Guided Story Generation

Lara J. Martin (she/they)

https://laramartin.net/interactive-fiction-class

Learning Objectives

Appraise different ways people have extracted “plots” from stories

Appraise different ways people have used script/plot-like structures to guide text generation

Consider how a guided system would work with transformers

Compare and contrast old guided story systems

Define the Story Cloze Test and determine its place in guided story generation

Review: Levels of Information

'What's it going to be then, eh?'

There was me, that is Alex, and my three droogs, that is Pete, Georgie, and Dim, Dim being really dim, and we sat in the Korova Milkbar making up our rassoodocks what to do with the evening, a flip dark chill winter bastard though dry. The Korova Milkbar was a milk-plus mesto, and you may, O my brothers, have forgotten what these mestos were like, things changing so skorry these days and everybody very quick to forget, newspapers not being read much neither. Well, what they sold there was milk plus something else. They had no licence for selling liquor, but there was no law yet against prodding some of the new veshches which they used to put into the old moloko, so you could peet it with vellocet or synthemesc or drencrom or one or two other veshches which would give you a nice quiet horror-show fifteen minutes admiring Bog and All His Holy Angels and Saints in your left shoe with lights nursing all over your mozg. …

Text from *A Clockwork Orange* by Anthony Burgess

The story begins with the droogs sitting in their favourite hangout, the Korova Milk Bar, and drinking "milk-plus" – a beverage consisting of milk laced with the customer's drug of choice – to prepare for a night of ultra-violence.

Summary from Wikipedia

Alex begins his narrative from the Korova, where the boys sit around drinking.

Summary from SparkNotes.com

Review: What are procedures?

- A procedure is "a series of **actions** conducted in a certain **order** or manner," as defined by Oxford
- A more refined definition: "a series of **steps** happening to achieve some **goal**[1]"
  - Why?
- Examples of procedures: instructions (recipes, manuals, navigation info, how-to guide), algorithm, scientific processes, etc.
  - We focus on **instructions**, which is human-centered and task-oriented
- Examples of non-procedures: news articles, novels, descriptions, etc.
  - Those are often narrative: events do not have a specific goal
- The umbrella term is **script**[2]

[1] (Momouchi, 1980) [2] (Schank, 1977)

This work* answers the questions…

How well can LLMs reason about the steps of a procedure?

How can we combine procedures to create new scripts?

How can procedures help us do intent detection?

How can LLMs expand procedures to show more detailed steps?

* Work by Li “Harry” Zhang and Qing “Veronica” Lyu, and others

Review:
Testing LLM Knowledge of Procedures

- Task #1 Goal Inference: Given a goal, choose the most likely step out of 4 candidates.
  - **Input**: "How to prevent coronavirus"
  - **Choices**: Wash your hands? Wash your cat? Clap your hands? Eat your protein?
- Task #2 Step Inference: Given a step, choose the most likely goal out of 4 candidates.
  - **Input**: "Blink repeatedly."
  - **Choices**: Handle Pepper Spray in Your Eyes? Relax Your Eyes? Draw Eyes? Diagnose Pink Eye?
- Task #3 Step Ordering: Given a goal and two unordered steps, determine which comes first.
  - **Input**:

  Goal: How to Act After Getting Arrested.

  Step (a): Get a lawyer. Step (b): Request bond from the judge

Review: Combining Procedures

- Models can infer goals, steps, and ordering in **existing procedures**. Can we go one step further?
- **Creating new procedures**:

  If you know

  how to make an apple pie and how to make a banana cake

  can you infer

  how to make a banana pie ?

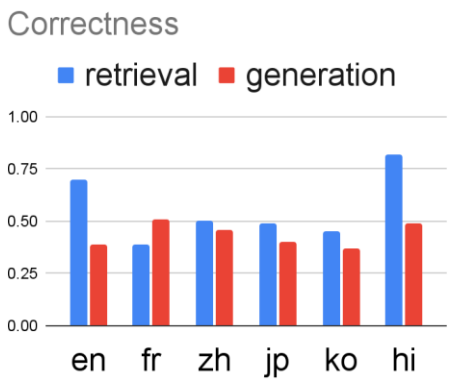
- This is commonsense knowledge to humans; do language models have it?

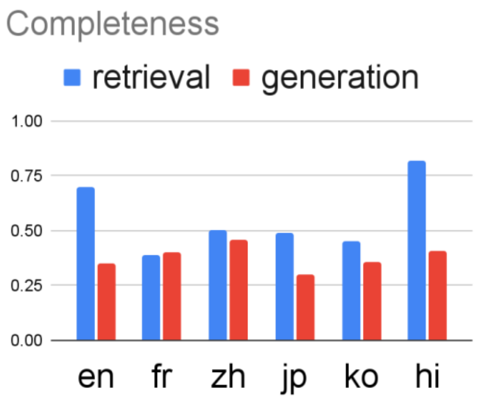
Crowdsourcing Evaluation

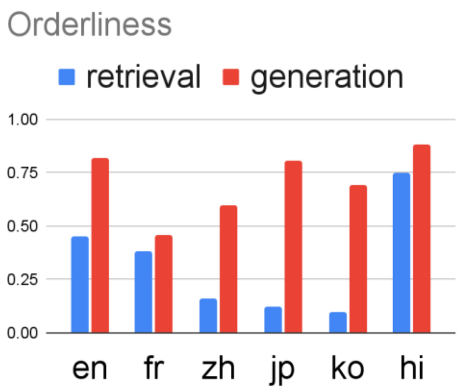
Asking “the crowd”

Evaluating on various metrics

- *“Correctness”*: len(edited script) / len(predicted script)
- *“Completeness”*: len(edited script) / len(gold script)
- *“Orderliness”*: Kendall’s Tau of steps in the edited script

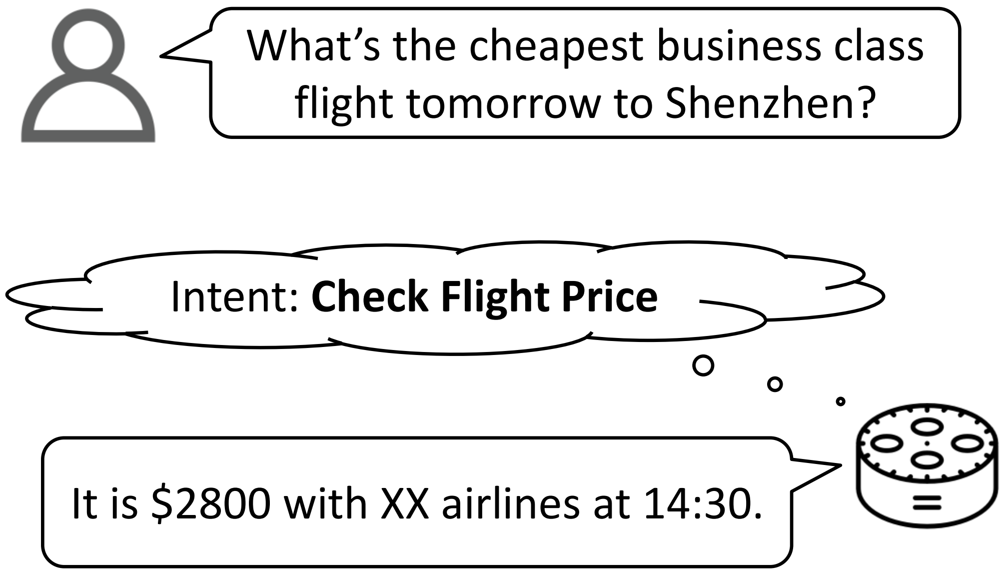






Review: Intent Detection

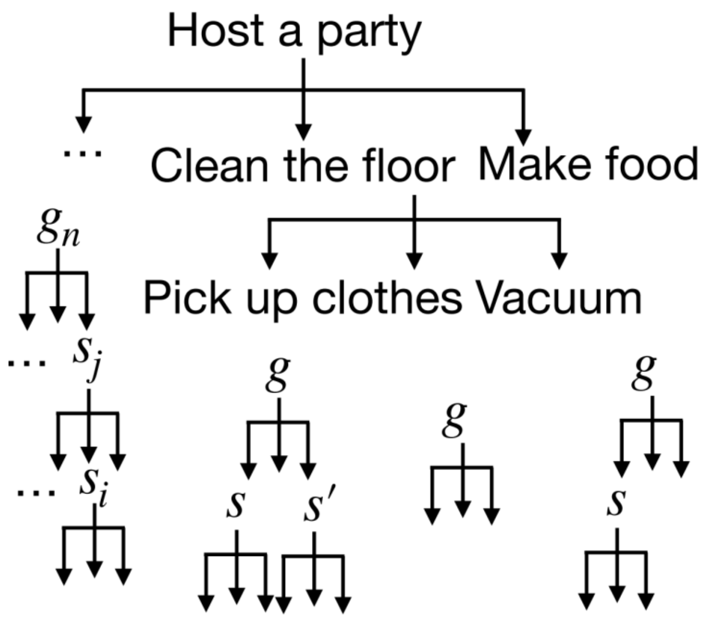
- Task-oriented dialog systems needs to match an **utterance** to an **intent**, before making informed responses
- Sentence classification task
  - Given an utterance, and some candidate intents
  - Choose the correct intent
  - Evaluated by accuracy



Example from Snips (Coucke et al., 2018)
Utterance: "Find the schedule at Star Theatres."
Candidate intents: Add to Playlist, Rate Book, Book Restaurant, Get Weather, Play Music, Search Creative Work, **Search Screening Event**

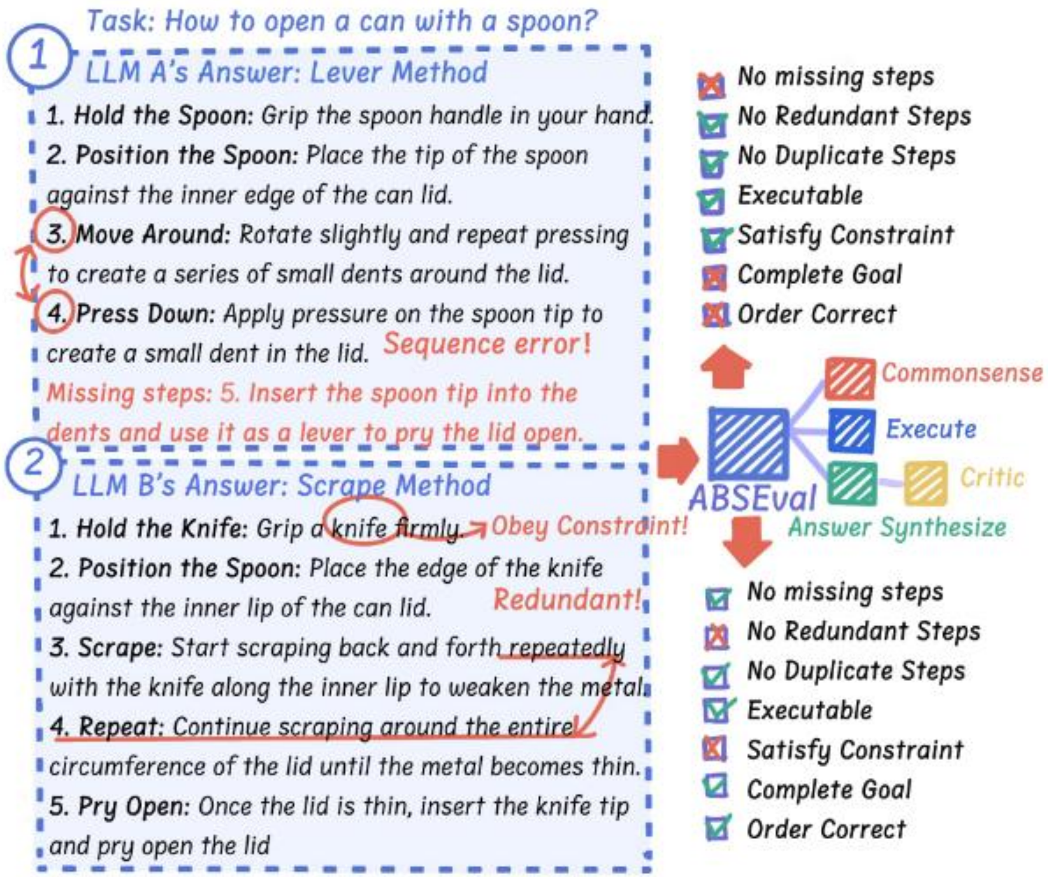
Review: Procedures are Hierarchical

- An event can simultaneously be a **goal** of one procedure, and a **step** in another
- A procedural hierarchy… So what?
  - Can "explain in more details" by expansion
  - Can shed light on event **granularity** (why?)
- How do you build such hierarchy?
  - To "host a party", I need to "clean the floor"; to "clean the floor", I need to do what?



Show Me More Details: Discovering Hierarchies of Procedures from Semi-structured Web Data (Zhou et al., ACL 2022)

Review: LLMs as Evaluators



[ABSEval: An Agent-based Framework for Script Evaluation](#) (Liang et al., EMNLP 2024)

Review: Agreement with Human Judgements

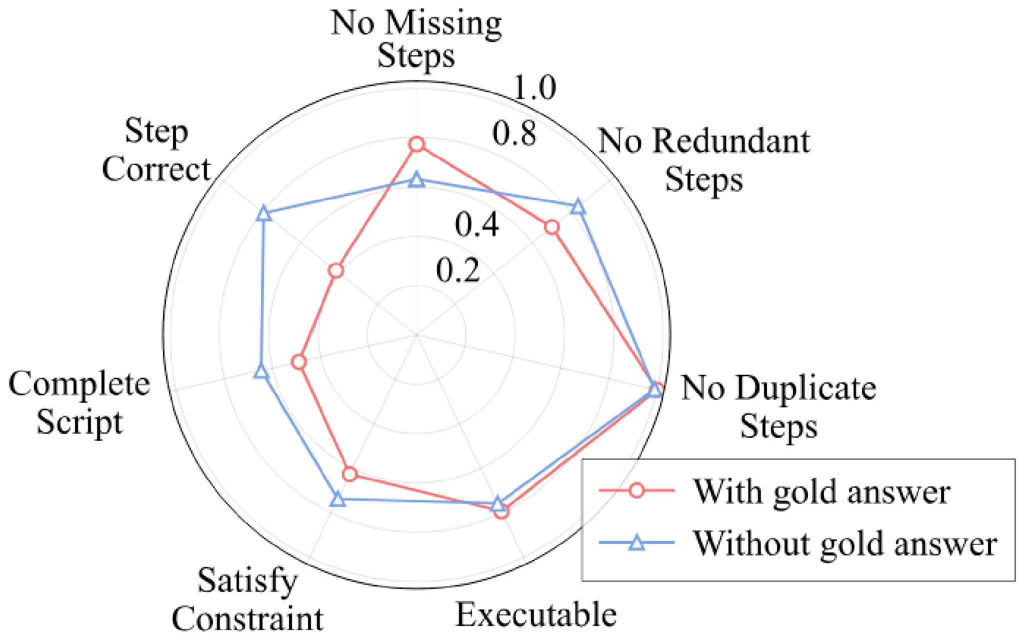


Figure 4: Comparing the consistency of evaluation results with human assessments when directly using LLM for evaluation, with and without providing an answer.

