Characters

Lara J. Martin (she/they)

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

Learning Objectives

Determine how task-oriented systems can be made with neural/ML-based methods

Tie task-oriented dialog back into IF/storytelling

Consider how modeling various aspects of characters affects a story

Speculate on how a system can be created to make rich characters

Review: Two Classes of Dialog Systems

1. **Chatbots**
   - Systems designed for extended conversations
   - Chatting for fun and entertainment

2. **Task-Oriented Dialogue Agents**
   - Goal-Based Agents
   - Siri/Alexa, interface with robots, booking flights or hotels

Review: Chatbots

Systems designed for extended conversations. Chatbots mimic unstructured conversations or ‘chats’ that are characteristic of informal human-human interaction

Architectures include:

Rule-Based

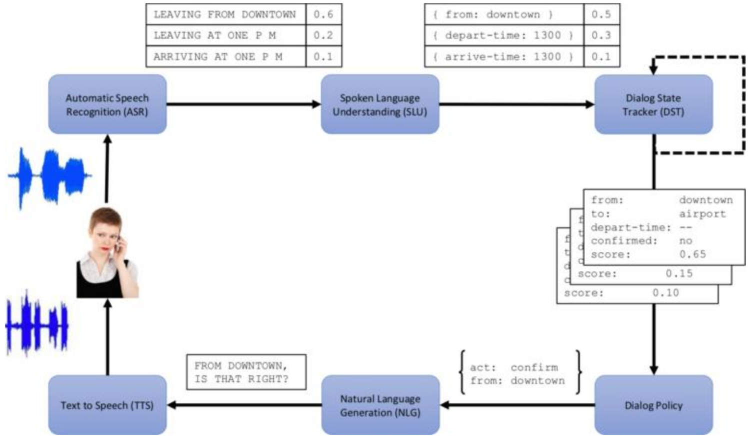
- Pattern-action rules

Corpus-Based

- Information Retrieval
- Neural networks

Review: Frame-based Dialog Systems

- Task-based Dialog Agents
- Based on “Domain Ontology”
  - A set of “Frames”
- Frame:
  - A knowledge structure representing user intentions
  - A collection of “slots”
  - Each “slot” having a set of “values”



Natural Language Understanding Component:

- Extract slot fillers using machine learning rather than rules

Dialogue State Tracker:

- Maintains current state of dialogue, user's most recent dialogue act

Dialogue policy:

- Decides what the system should do or say next
- When to answer user's questions, when to make a suggestion

Natural Language Generation Component:

- Condition on exact context to produce turns that seem much more natural

Review: State Tracking Evaluation

Slot Error Rate for a Sentence

$$\frac{\text{\# of inserted/deleted/substituted slots}}{\text{\# of total reference slots for sentence}}$$

"Make an appointment with Lara at 10:30 in ITE 342-A"

Slot	Filler
PERSON	Lara
TIME	11:30 a.m.
ROOM	ITE 342-A

Slot error rate: 1/3

Task success: At end, was the correct meeting added to the calendar?

Review: Dialog Policy Evaluation

End-to-end evaluation (Task Success)

Other potential metrics:

- Customer satisfaction (Survey questions)
- Length of conversation (Number of turns) – collecting all the information you need but not taking forever
- Relevance of response
- Accuracy of choosing the response similar to test data

Machine Learning for Slot Filling

- Supervised semantic parsing
- Model to map from input words to slot fillers, domain and intent
- Given a set of labeled sentences

  "I want to fly to San Francisco on Tuesday"

  Destination: SF Depart-date: Tuesday
- Requirements: Lots of labeled data (or perhaps an LLM?)

Slot Filling

“I want to fly to San Francisco on Monday afternoon please”

Use 1-of-N classifier (Naive Bayes, Logistic Regression, Neural Network, etc.)

