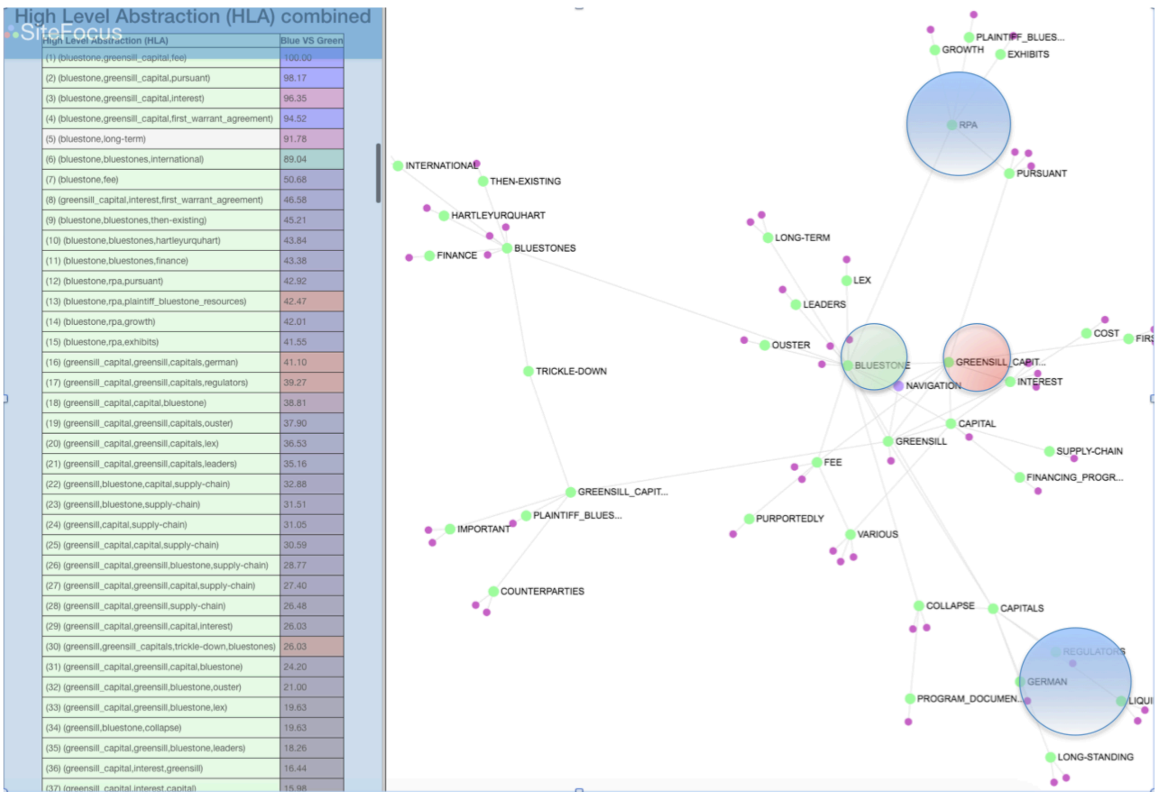


A. Key focus – most relevant excerpts
B. High Level Abstractions (HLA) identified as momentum, challenge and work-in-progress
C. Donut graph depicting the proportion of (B)
D. A table of HLAs ranked by relevancy
E. Excerpts associated with corresponding HLA
F. Narrative Diagram linking actors, facts, and stories; a visual navigational diagram with pop-up text box to show corresponding excerpts

A default top node called "Navigation" is always present. Hovering over this node will result in a popup textbox showing instruction for navigation.

Insights from Narrative Cognition Example

Output from ELAINE is consisted of components A-F. The interactive report is available for reference - URL(1). Narrative diagram depicts a topological view of Bluestone's complaint document. Following is a diagram showing an interactive WEB report:



In studying the narrative map, we should be mindful that this is derived from a document prepared by Bluestone reflecting plaintiff's belief. From a strategic perspective, it inspires some important questions based on the observation of the narrative map:

1. RPA was executed between Bluestone and Greensill. Notice there is no direct link to the node "GERMAN" or "REGULATORS". Why? Did Bluestone perform due diligence to inquire on the source of funding received form Greensill, especially when its business viability is dependent on the forth coming of such funding?
2. Source of funding that Greensill provided to Bluestone has no direct link between "CAPITALS" and "BLUESTONE". Does the German bank who supplied the capital did not conduct due diligence on the down stream borrower of such capital while assuming such transaction is safe?

3. In the dealings between Bluestone and Greensill, it is obvious that the definition of receivable is deviated from the norm of supply chain financing when "prospective" customers and "prospective" receivables from "prospective" transactions are involved in the RPA agreement. Proper due diligence would have caught such anomaly.

Conclusion

Understanding a complex narrative is always difficult, especially when it involves dispute of international parties and complicated business transactions. Using a topological narrative map to deconstruct a narrative makes it possible to gain insights into what went wrong. Thus enabling involved parties to formulate their discovery strategy. Leveraging on this technology to mitigate risk can certainly help management to make better decisions. This is especially true for conducting due diligence on merger and acquisition.

References

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(2) Angus Fletcher, Why computers Will Never Read (or Write) Literature: A Logical Proof and a Narrative, Volume 29, Number 1, Jan. 2021 Narrative Journal of International Society for the Study of Narrative

(3) Sing Koo, A Fact Based Expert System Model, Expert Systems in Government Symposium Oct. 1985 IEEE Computer Society

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(5) Sing Koo, ELAINE Symbolic AI offers community tool to cure "TL;DR" Syndrome, https://www.datasciencecentral.com/profiles/blogs/elaine-symbolic-ai-offers-community-tool-to-cure-tl-dr-syndrome