Review:
Potential Ways to Use Procedures in IF

- Infer likely steps given a goal (c.f. our goal-step relation work)
  - If a user decides to “conquer a dragon”, they need to “buy potions”, “level up”, “get equipment”, “swing the sword”, etc.; they won’t need to “get a PhD”, “play music”, etc.

- Reason about entity states
  - If a user “uses a *key* to open a *door*”, the *key* would remain intact, but the *door* changes from “locked” to “unlocked”, both of which are implicit (c.f. Tandon et al., 2020)
  - If a user “throws away the *only* key they have”, they would have 0 keys. (c.f. Li et al., 2021)

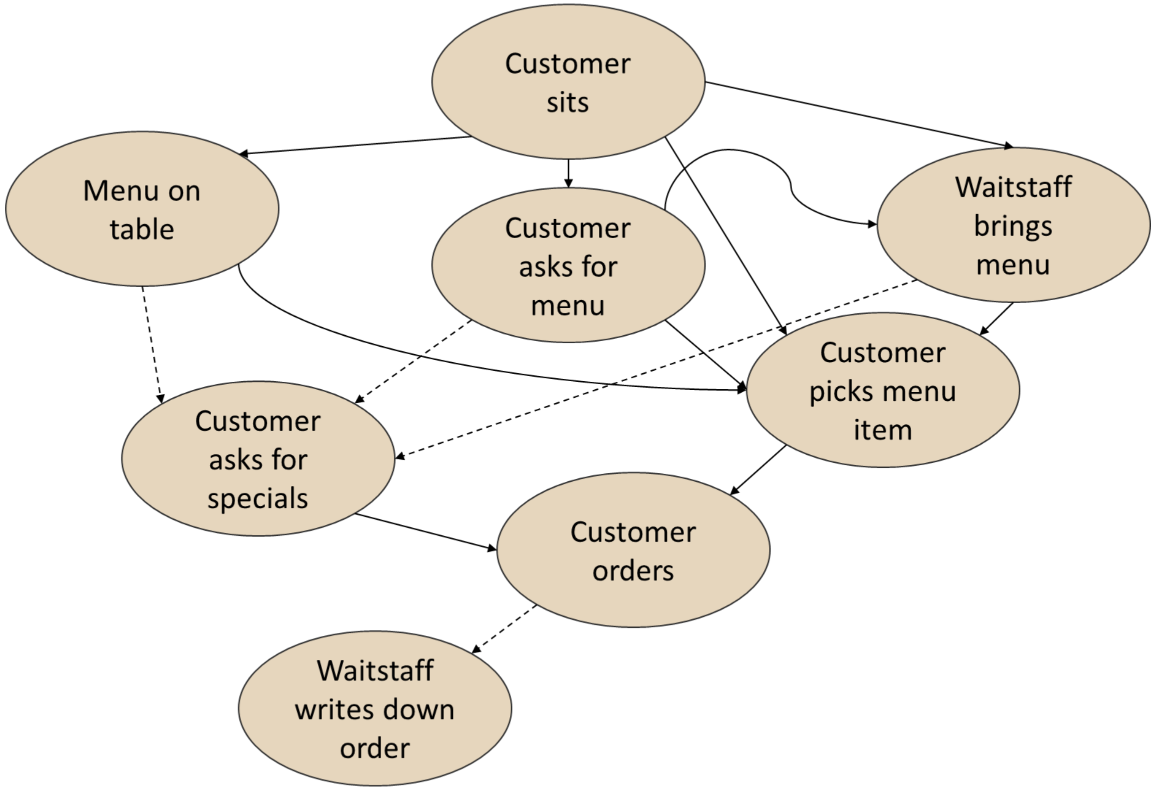
- Use procedures as scaffolding of the story
  - Language models tend to hallucinate given too much freedom
  - Instead, use procedures to guide them

Scripts, Procedures, and Plots…oh my!

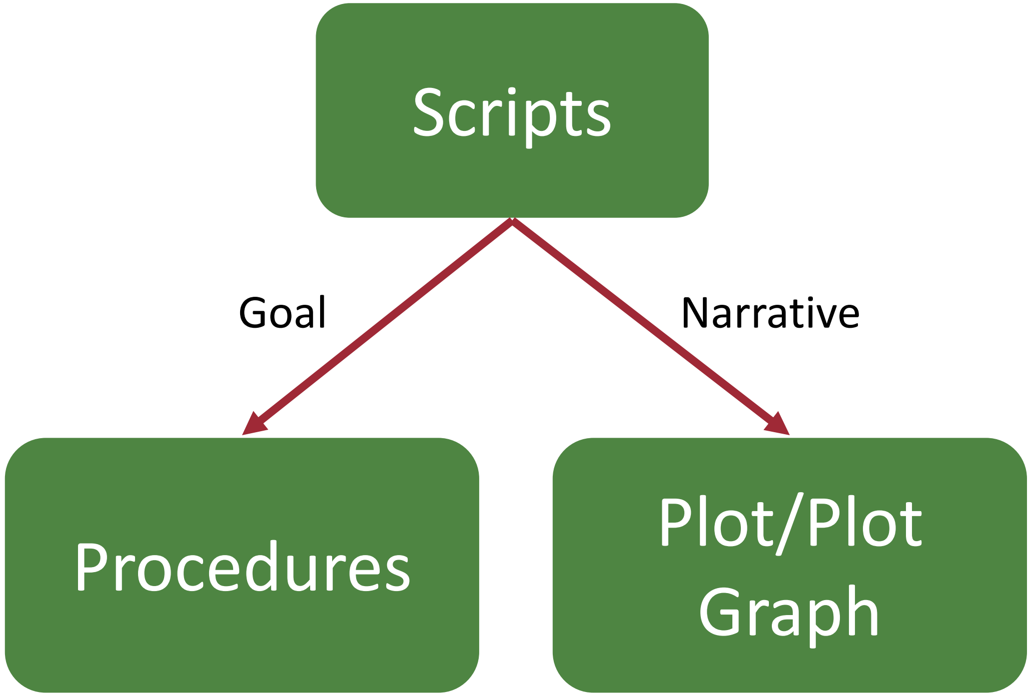
There are multiple ways of tying together *events*

Scripts, Procedures, and Plots…oh my!

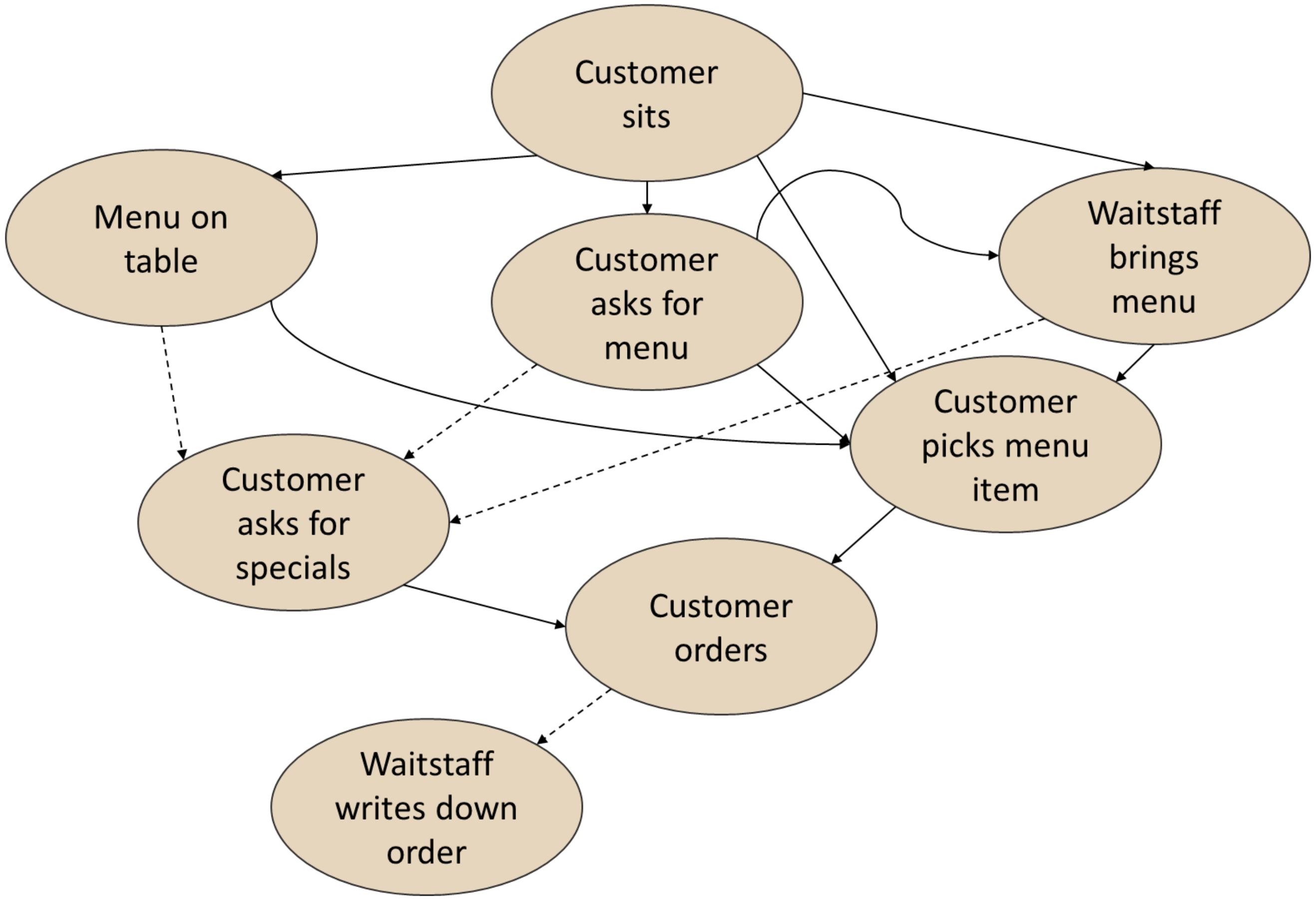
Schank & Abelson believe that everyone has **scripts** in their heads built from common experiences



Scripts, Procedures, and Plots...oh my!



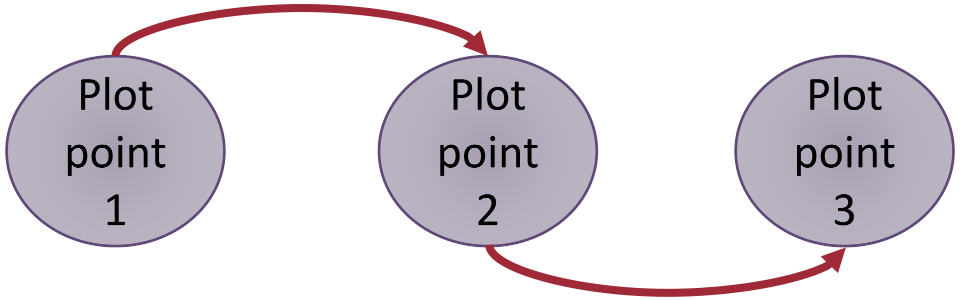
(Rough Dichotomy)

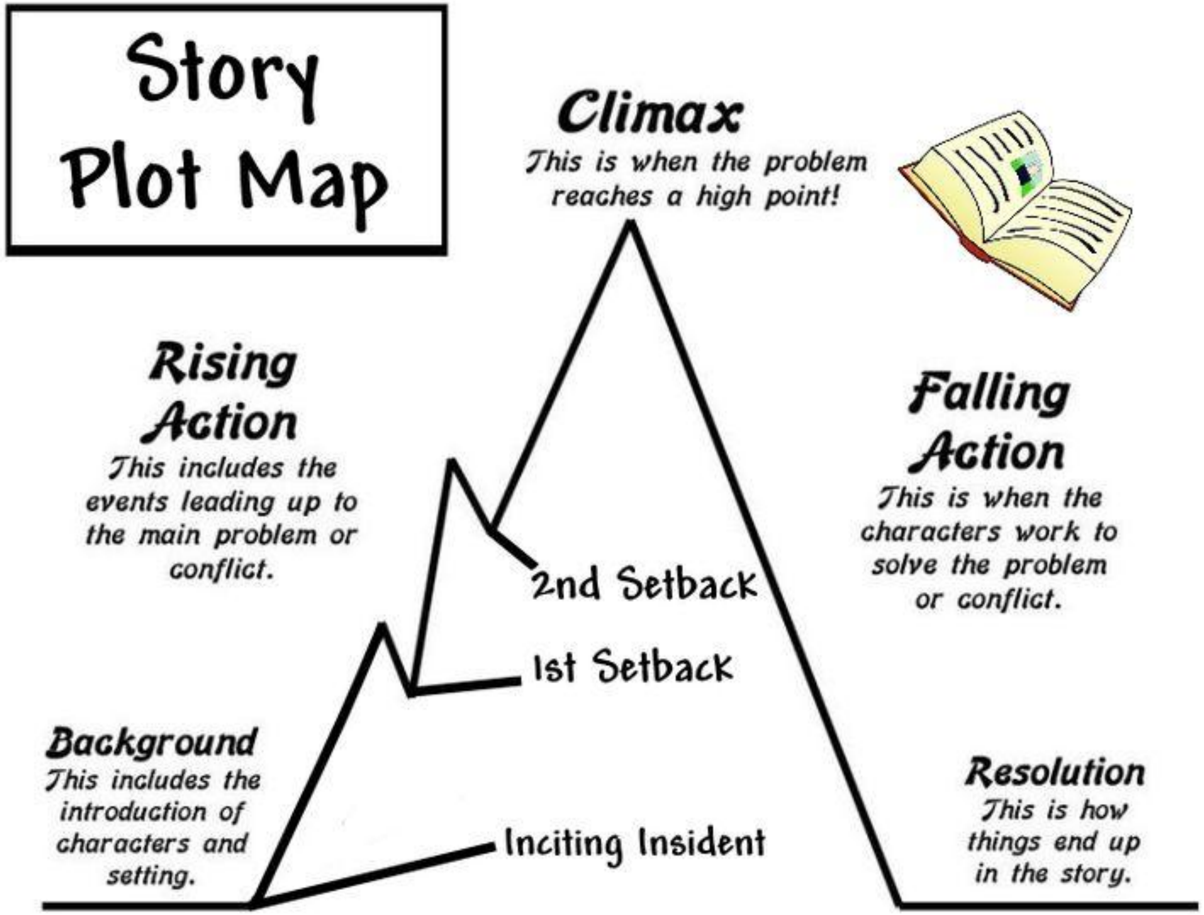


Scripts, Procedures, and Plots…oh my!