- Input:

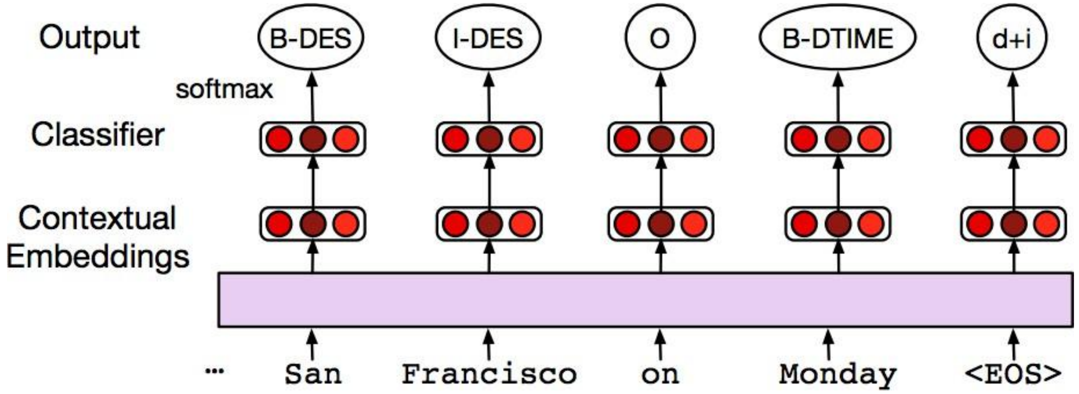
  features like word N-grams

- Output:

  Domain: AIRLINE Intent: SHOWFLIGHT

More sophisticated algorithm for Slot Filling: IOB Tagging

- IOB Tagging
  - Tag for the beginning (B) and inside (I) of each slot label,
  - plus one for tokens outside (O) any slot label
  - $2n + 1$ tags, where n is the number of slots
- Training Data: Sentences paired with sequences of IOB labels

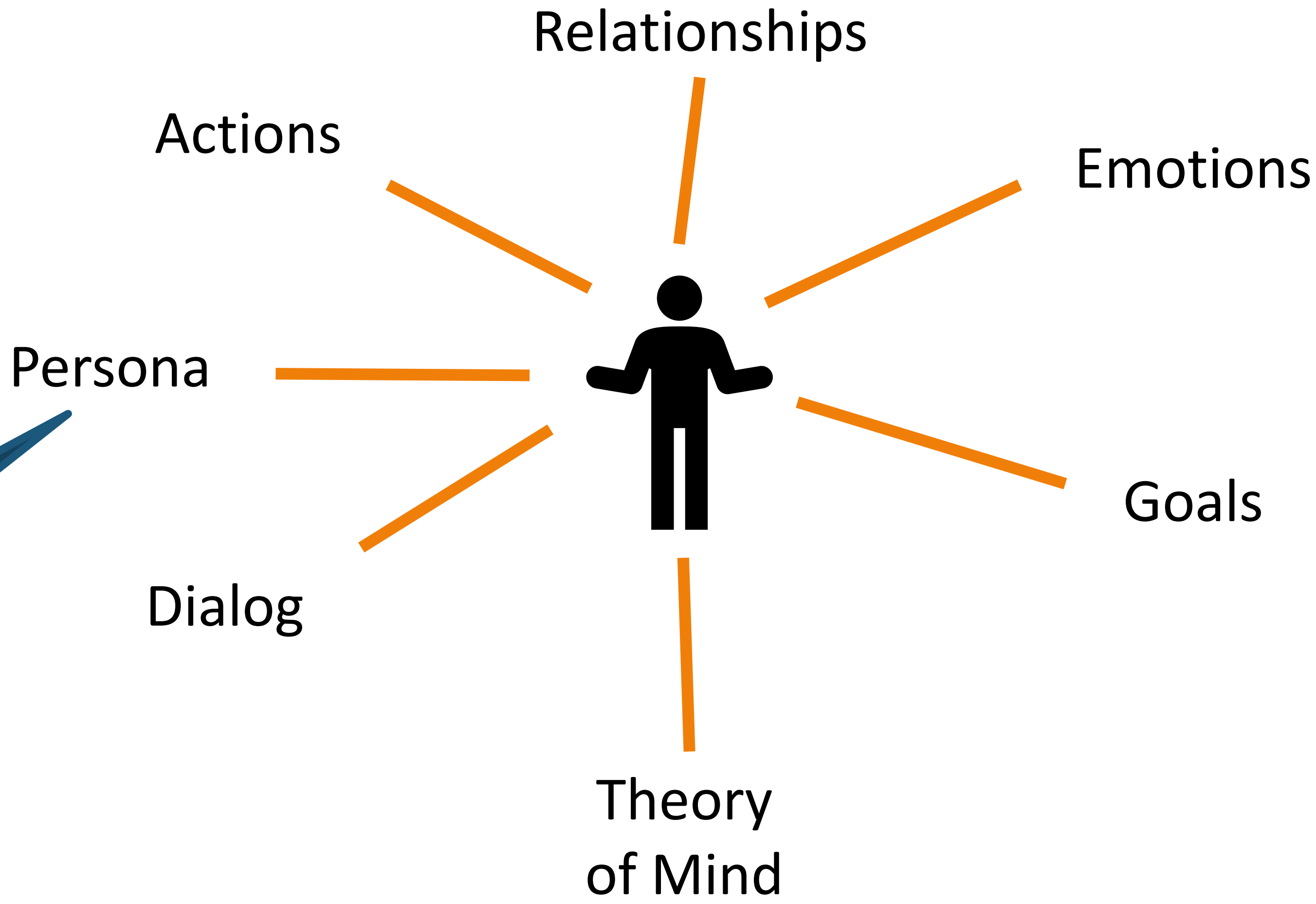


O O O O O B-DES I-DES O B-DEPTIME I-DEPTIME O
I want to fly to San Francisco on Monday afternoon please

Think-Pair-Share

How might **task-oriented** dialog be used in interactive fiction or storytelling?

What makes up a character?



We'll look at this next lecture

What else might you want to model about a character?

Actions

Category:	Graveyard
Description:	Two-and-a-half walls of the finest, whitest stone stand here, weathered by the passing of countless seasons. There is no roof, nor sign that there ever was one. All indications are that the work was abruptly abandoned. There is no door, nor markings on the walls. Nor is there any indication that any coffin has lain here... yet.
Backstory:	Bright white stone was all the fad for funerary architecture, once upon a time. It's difficult to understand why someone would abandon such a large and expensive undertaking. If they didn't have the money to finish it, they could have sold the stone, surely - or the mausoleum itself. Maybe they just haven't needed it yet? A bit odd, though, given how old it is. Maybe the gravedigger remembers... if he's sober.
Neighbors:	Dead Tree, south, following a dirt trail behind the mausoleum Fresh Grave, west, walking carefully between fallen headstones
Characters:	gravedigger, *thief, peasant, mouse, bat*
Objects:	wall, *carving, leaf, dirt*

(a) Example room created from the room collection and labelling tasks.

J. Urbanek *et al.*, "Learning to Speak and Act in a Fantasy Text Adventure Game," in *EMNLP-IJCNLP*, 2019. doi: 10.18653/v1/D19-1062.

Actions

Query:	chicken	pirate	coffin	rake	tavern	meadow
objects	chicken coop	Pirate swords	the remains	shovel	Ale bottles	flower pot
	eggs	dock	remains	garden	beer	fruit
	a pen for the chickens	cargo	bones	a garden	mug of mead	An enchanted amulet.
	chimney	ship	bones of the innocent	Hand carved stone	a large ornate table	citrus fruit
	corn	seagulls on the dock	adventurer's remains	garden bench	beer keg	fruit trees
characters	chickens	boat captain	spirits of our ancestors	gardener	tavern owner	a deer
	fox trying to steal chickens	captain	mourner	stable hand	bartender	a songbird
	farmers	merchant	zombies	Garden dog	Goblin King's bartender	fruit bats
	The farmers	boat workers	families	stable boy	A serving wench	parent
	farmer	workers	bandit	A stable boy	Serving wench	butterfly
locations	Chicken Pen	Pirate Ship	Old Crypt	Across the King's Garden	The werewolves tavern	Lush meadow
	Corn field	Dock at the Port	sacristy	Hidden garden	Tavern of Browntavia	Flower Field
	Farmer's house	Loading Dock	Disposal area	The garden courtyard	Port Tavern	flower garden
	Large Farm	Fishing Dock	inside temple crypt	Church garden	The bar	Mushroom Hut
	Pig Pen	crew berthing	Sacrifice Chamber	Tool Shed	bazaar outside the royal city	Archery zone
actions	get chicken	hug pirate	put torch in coffin	get rake	hug tavern owner	get flower from meadow
	hug chicken	hit pirate	get torch from coffin	drop Rake	give food item to tavern owner	put flower in Meadow
	hit chicken	steal sword from pirate	put bone in coffin	steal Rake from gardener	give telescope to tavern owner	give Flower to a deer
	give cowbell to chicken	steal cargo from pirate	get bone from coffin	give Rake to thing	drink drink	give Flower to deer
	steal sword from chicken	give cargo to pirate	hit archaeologist	give Rake to person	drop drink	steal Flower from a deer
vocabulary	bock	crew	archaeologist	vegetable	drink	flower
	tasty	ye	robber	carved	drinks	amulet
	bawk	port	crypt	alice	regular	songbird
	moo	sea	loss	hook	item	wasp
	egg	seas	adventures	exorcisms	tip	an

Table 3: Neighboring Starspace phrase embeddings (no pretraining from other data) for different types of entities and actions. The first row are arbitrarily chosen queries (chicken, pirate, coffin, rake, tavern, meadow), and the subsequent rows are their nearest objects, agents, locations, actions and vocabulary in embedding space.