Schank & Abelson believe that everyone has scripts in their heads built from common experiences

Authors often plan out **plots** before they write stories





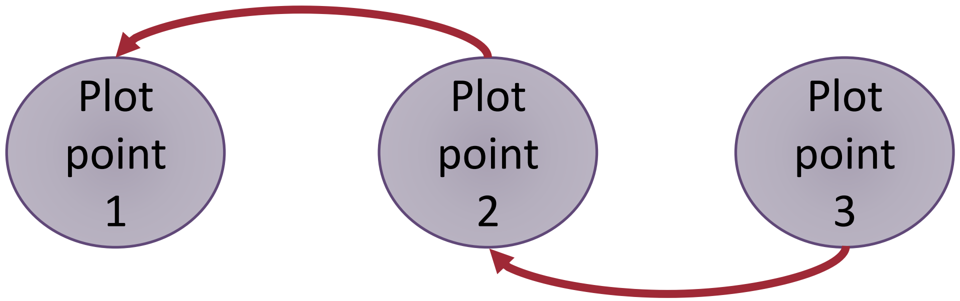
https://i.pinimg.com/736x/57/f7/03/57f703afc709080bddc2c3cfed8dd061.jpg

Scripts, Procedures, and Plots…oh my!

Schank & Abelson believe that everyone has scripts in their heads built from common experiences

Authors often plan out plots before they write stories

Stories that aren't planned out either have to "**reincorporate**"[1] ideas or the stories feel unfinished



[1] The idea of *reincorporation* is explored in the book Impro by Keith Johnstone

The Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19)

Plan-and-Write: Towards Better Automatic Storytelling

Lili Yao,[1,3*] Nanyun Peng,[2*] Ralph Weischedel,[2] Kevin Knight,[2] Dongyan Zhao,[1] Rui Yan[1†]
liliyao@tencent.com, {npeng,weisched,knight}@isi.edu
{zhaodongyan,ruiyan}@pku.edu.cn
[1]Institute of Computer Science and Technology, Peking University
[2]Information Sciences Institute, University of Southern California, [3]Tencent AI Lab

Abstract

Automatic storytelling is challenging since it requires generating long, coherent natural language to describes a sensible sequence of events. Despite considerable efforts on automatic story generation in the past, prior work either is restricted in plot planning, or can only generate stories in a narrow domain. In this paper, we explore open-domain story generation that writes stories given a title (topic) as input. We propose a *plan-and-write* hierarchical generation framework that first plans a storyline, and then generates a story based on the storyline. We compare two planning strategies. The *dynamic* schema interweaves story planning and its surface realization in text, while the *static* schema plans out the entire storyline before generating stories. Experiments show that with explicit storyline planning, the generated stories are more diverse, coherent, and on topic than those generated without creating a full plan, according to both automatic and human evaluations.

Introduction

A narrative or story is anything which is told in the form of a causally/logically linked set of events involving some

Title (Given)	The Bike Accident
Storyline (Extracted)	Carrie → bike → sneak → nervous → leg
Story (Human Written)	Carrie had just learned how to ride a bike. She didn't have a bike of her own. Carrie would sneak rides on her sister's bike. She got nervous on a hill and crashed into a wall. The bike frame bent and Carrie got a deep gash on her leg.

Table 1: An example of title, storyline and story in our system. A storyline is represented by an ordered list of words.

and Young 2010), we propose to decompose story generation into two steps: 1) story planning which generates plots, and 2) surface realization which composes natural language text based on the plots. We propose a *plan-and-write* hierarchical generation framework that combines plot planning and surface realization to generate stories from titles.

Extracting Plots

<u>Carrie</u> had just learned how to ride a bike. She didn't have a <u>bike</u> of her own. Carrie would <u>sneak</u> rides on her sister's bike. She got <u>nervous</u> on a hill and crashed into a wall. The bike frame bent and Carrie got a deep gash on her <u>leg</u>.

Carrie→bike→sneak→nervous→leg

Yao, L., Peng, N., Weischedel, R., Knight, K., Zhao, D., & Yan, R. (2019). Plan-And-Write: Towards Better Automatic Storytelling. *AAAI Conference on Artificial Intelligence (AAAI)*, *33*(1), 7378–7385. https://aaai.org/ojs/index.php/AAAI/article/view/4726

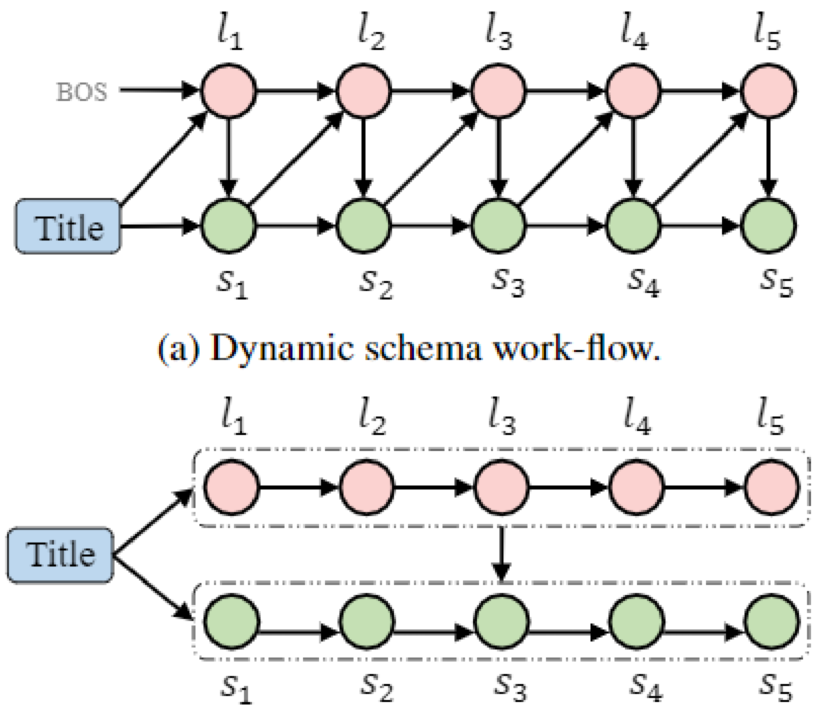
Plan-and-Write Overview

Extracted most important word from each sentence using RAKE algorithm (keyword extraction) to create a storyline (aka plot)

Used storyline as input to plan out stories

Dynamic generation → using storyline and sentences to inform each other

Static generation → plan ahead and then generate



(a) Dynamic schema work-flow.

(b) Static schema work-flow.

Plan-and-Write System

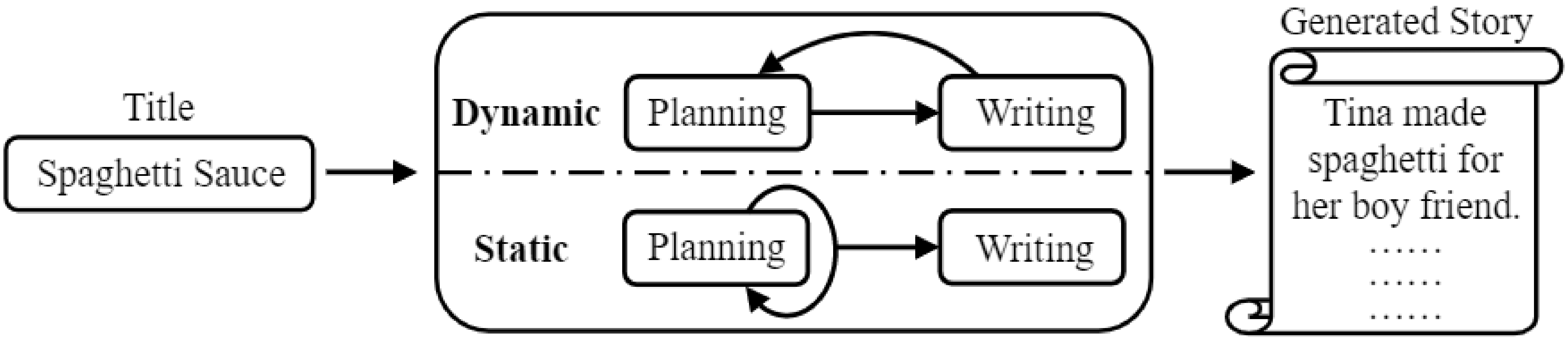


Figure 1: An overview of our system.

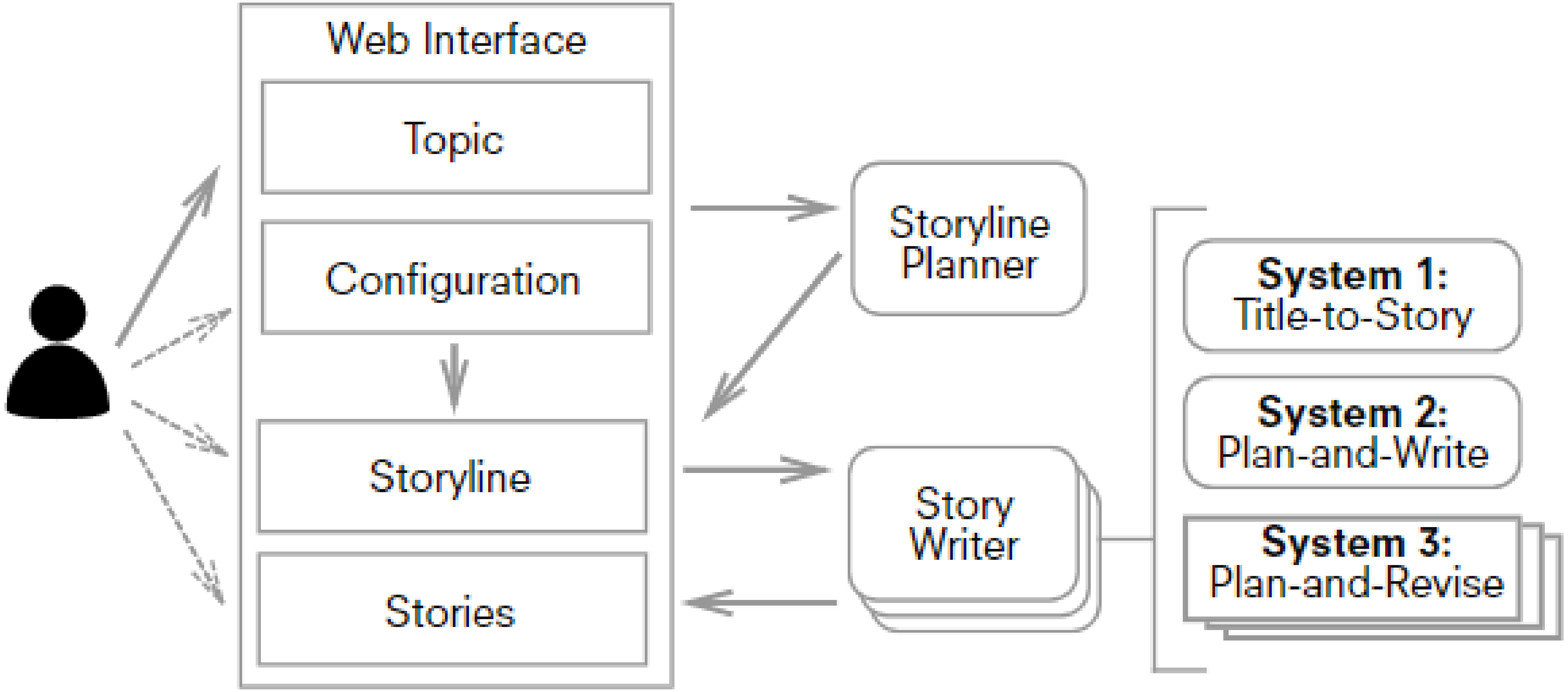
Examples

Which story would you consider better?

		Title: Computer
Baselines	Inc-S2S	Tom's computer broke down. He needed to buy a new computer. He decided to buy a new computer. Tom bought a new computer. Tom was able to buy a new computer.
	Cond-LM	The man bought a new computer. He went to the store. He bought a new computer. He bought the computer. He installed the computer.
Dynamic	Storyline	needed → money → computer → bought → happy
	Story	John needed a computer for his birthday. He worked hard to earn money. John was able to buy his computer. He went to the store and bought a computer. John was happy with his new computer.
Static	Storyline	computer → slow → work → day → buy
	Story	I have an old computer. It was very slow. I tried to work on it but it wouldn't work. One day, I decided to buy a new one. I bought a new computer .

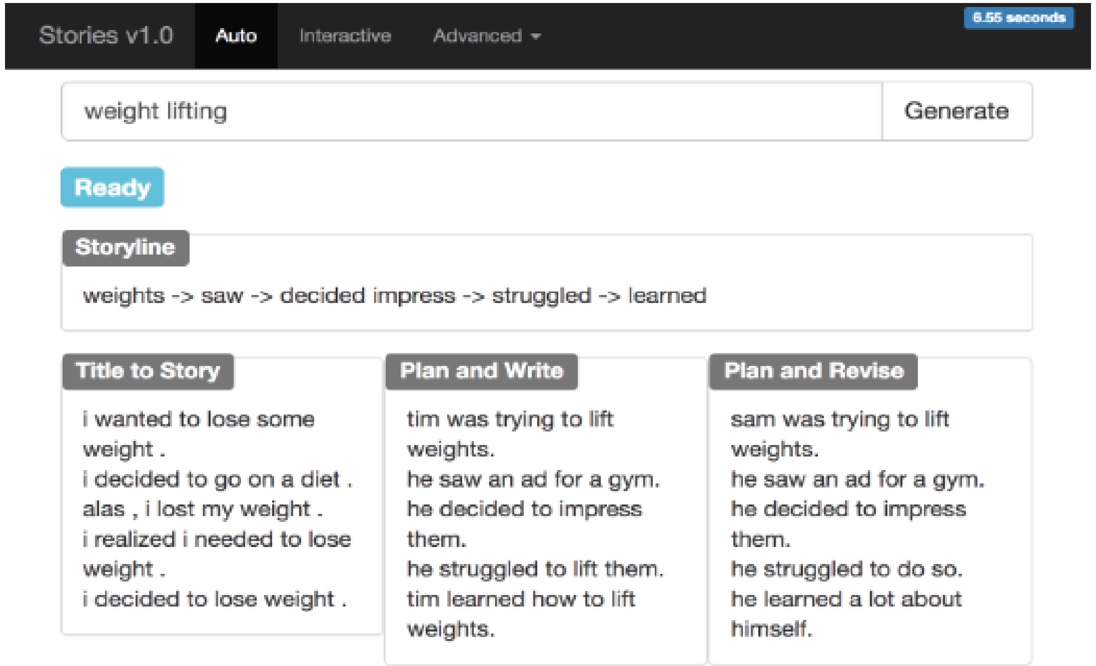
Yao, L., Peng, N., Weischedel, R., Knight, K., Zhao, D., & Yan, R. (2019). Plan-And-Write: Towards Better Automatic Storytelling. *AAAI Conference on Artificial Intelligence (AAAI)*, *33*(1), 7378–7385. https://aaai.org/ojs/index.php/AAAI/article/view/4726

Plan, Write, *and Revise*

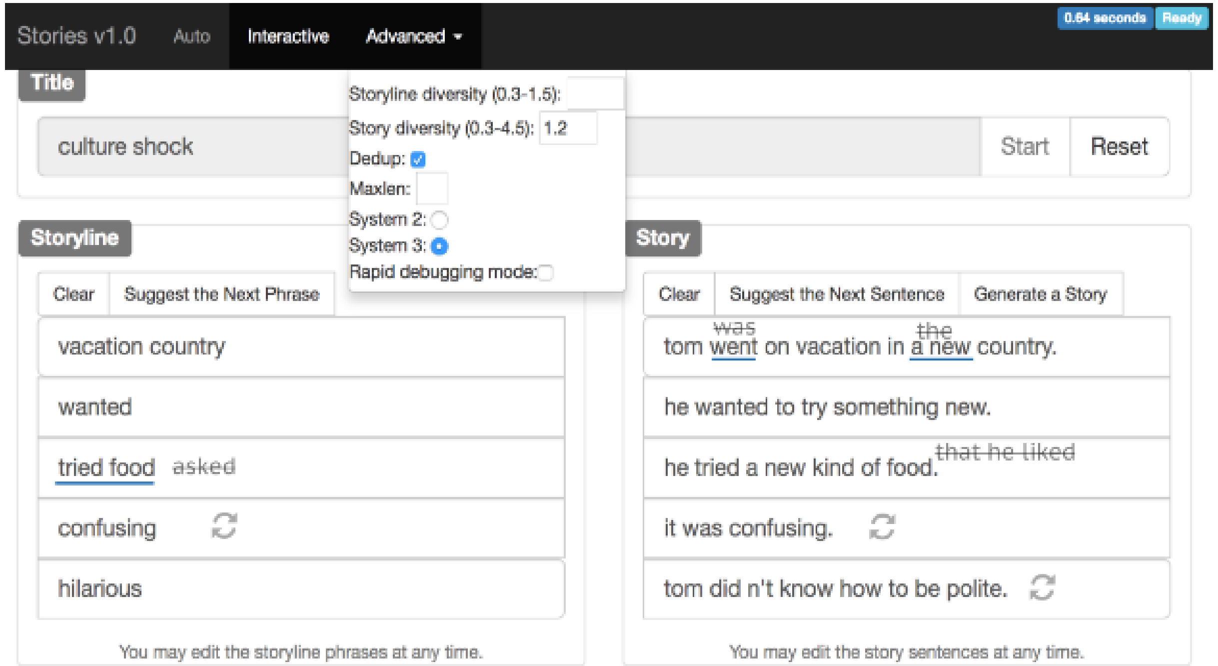


Goldfarb-Tarrant, S., Feng, H., & Peng, N. (2019). Plan, Write, and Revise: an Interactive System for Open-Domain Story Generation. *Conference of the North American Chapter of the Association for Computational Linguistics (NAACL) Demo Track*.

Plan, Write, and Revise



(a) cross-model interaction, comparing three models with advanced options to alter the storyline and story diversities.

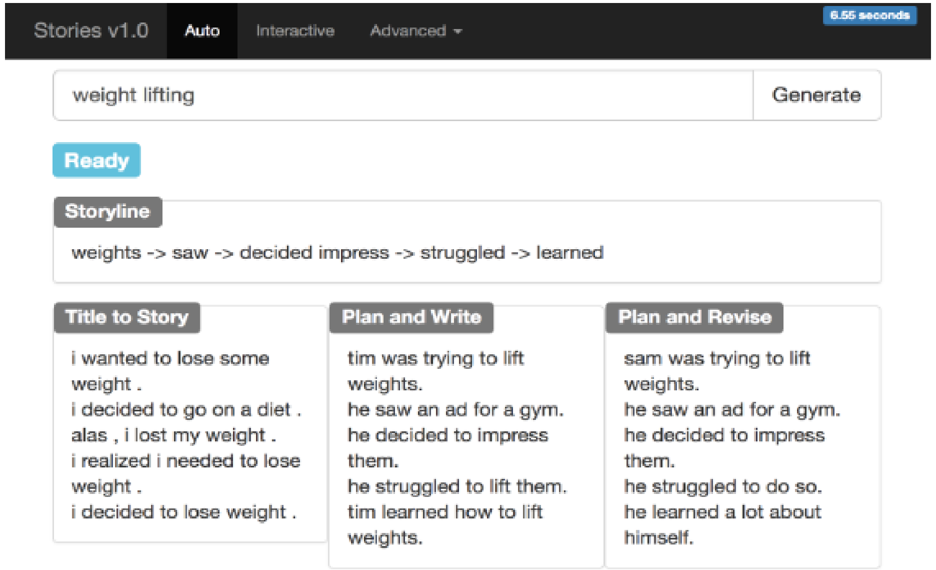


(b) intra-model interaction, showing advanced options and annotated with user interactions from an example study.

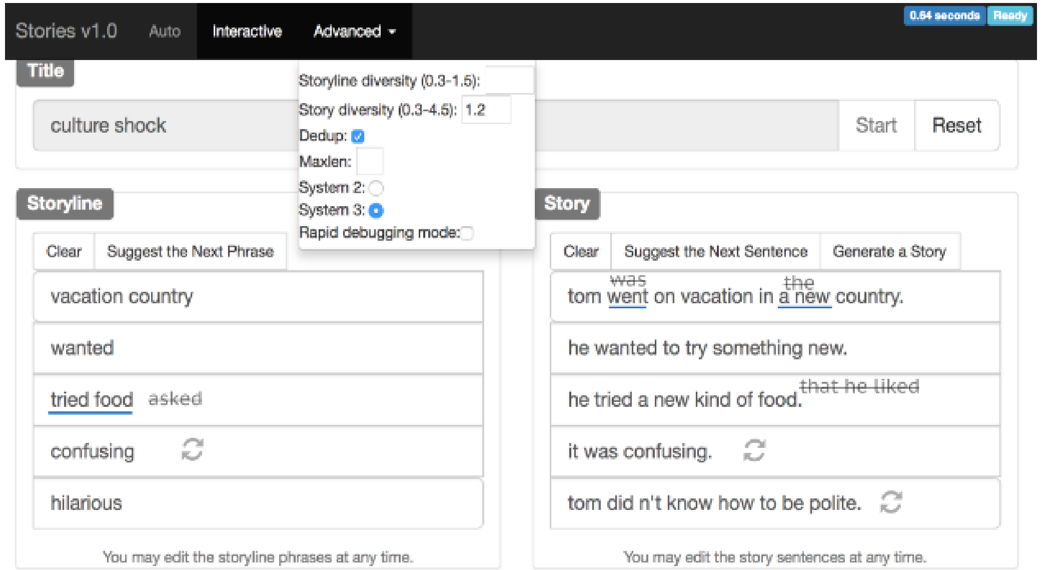
Goldfarb-Tarrant, S., Feng, H., & Peng, N. (2019). Plan, Write, and Revise: an Interactive System for Open-Domain Story Generation. *Conference of the North American Chapter of the Association for Computational Linguistics (NAACL) Demo Track*.

Think-Pair-Share

Plan, Write, and Revise was written in 2019. How might you “update” this work? Does it need to be updated?



(a) cross-model interaction, comparing three models with advanced options to alter the storyline and story diversities.



(b) intra-model interaction, showing advanced options and annotated with user interactions from an example study.

Goldfarb-Tarrant, S., Feng, H., & Peng, N. (2019). Plan, Write, and Revise: an Interactive System for Open-Domain Story Generation. *Conference of the North American Chapter of the Association for Computational Linguistics (NAACL) Demo Track*.

<Hidden Slide>

The Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI-20)

Story Realization: Expanding Plot Events into Sentences

Prithviraj Ammanabrolu, Ethan Tien, Wesley Cheung,
Zhaochen Luo, William Ma, Lara J. Martin, Mark O. Riedl
School of Interactive Computing
Georgia Institute of Technology
{raj.ammanabrolu, etien, wcheung8, zluo, wma61, ljmartin, riedl}@gatech.edu

Abstract

Neural network based approaches to automated story plot generation attempt to learn how to generate novel plots from a corpus of natural language plot summaries. Prior work has shown that a semantic abstraction of sentences called *events* improves neural plot generation and and allows one to decompose the problem into: (1) the generation of a sequence of events (event-to-event) and (2) the transformation of these events into natural language sentences (event-to-sentence). However, typical neural language generation approaches to event-to-sentence can ignore the event details and produce grammatically-correct but semantically-unrelated sentences. We present an ensemble-based model that generates natural language guided by events. We provide results—including a human subjects study—for a full end-to-end automated story generation system showing that our method generates more coherent and plausible stories than baseline approaches [1].

1 Introduction

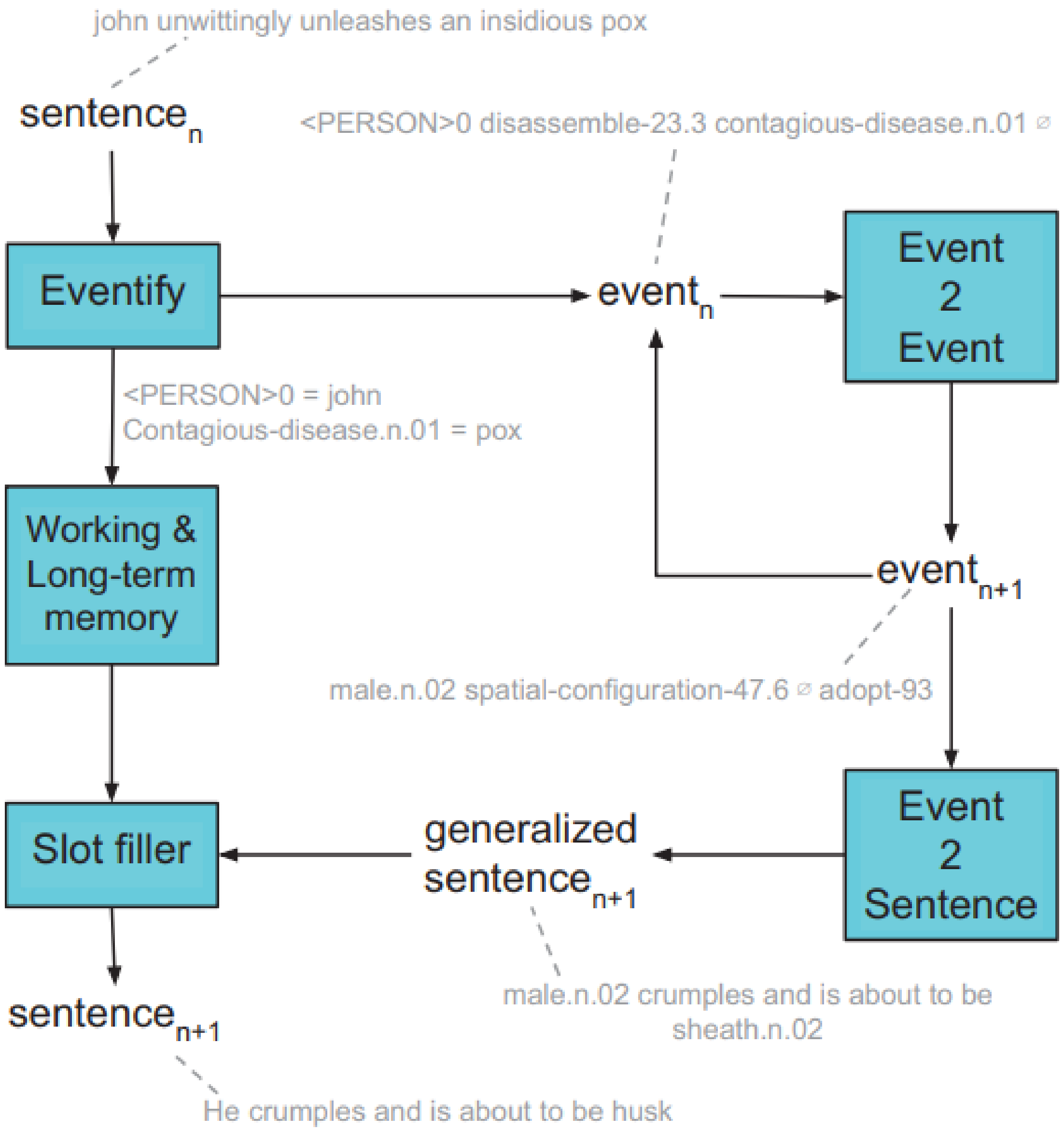
Automated story plot generation is the problem of creating a sequence of main plot points for a story in a given domain. Generated plots must remain consistent across the entire story, preserve long-term dependencies, and make for explicit domain modeling beyond providing a corpus of example stories. The primary pitfall of neural language model approaches for story generation is that the space of stories that can be generated is huge, which in turn, implies that, in a textual story corpora, any given sentence will likely only be seen once.