J. Urbanek *et al.*, "Learning to Speak and Act in a Fantasy Text Adventure Game," in *EMNLP-IJCNLP*, 2019. doi: 10.18653/v1/D19-1062.

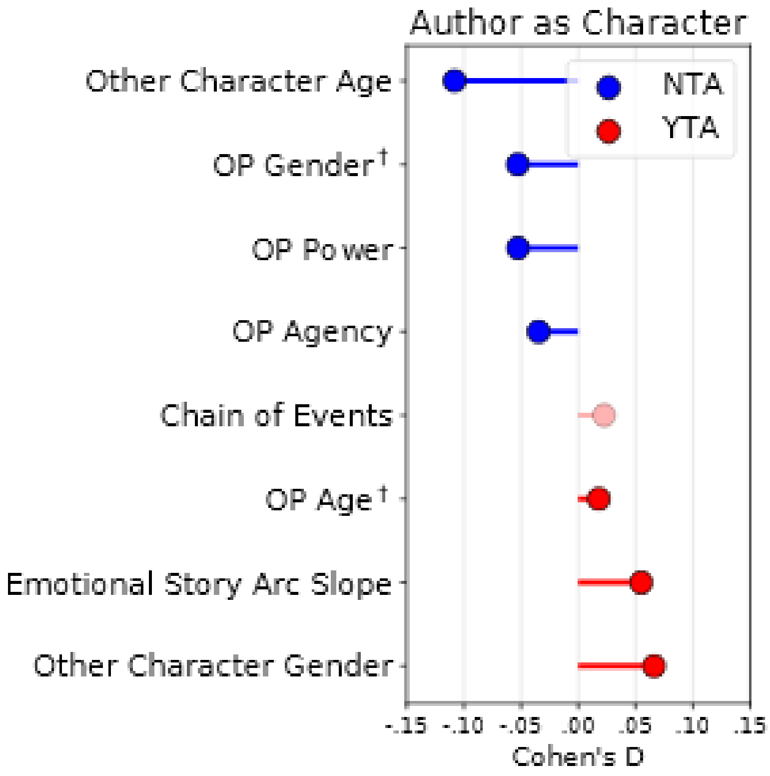
Actions

“The currently played role fills in once the player initiates conversation. It has information regrading the character’s personality, profession, age, gender, marital status, physical appearance, and their reason for being at the current location (work, errands, leisure, etc.)”

“When not updating the simulation, the wizard has time to explore the history of the town and the interweaving relationships of its denizens. When he unearths narratively interesting tidbits, he communicates them to the actor via a chat window. “

B. Samuel, J. Ryan, A. J. Summerville, M. Mateas, and N. Wardrip-Fruin, “Bad News: An Experiment in Computationally Assisted Performance,” in *ICIDS*, 2016.
https://link.springer.com/chapter/10.1007/978-3-319-48279-8_10

Actions



(a) Cohen's D values showing the correlation of features for YTA & NTA classes. Lighter shaded points are not significant at a with Benjamini-Hochberg corrected significance $\alpha < 0.05$). The higher the absolute effect size, the more that feature is associated with the YTA/NTA class. † includes a binary covariate equal to 1 for undisclosed age/gender when calculating significance via the logistic regression (Cohen's D is a bivariate measure and, thus, unable to account for this covariate).

S. Giorgi, K. Zhao, A. Feng, and L. J. Martin, "Author as Character and Narrator: Understanding Moral Judgements of Storytellers within the r/AmITheAsshole Reddit Community," *ICWSM*, 2023. doi: 10.1609/icwsm.v17i1.22141.