Martin et al. (2018) propose the use of a semantic abstraction called an *event*, reducing the sparsity in a dataset that comes from an abundance of unique sentences. They define an event to be a unit of a story that creates a change in the story world's state. Technically, an event is a tuple containing a subject, verb, direct object, and some additional disambiguation token(s).

The event representation enables the decomposition of the plot generation task into two sub-problems: *event-to-event* and *event-to-sentence*. Event-to-event is broadly the problem of generating the sequence of events that together comprise a plot. Models used to address this problem are also responsible for maintaining plot coherence and consistency. Once new events are generated, however, they are still not human-readable. Thus the second sub-problem, event-to-sentence, focuses on transforming these events into natural language sentences.

Story Realization

Extract events from stories



Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Review: Probabilistic Event Representation

From sentence, extract event representation:

(subject, verb, direct object, modifier, preposition)

Original sentence: yoda uses the force to take apart the platform

Events:

- yoda use force Ø Ø
- yoda take_apart platform Ø Ø

Generalized Events:

<PERSON>0 fit-54.3 power.n.01 Ø Ø

<PERSON>0 destroy-44 surface.n.01 Ø Ø

Martin, Lara J., et al. "Event representations for automated story generation with deep neural nets." *Thirty-Second AAAI Conference on Artificial Intelligence*. 2018.

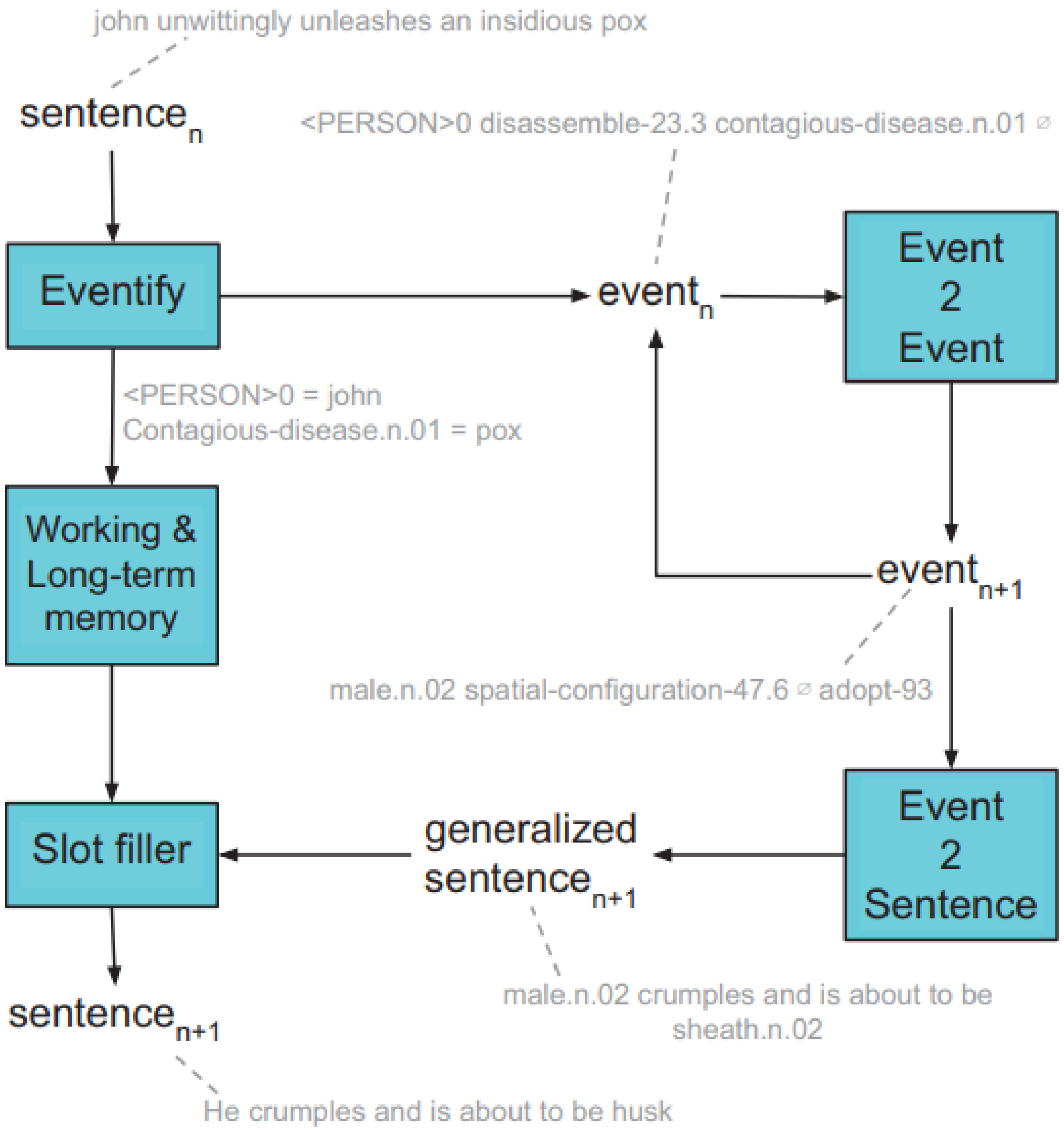
Story Realization

Extract events from stories

Generate the plot using a seq2seq network

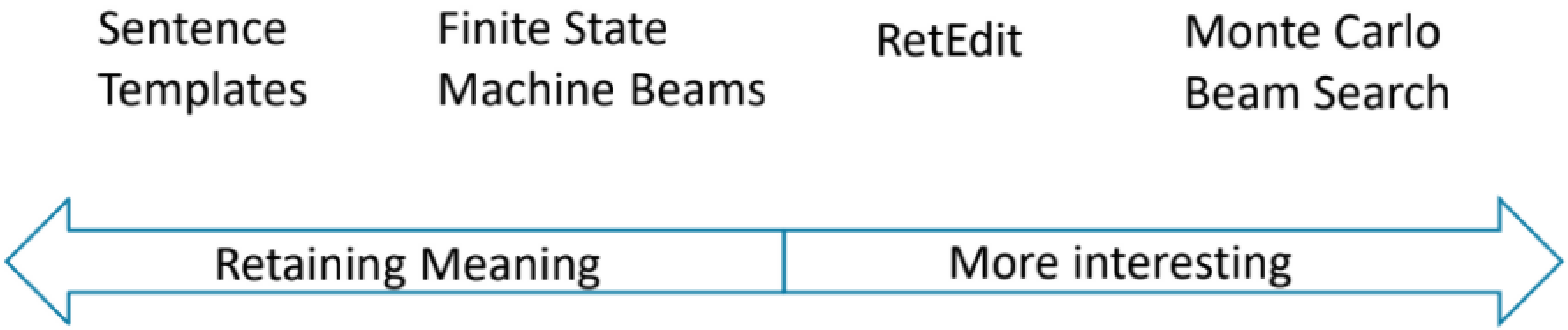
Use an ensemble of methods to find the best sentence given an event

Get a confidence score from each model, and accept the sentence if it's above a threshold



Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Balance of Meaning and Interestingness



Story Realization: Cascading Ensemble

RetEdit

Sentence Templates

Monte Carlo Beam Search

Finite State Machine Constrained Beams

Seq2Seq (Greedy Decoding)

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

RetEdit

Retrieve: Map event to its closest sentence and retrieve that

Edit:

- Seq2seq with attention and copying (Gu et al., 2016)
- Takes the retrieved sentence and the original input event, then edits

Confidence score: proportional to 1 – retrieval distance

Input Event	**RetEdit**
⟨<PRP>, act-114-1-1, to, ∅, event.n.01⟩	<PRP> and <PERSON>0 move to the event.n.01 of the natural_object.n.01.
⟨<PERSON>2, send-11.1, through, <PERSON>6, <LOCATION>1⟩	<PERSON>2 sends <PERSON>6 through the <LOCATION>1.

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Sentence Templates

Input Event	Templates
⟨<PRP>, act-114-1-1, to, ∅, event.n.01⟩	<PRP> act-114-1-1 to event.n.01.
⟨<PERSON>2, send-11.1, through, <PERSON>6, <LOCATION>1⟩	The <PERSON>2 send-11.1 the <PERSON>6 through <LOCATION>1.

$$S \rightarrow NP \quad v \quad (NP) \quad (PP)$$
$$NP \rightarrow d \quad n$$
$$PP \rightarrow p \quad NP$$

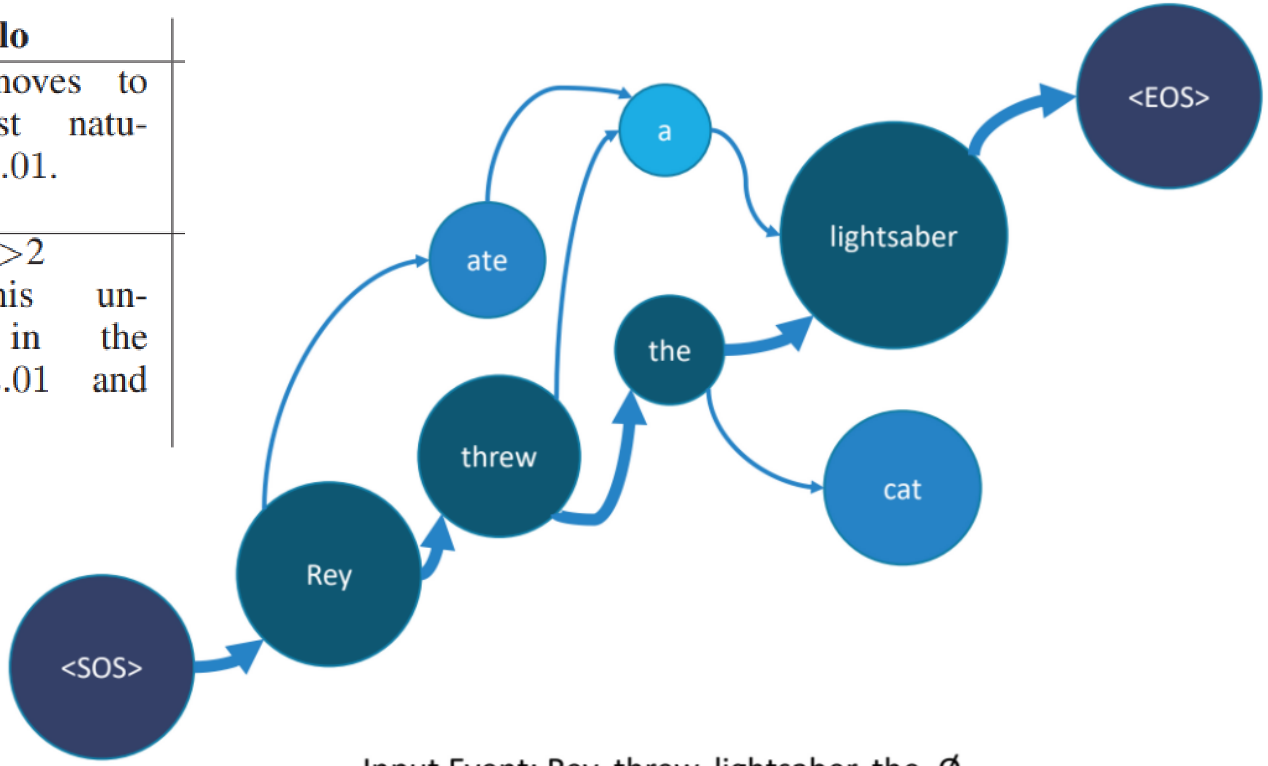
$$[\_\_ \ s]\{v \ [\_\_ \ o] \ [p \ \_\_ \ m]\}$$

Confidence score: $1 - \frac{\sum loss}{sentence\ length}$

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Monte Carlo Beam Search

Input Event	**Monte Carlo**
⟨<PRP>, act-114-1-1, to, ∅, event.n.01⟩	<PRP> moves to the nearest natural_object.n.01.
⟨<PERSON>2, send-11.1, through, <PERSON>6, <LOCATION>1⟩	<PERSON>2 passes this undercover in the body_part.n.01 and collapses.



Input Event: Rey, threw, lightsaber, the, Ø

Confidence Score: $s_t = \alpha * s_{t-1} + (1 - \alpha) * AVG(playout_t)$

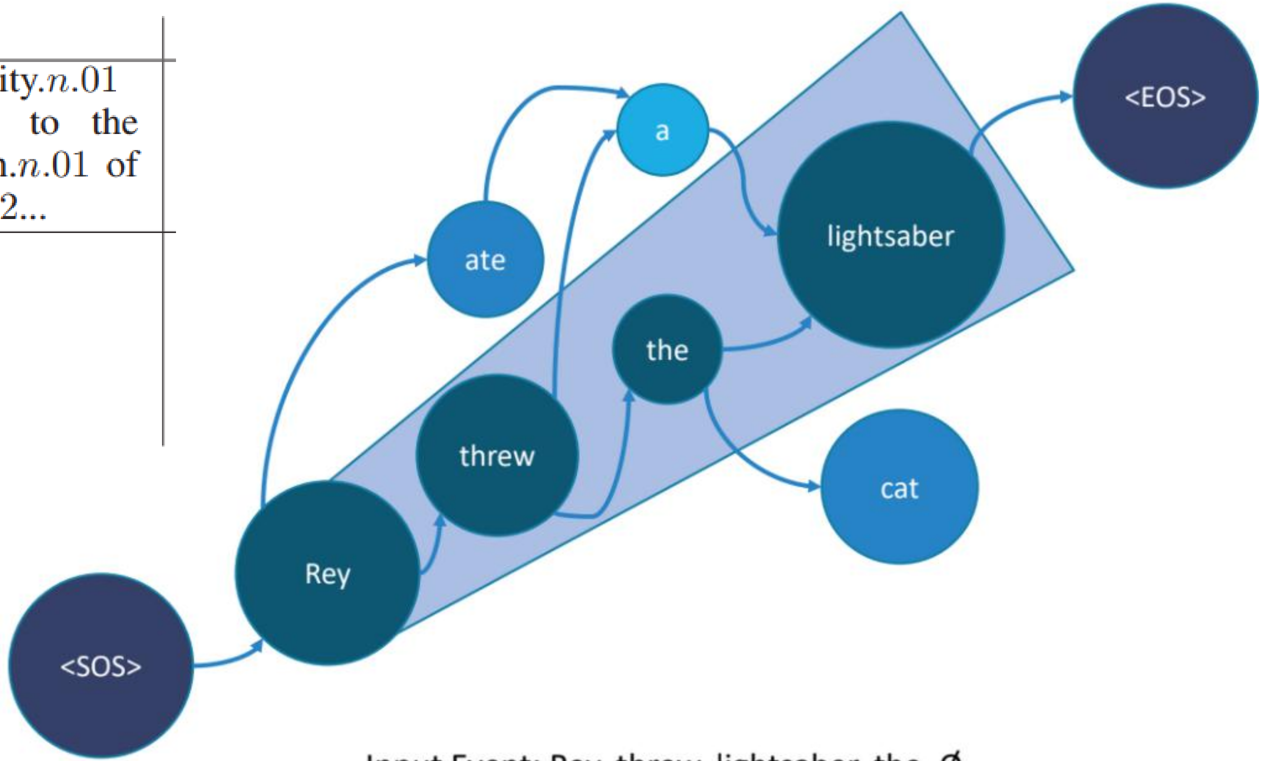
Beams weighted to favor tokens in input

Weights learned at validation

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Finite State Machine Constrained Beams

Input Event	**FSM**
⟨<PRP>, act-114-1-1, to, ∅, event.n.01⟩	physical_entity.n.01 move back to the phenomenon.n.01 of the craft.n.02...
⟨<PERSON>2, send-11.1, through, <PERSON>6, <LOCATION>1⟩	∅



Input Event: Rey, threw, lightsaber, the, Ø

Confidence Score: Match at least 3 tokens in input

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI), 34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Examples

Table 1: Event-to-sentence examples for each model. ∅ represents an empty parameter; <PRP> is a pronoun.

Input Event	RetEdit	Templates	Monte Carlo	FSM	Gold Standard
⟨<PRP>, act-114-1-1, to, ∅, event.n.01⟩	<PRP> and <PERSON>0 move to the event.n.01 of the natural_object.n.01.	<PRP> act-114-1-1 to event.n.01.	<PRP> moves to the nearest natural_object.n.01.	physical_entity.n.01 move back to the phenomenon.n.01 of the craft.n.02...	<PRP> move to the event.n.01.
⟨<PERSON>2, send-11.1, through, <PERSON>6, <LOCATION>1⟩	<PERSON>2 sends <PERSON>6 through the <LOCATION>1.	The <PERSON>2 send-11.1 the <PERSON>6 through <LOCATION>1.	<PERSON>2 passes this undercover in the body_part.n.01 and collapses.	∅	In activity.n.01 to avoid <PRP> out.n.01 <PERSON>2 would transport <PERSON>6 through the <LOCATION>1.

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

End-to-End Examples

Table 2: End-to-end pipeline examples on previously-unseen input data. The Event-to-Sentence model used is the full ensemble. Sentences are generated using both the extracted and generated events.

Input Sent.	Extracted event	Generated Events (Event-to-Event)	Generated Sentences (Event-to-Sentence)	Slot-filled Sentences
On Tatooine, Jabba the Hutt inspects the drone barge recently delivered to him.	⟨<ORG>0, assessment-34.1, ∅, vessel.n.02, ∅⟩	⟨<PERSON>1, settle-36.1.2, ∅, indicator.n.03, indicator.n.03 ⟩ ; ⟨music.n.01, escape-51.1-1, from, ∅, ∅⟩; ⟨<PRP>, discover-84, to, run-51.3.2, progenitor.n.01⟩	The <ORG>0 can not scan the vessel.n.02 of the <VESSEL>0. <PERSON>1 decides to be a little person.n.01 at the structure.n.01. the music.n.01 arrives. <PRP> finds a lonely person.n.01 on the upper one of the craft.n.02 which is not a personal_letter.n.01 but does not respond to hails .	The Jabba the Hutt can not scan the bareboat of the Uss Lakota. O Yani decides to be a little mailer at the airdock. The Music arrives. She finds a lonely mailer on the upper one of the bareboat which is not a love letter but does not respond to hails.
Boba Fett has just chased down another bounty, a Rodian art dealer who sold fake works to Gebbu the Hutt.	⟨<PERSON>0, chase-51.6, ∅, bounty.n.04, ∅⟩	⟨<PERSON>0, chase-51.6, to, magnitude.n.01, ∅⟩; ⟨magnitude.n.01, comprehend-87.2, off, craft.n.02, magnitude.n.01⟩; ⟨<PERSON>2, amuse-31.1, off, ∅, ∅⟩; ⟨<PERSON>2, discover-84, off, change_of_integrity.n.01, ∅⟩	<PERSON>0 enters the bounty.n.04 and tells <PRP>. <PERSON>0 attaches the explosive.a.01 to the person.n.01 who is trying to fix the device.n.01. the magnitude.n.01 doesn't know the craft.n.02 off the craft.n.02. <PERSON>2 is surprised when <PRP> learns that the person.n.01 is actually <PERSON>7. <PERSON>2 sees the change_of_integrity.n.01 and tells <PRP>.	Boba Fett enters the bounty and tells it. Boba Fett attaches the explosive to the peer who is trying to fix the toy. The multiplicity doesn't know the bounty off the bounty. Dark Jedi Lomi Plo is surprised when it learns that the peer is actually Mrs Conners. Dark Jedi Lomi Plo sees the combination off the Orbs and tells them.

Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. J., & Riedl, M. O. (2020). Story Realization: Expanding Plot Events into Sentences. *AAAI Conference on Artificial Intelligence (AAAI)*, *34*(5), 7375–7382. https://ojs.aaai.org//index.php/AAAI/article/view/6232

Guided Open Story Generation Using Probabilistic Graphical Models

Sagar Gandhi*
University of Kentucky
Lexington, Kentucky
sga267@uky.edu

Brent Harrison
University of Kentucky
Lexington, Kentucky
harrison@cs.uky.edu

ABSTRACT

In this work, we present an approach for performing computational storytelling in open domain based on Author Goals. Author Goals are constraints placed on a story event directed by the author of the system. There are two challenges present in this type of story generation: (1) automatically acquiring a model of story progression, and (2) guiding the progress of story progression in light of different goals. We propose a novel approach to story generation based on probabilistic graphical models and Loopy Belief Propagation (LBP) that addresses both of these problems. We show the applicability of our technique through a case study on the Visual Storytelling (VIST) 2017 dataset. We use image descriptions as author goals. This empirical analysis suggests that our approach is able to utilize goals information to better automatically generate stories.

CCS CONCEPTS

• **Computing methodologies → Probabilistic reasoning**; *Discourse, dialogue and pragmatics*; *Natural language generation*; *Learning in probabilistic graphical models.*

KEYWORDS

Belief Propagation, Computational Storytelling, Natural Language Generation, Probabilistic Graphical Models

ACM Reference Format:

Sagar Gandhi and Brent Harrison. 2019. Guided Open Story Generation Using Probabilistic Graphical Models. In *The Fourteenth International Conference on the Foundations of Digital Games (FDG '19), August 26–30, 2019, San Luis Obispo, CA, USA*, Jennifer B. Sartor, Theo D'Hondt, and Wolfgang De Meuter (Eds.). ACM, New York, NY, USA, Article 4, 7 pages. https://doi.org/10.1145/3337722.3341871

problem *domain model* [3, 5, 25]. This type of story generation is sometimes called *Closed Story Generation.* While stories generated in this way are often coherent, the space of possible stories that can be generated is tightly coupled with the domain model. In order to generate different types of stories, a new domain model must be authored, which is often a time consuming task.

Open Story Generation seeks to address this limitation by enabling stories to be told in any conceivable domain through the use of machine learning. The goal is to use these systems to tell a variety of stories without the need for re-learning specific domain models.

One limitation of open story generation systems is that, due to the complexity of the models used for training, it can be difficult to encode specific author goals into the story generation process. To address this limitation of open story generation systems, we propose a new framework that can reason about the overall structure of a story as well as how to incorporate author goals into the story generation process. This system enables many different types of stories to be generated based on these author goals without needing to retrain or re-learn a domain model.

In this paper, we use a novel approach for open story generation based on probabilistic graphical models. This gives us an enhanced ability to reason about story structure when compared to neural-based approaches. There are also several ways to perform inference over these structures including MCMC sampling and reinforcement learning, but we choose to model story structure and author goals using bipartite graphs and perform inference over them using Loopy Belief Propagation (LBP). We use LBP rather than MCMC or reinforcement learning because the latter approaches often require a large amount of data to perform inference which may not be readily available in practice.

1) Extract Semantic Relationships

Use discourse representation structure (DRS) parser to get semantic relationships

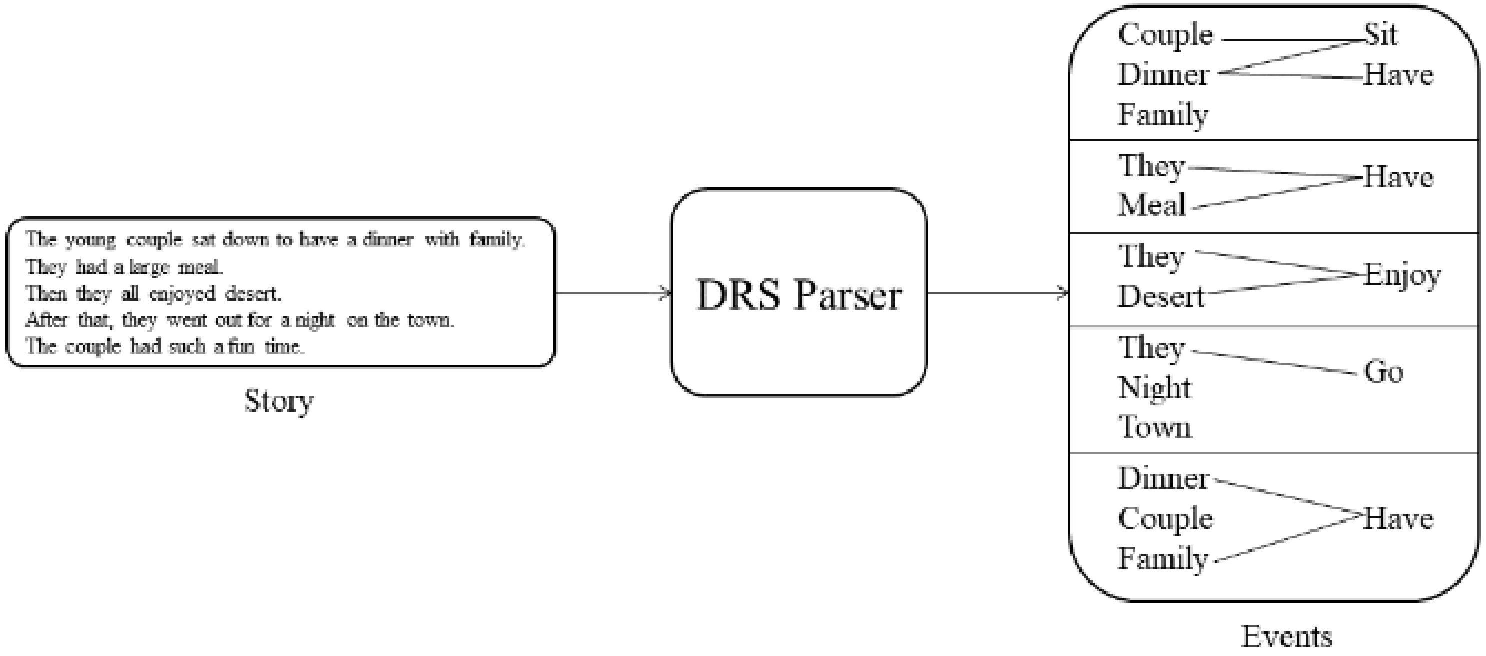


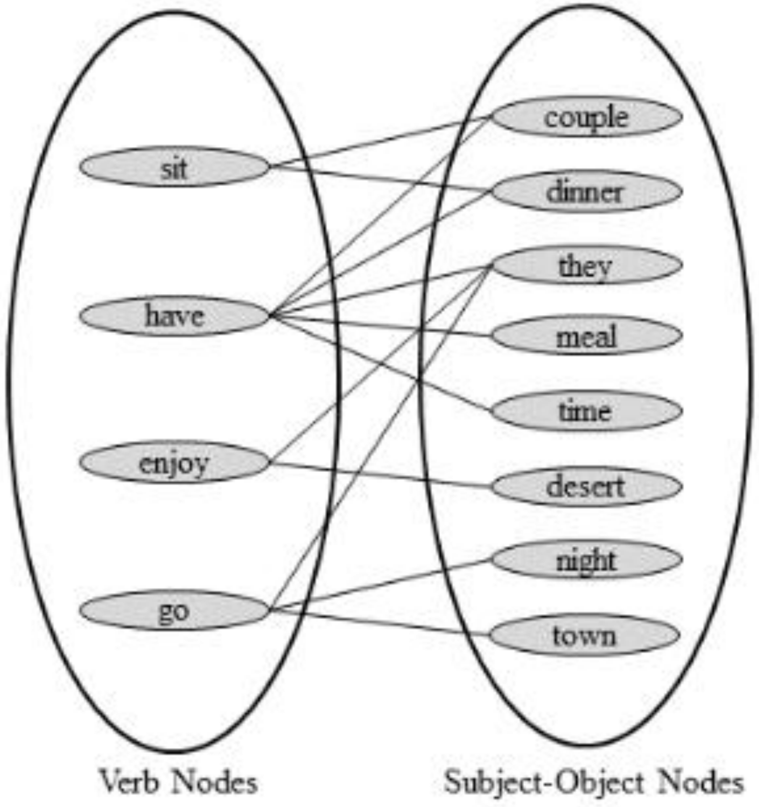
Figure 1: Event Representation using DRS Parser. Note that the words without edges are removed while forming the graphs.