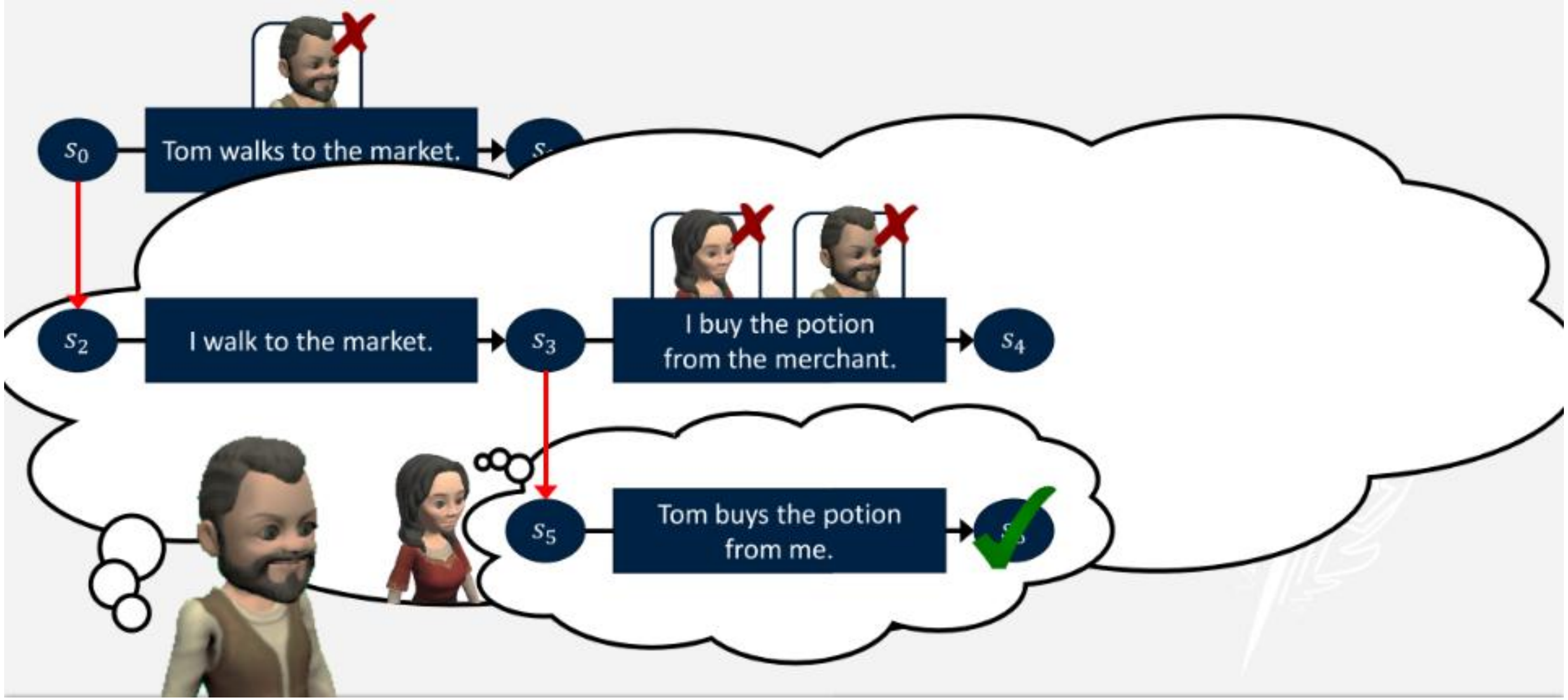
Actions

Control Feature	Description	Expected Impact on Model's Output
Player ID	Player writing a given dialog turn	Connects the current turn to the player's previous turns, which is important in multi-party conversations.
IC versus OOC	Whether a player is in-character or out-of-character for a given dialog turn	Changes whether the generated text is more like descriptive text found in a novel, or more like a discussion of rules and strategies.
Character Name	Name of the character being played by the player of a given dialog turn	IC descriptions use the character's name.
Character Class	D&D classes	Character classes perform different actions (e.g. wizards cast spells, thieves pick locks)
Character Race	D&D fantasy races	Different physical characteristics (e.g. halflings are small, dragonborn have scales).
Character Pronouns	The character's pronouns	Uses the correct pronouns when describing the character.
Character Actions	List of actions taken by the character in the current turn	Allows a description to be generated for a given action. The action can be thought of as a goal for the description.
Combat	Whether the players are currently engaged in combat or not during a given dialog turn	Affects the likelihood of actions (e.g. attacks are more likely during combat and investigations checks are more likely outside of combat)