Gandhi, S., & Harrison, B. (2019). Guided open story generation using probabilistic graphical models. *International Conference on the Foundations of Digital Games (FDG)*, 1–7. https://doi.org/10.1145/3337722.3341871

2) Create Story Graphs from Semantic Relationships

Story Graph: “edges […] between story verb nodes and story subject-object nodes.”

Gandhi, S., & Harrison, B. (2019). Guided open story generation using probabilistic graphical models. *International Conference on the Foundations of Digital Games (FDG)*, 1–7. https://doi.org/10.1145/3337722.3341871



Instance of a Story Graph

Figure 2: Story graph example. By adding the events generated in Figure 1, we get this instance of a graph.

3) Create Goal Graph

Goal Graph: "relationship between author goals and story events"

Gandhi, S., & Harrison, B. (2019). Guided open story generation using probabilistic graphical models. *International Conference on the Foundations of Digital Games (FDG)*, 1–7. https://doi.org/10.1145/3337722.3341871

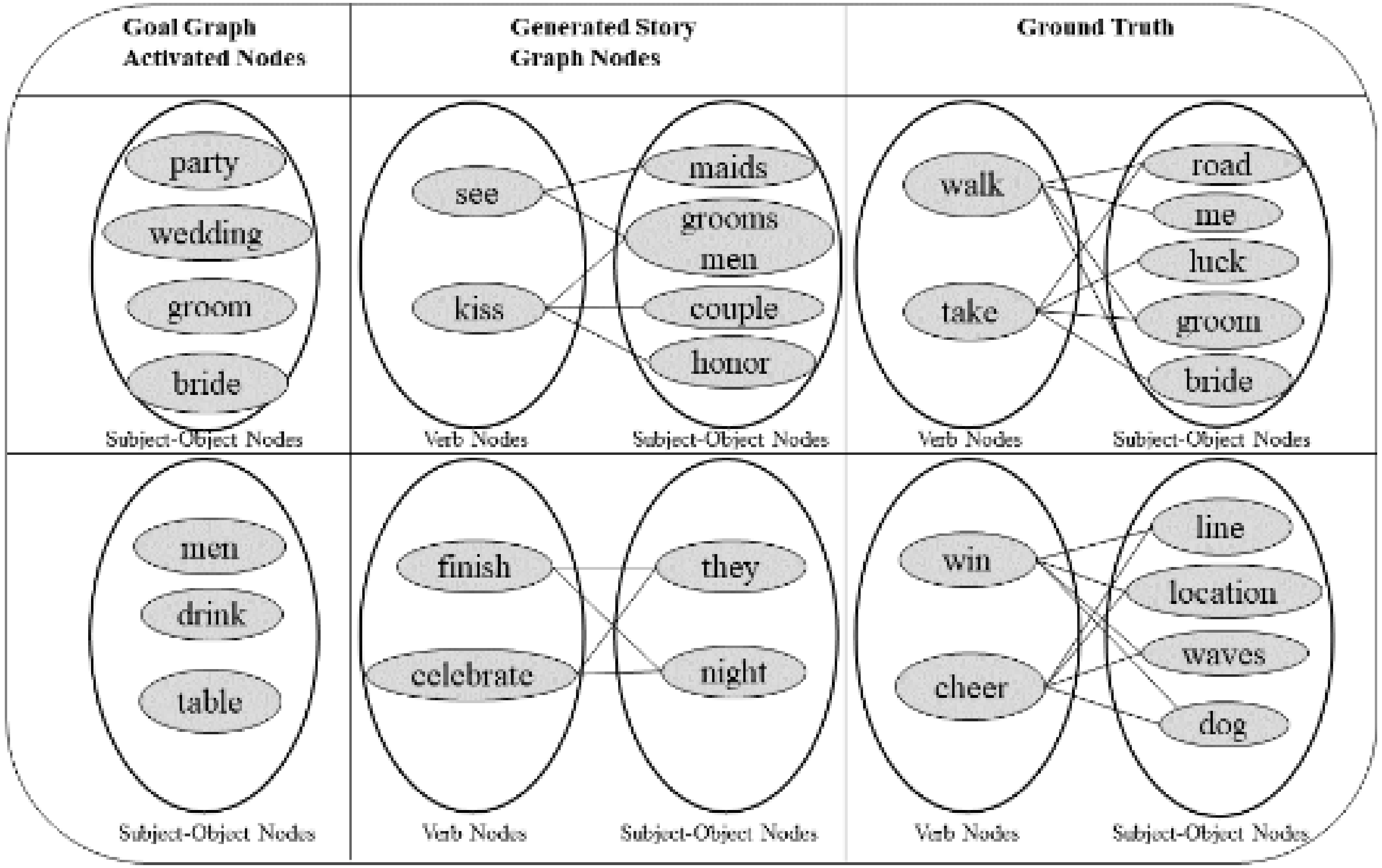
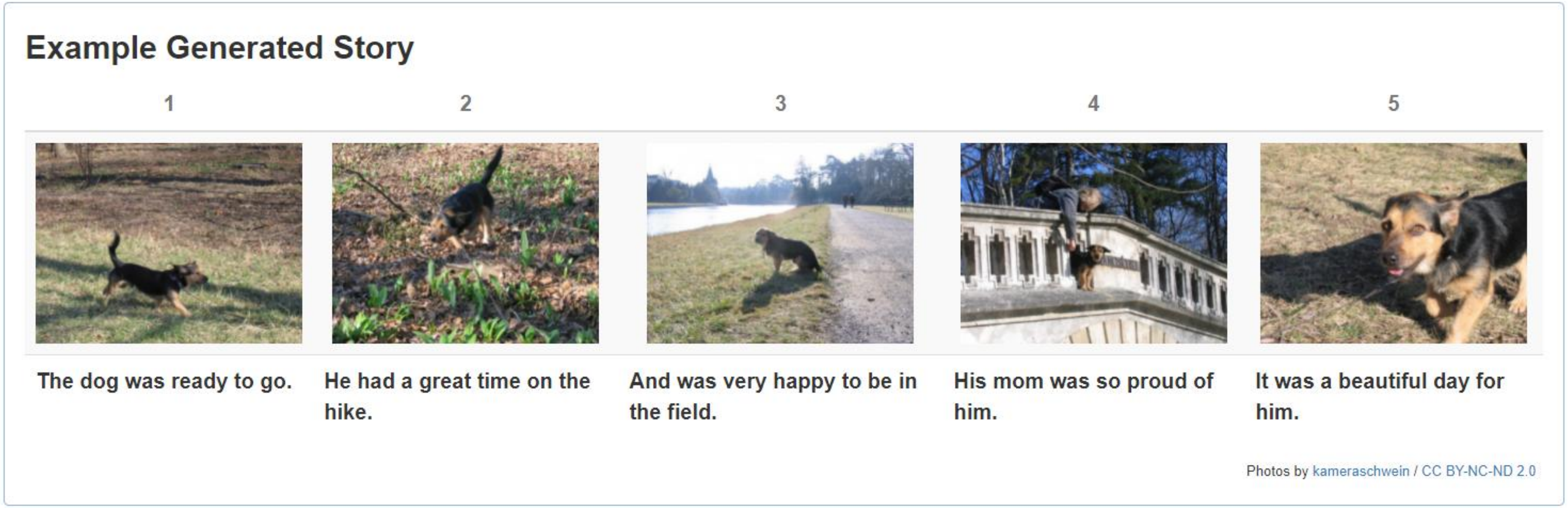


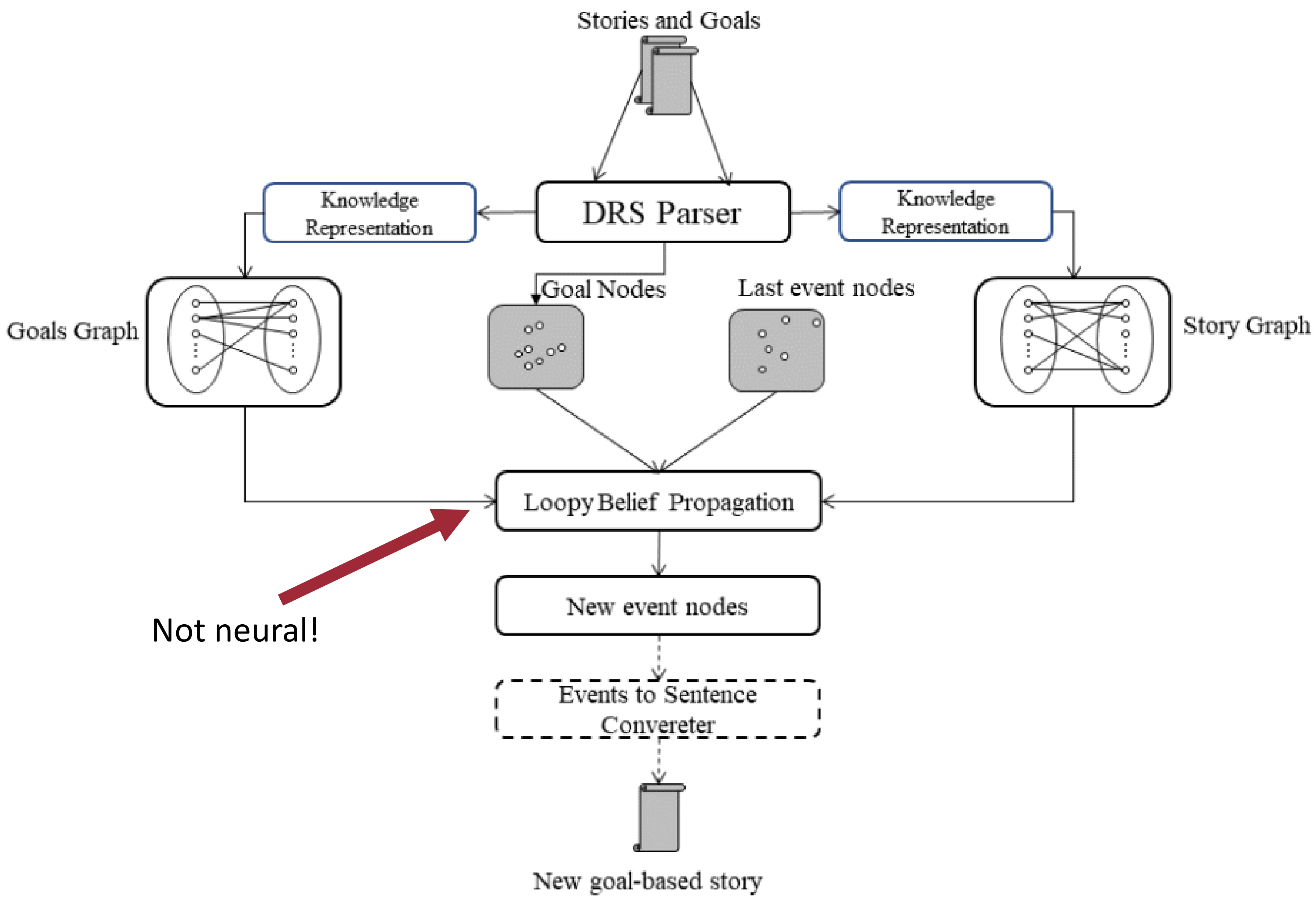
Figure 4: Evaluation Intricacies. Shown are two examples of generated action verbs and subject-action words from the given author goal (Description).

Using VIST for Stories



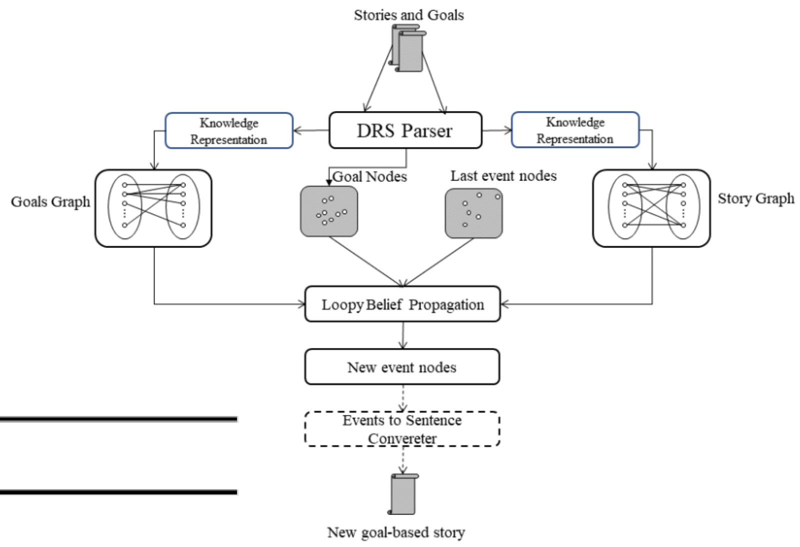
From [VIST: Visual Storytelling Dataset (visionandlanguage.net)]

T.-H. Huang *et al.*, “Visual Storytelling,” in *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL)*, San Diego, California: Association for Computational Linguistics, Jun. 2016, pp. 1233–1239. Available: https://aclanthology.org/N16-1147/


Stories and Goals
Knowledge Representation
DRS Parser
Knowledge Representation
Goal Nodes
Last event nodes
Goals Graph
Story Graph
Loopy Belief Propagation
New event nodes
Events to Sentence Convereter
New goal-based story

Not neural!

Story Generation



ALGORITHM 1: Story generation algorithm

Data: *Story Graph*, *Goal Graph*

Result: Story S

for $event_i \leftarrow 1 : n$ **do**

  if $CG! = ParseCurrentGoal()$ **then**

    $CG = ParseCurrentGoal()$

  end

  $Initial\ SVN = LBPInfer(StoryGraph, SSON_{i-1})$

Subject-Verb

  $SVN_i = LBPInfer(GoalGraph, Initial\ SVN, CG)$

Subject-Object

  $SSON_i = LBPInfer(StoryGraph, SVN_i)$

  $S+ = GetEvent(SVN_i, SSON_i)$

end

Gandhi, S., & Harrison, B. (2019). Guided open story generation using probabilistic graphical models. *International Conference on the Foundations of Digital Games (FDG)*, 1–7. https://doi.org/10.1145/3337722.3341871

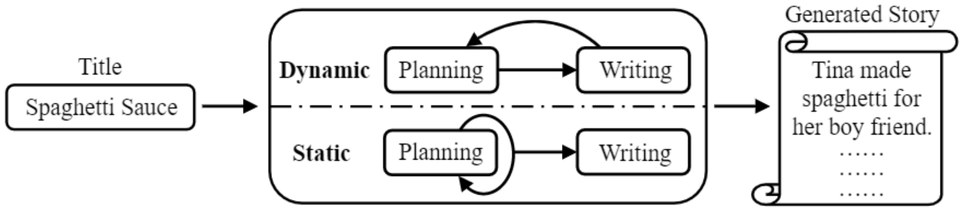
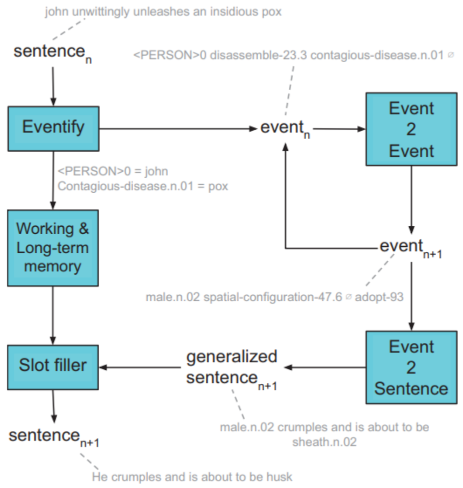
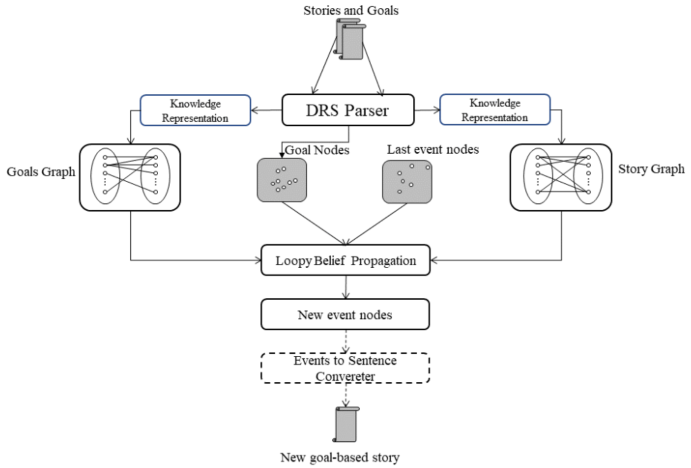


Figure 1: An overview of our system.





How are these three systems similar?

When poll is active respond at **PollEv.com/laramartin527**

Send **laramartin527** and your message to **22333**

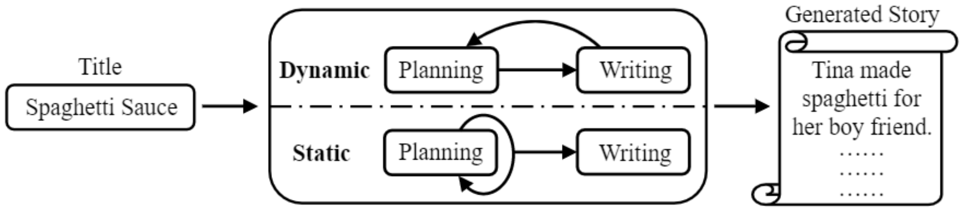
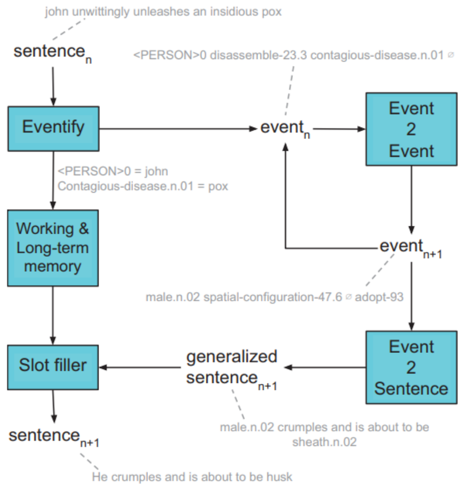
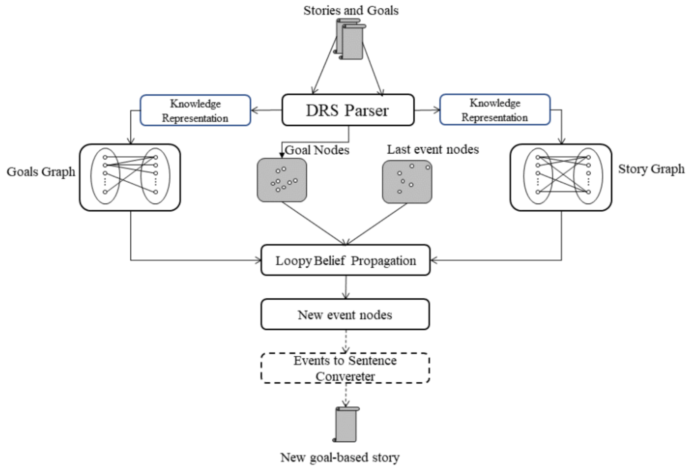


Figure 1: An overview of our system.





How do they differ?

When poll is active respond at **PollEv.com/laramartin527**

Send **laramartin527** and your message to **22333**

The Story Cloze Test

What is a Cloze Test?

- Something is removed from a text; try to guess what's missing
- Used for reading comprehension, grammar, etc. (with humans)

Unsupervised Learning of Narrative Event Chains

Nathanael Chambers and **Dan Jurafsky**
Department of Computer Science
Stanford University
Stanford, CA 94305
{natec,jurafsky}@stanford.edu

Abstract

Hand-coded *scripts* were used in the 1970-80s as knowledge backbones that enabled inference and other NLP tasks requiring deep semantic knowledge. We propose unsupervised induction of similar schemata called *narrative event chains* from raw newswire text.

A narrative event chain is a partially ordered set of events related by a common protagonist. We describe a three step process to learning narrative event chains. The first uses unsupervised distributional methods to learn narrative relations between events sharing coreferring arguments. The second applies a temp

tate learning, and thus this paper addresses the three tasks of chain induction: *narrative event induction*, *temporal ordering of events* and *structured selection* (pruning the event space into discrete sets).

Learning these prototypical schematic sequences of events is important for rich understanding of text. Scripts were central to natural language understanding research in the 1970s and 1980s for proposed tasks such as summarization, coreference resolution and question answering. For example, Schank and Abelson (1977) proposed that understanding text about restaurants required knowledge about the Restaurant Script, including the participants (Cus-
er, Waiter, Cook, Tables, etc.) the e consti-

Narrative Cloze Test

Evaluate “event relatedness”

Find which events could be missing from a narrative chain

Uses verbs only

N. Chambers and D. Jurafsky, “Unsupervised Learning of Narrative Event Chains,” in *Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL-HLT)*, 2008, pp. 789–797, doi: 10.1.1.143.1555.

Narrative Cloze Test

Known events:
(pleaded subj), (admits subj), (convicted obj)

Likely Events:

sentenced obj	0.89	indicted obj	0.74
paroled obj	0.76	fined obj	0.73
fired obj	0.75	denied subj	0.73

Figure 1: Three narrative events and the six most likely events to include in the same chain.

X pleaded _

X admits _

_ convicted X

N. Chambers and D. Jurafsky, "Unsupervised Learning of Narrative Event Chains," in *Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL-HLT)*, 2008, pp. 789–797, doi: 10.1.1.143.1555.

A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories

Nasrin Mostafazadeh[1], Nathanael Chambers[2], Xiaodong He[3], Devi Parikh[4], Dhruv Batra[4], Lucy Vanderwende[3], Pushmeet Kohli[3], James Allen[1,5]

1 University of Rochester, 2 United States Naval Academy, 3 Microsoft Research, 4 Virginia Tech, 5 The Institute for Human & Machine Cognition

{nasrinm, james}@cs.rochester.edu, nchamber@usna.edu, {parikh, dbatra}@vt.edu, {xiaohe, lucyv, pkohli}@microsoft.com

Abstract

Representation and learning of commonsense knowledge is one of the foundational problems in the quest to enable deep language understanding. This issue is particularly challenging for understanding casual and correlational relationships between events. While this topic has received a lot of interest in the NLP community, research has been hindered by the lack of a proper evaluation framework. This paper attempts to address this problem with a new framework for evaluating st

Recently, there has been a renewed interest in story and narrative understanding based on progress made in core NLP tasks. This ranges from generic story telling models to building systems which can compose meaningful stories in collaboration with humans (Swanson and Gordon, 2008). Perhaps the biggest challenge of story understanding (and story generation) is having commonsense knowledge for the interpretation of narrative events. The question is how to provide commonsense knowledge regarding daily events to machines.

Finish the story

Gina was worried the cookie dough in the tube would be gross.

She was very happy to find she was wrong.

The cookies from the tube were as good as from scratch.

Gina intended to only eat 2 cookies and save the rest.

A. Gina liked the cookies so much she ate them all in one sitting. ✓
B. Gina gave the cookies away at her church.

Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., & Allen, J. (2016). A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 839–849. http://www.aclweb.org/anthology/N16-1098

Story Cloze Test

Predict/select the most likely story *ending*

- Given the first 4 sentences of the story

Full sentences

Multiple choice evaluation

Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., & Allen, J. (2016). A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 839–849. http://www.aclweb.org/anthology/N16-1098

An RNN-based Binary Classifier for the Story Cloze Test

Melissa Roemmele
Institute for Creative Technologies
University of Southern California
roemmele@ict.usc.edu

Sosuke Kobayashi*
Preferred Networks, Inc.
sosk@preferred.jp

Naoya Inoue
Tohoku University
naoya-i@ecei.tohoku.ac.jp

Andrew M. Gordon
Institute for Creative Technologies
University of Southern California
gordon@ict.usc.edu

Enhanced Story Representation by ConceptNet for Predicting Story Endings

Shanshan Huang
huangss_33@sjtu.edu.cn
Shanghai Jiao Tong University

Kenny Q. Zhu*
kzhu@cs.sjtu.edu.cn
Shanghai Jiao Tong University

Qianzi Liao
liaoqz@sjtu.edu.cn
Shanghai Jiao Tong University

Libin Shen
libin@leyantech.com
Leyan Tech

Yinggong Zhao
ygzhao@leyantech.com
Leyan Tech

ABSTRACT

Predicting endings f
machine commonsen
resentation of the sto
Pre-trained language
in this task by exploi
dataset, instead of "u
we propose to improv
fying the sentences to
latent relationship be
enhanced sentence re
guage models, makes
the popular Story Clo
data.

CCS CONCEPTS

Toward Better Storylines with Sentence-Level Language Models

Daphne Ippolito*
daphnei@seas.upenn.edu

David Grangier
grangier@google.com

Douglas Eck
deck@google.com

Chris Callison-Burch
ccb@seas.upenn.edu

Abstract

We propose a sentence-level language model which selects the next sentence in a story from a finite set of fluent alternatives. Since it does not need to model fluency, the sentence-level language model can focus on longer range dependencies, which are crucial for multi-sentence coherence. Rather than dealing with individual words, our method treats the story so far as a list of pre-trained sentence embeddings and predicts an embedding for the next sentence, which is more efficient than predicting word embeddings. Notably this allows us to consider a large number of candidates for the next sentence during training. We demonstrate the effectiveness of our approach with state-of-the-art accuracy on the unsupervised Story Cloze task and with promising results on larger-scale next sentence prediction tasks.

Story Ending Selection by Finding Hints From Pairwise Candidate Endings

Mantong Zhou, Minlie Huang, and Xiaoyan Zhu

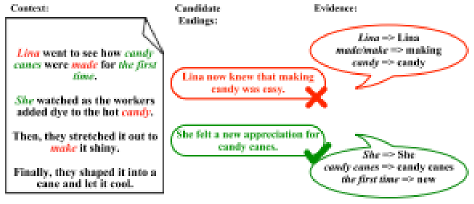


Fig. 1. **Evidence bias issue**: both a wrong ending (in red) and a correct ending (in green) can obtain sufficient evidence from the story context.

important linkages between a story context and a candidate ending. They suffer from the issue of **evidence bias**: both the wrong and correct endings can obtain sufficient support from the story context. As illustrated in Fig. 1, the wrong ending (in red) and the correct ending (in green) can be supported by the red-colored evidence and the green-colored evidence in the story context, respectively. Thus, it is difficult for matching-based models to distinguish such cases. The situation is not rare because both correct and wrong endings are written to fit the world of a story

Tackling the Story Ending Biases in The Story Cloze Test

Rishi Sharma[1], James F. Allen[1,2], Omid Bakhshandeh[3], Nasrin Mostafazadeh[4*]
1 University of Rochester, 2 Institute for Human and Machine Cognition, 3 Verneek.ai 4 Elemental Cognition
rishi.sharma@rochester.edu, nasrinm@cs.rochester.edu

Abstract

The Story Cloze Test (SCT) is a recent framework for evaluating story comprehension and script learning. There have been a variety of models tackling the SCT so far. Although the original goal behind the SCT was to require systems to perform deep language understanding and commonsense reasoning for successful narrative understanding, some recent models could perform significantly better than the initial baselines by leveraging human-authorship biases discovered in the SCT dataset. In order to shed some

this issue. This test evaluates a story comprehension system where the system is given a four-sentence short story as the 'context' and two alternative endings and to the story, labeled 'right ending' and 'wrong ending.' Then, the system's task is to choose the right ending. In order to support this task, Mostafazadeh et al. also provide the ROC Stories dataset, which is a collection of crowd-sourced complete five sentence stories through Amazon Mechanical Turk (MTurk). Each story follows a character through a fairly simple series of events to a conclusion.

Several shallow and neural models, including the state-of-the-art script learning approaches, were presented as baselines (Mostafazadeh et al.

The Story Cloze Test was created for evaluating systems’ performance on understanding stories.

How could you use it instead for *generation*?