Table 2: Our LLMs are conditioned on a variety of control features that allow the models to better learn what kind of text to generate for the next utterance prediction task

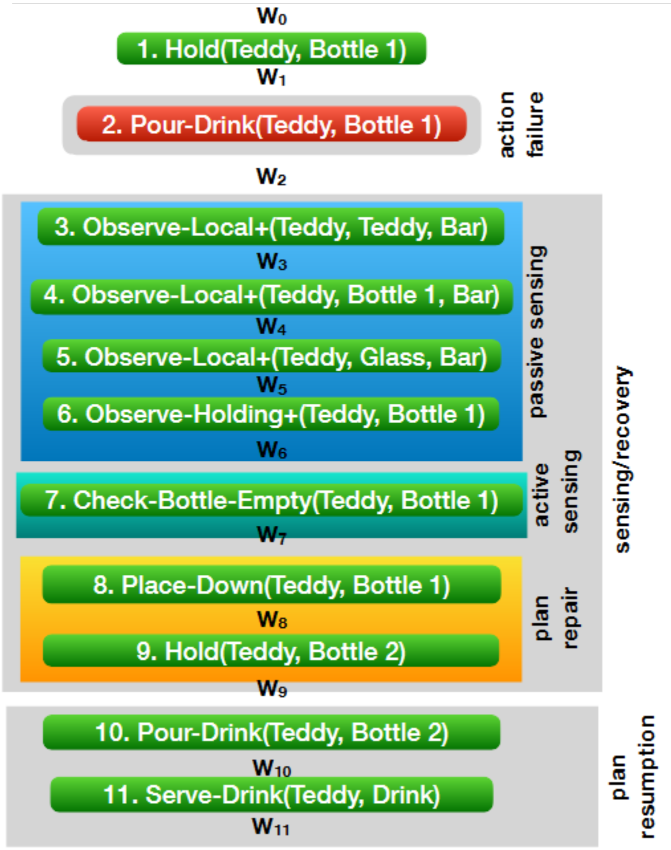
C. Callison-Burch, G. Singh Tomar, L. J. Martin, D. Ippolito, S. Bailis, and D. Reitter, "Dungeons and Dragons as a Dialogue Challenge for Artificial Intelligence," in *EMNLP*, 2022. doi: 10.18653/v1/2022.emnlp-main.637.

Theory of Mind (ToM)



S. G. Ware and C. Siler, "Sabre: A Narrative Planner Supporting Intention and Deep Theory of Mind," *AIIDE*, 2021, doi: 10.1609/aiide.v17i1.18896.

Theory of Mind (ToM)

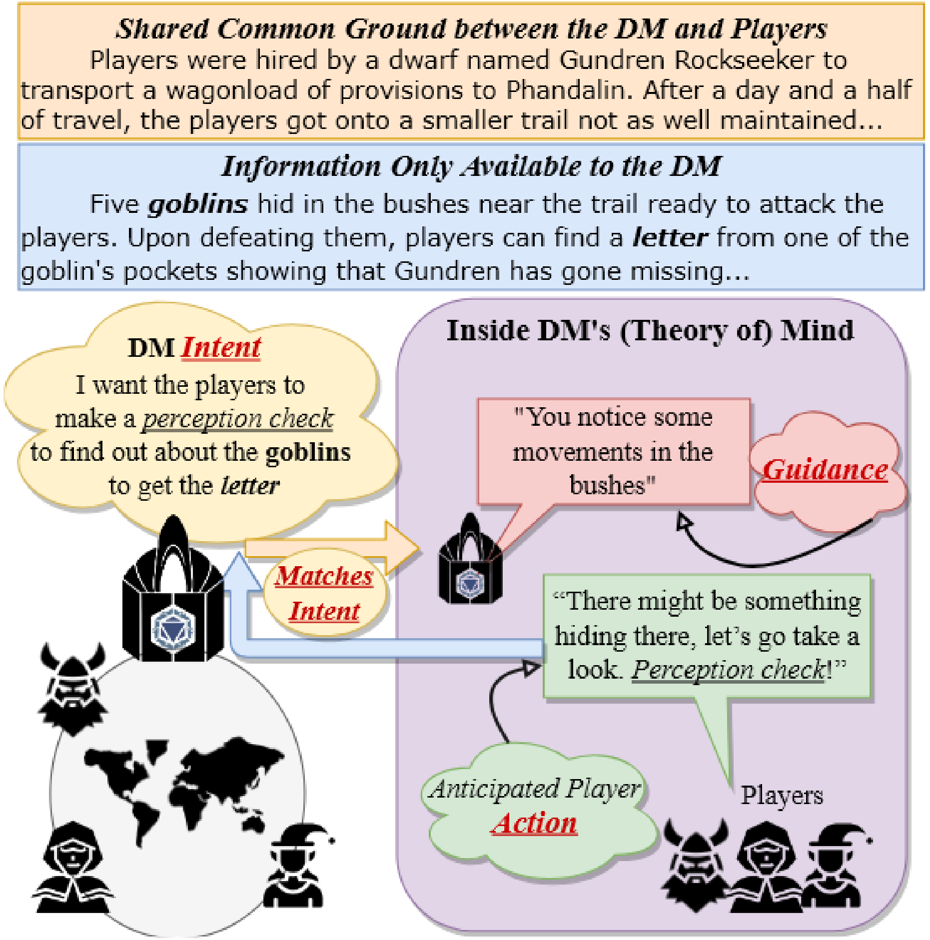


Definition (Belief State). *Given a world frame $W = \langle GL, C\rangle$, a belief state for some character $c \in C$ is a tuple $BS_c = \langle B_c^+, B_c^-, U_c\rangle$ such that B_c^+, B_c^- and U_c together form a partition of GL, where B_c^+ designates all the ground literals that c believes to be true, B_c^- includes all the ground literals that c believes to be false and U_c designates all the ground literals that c does not believe to be true and does not believe to be false.*

Figure 1: A solution plan for the Drink Refill domain's planning problem. Green actions are successfully performed actions. Red actions are ones that are attempted but that fail because their material preconditions are not all met in the world state where they are attempted.

R. Sanghrajka, R. M. Young, and B. Thorne, "HeadSpace: Incorporating Action Failure and Character Beliefs into Narrative Planning," *AIIDE,* 2022. https://ojs.aaai.org/index.php/AIIDE/article/view/21961

Theory of Mind (ToM)



P. Zhou *et al.*, "I Cast Detect Thoughts: Learning to Converse and Guide with Intents and Theory-of-Mind in Dungeons and Dragons," in *ACL*, 2023. doi: 10.18653/v1/2023.acl-long.624.

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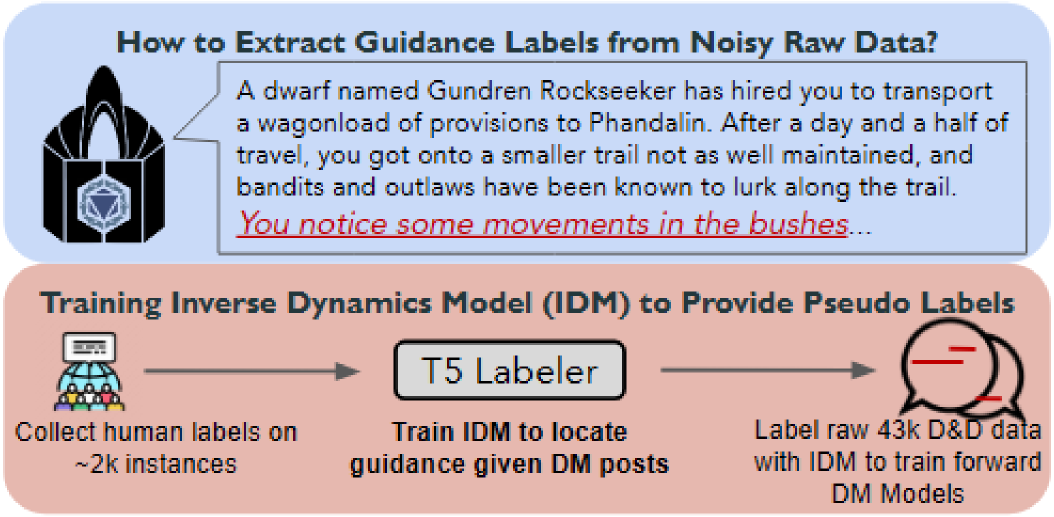

Figure 2: Illustration of IDM. We collect 2.5k human labels on guidance and train an IDM labeler to generate pseudo labels for unlabeled large corpus.

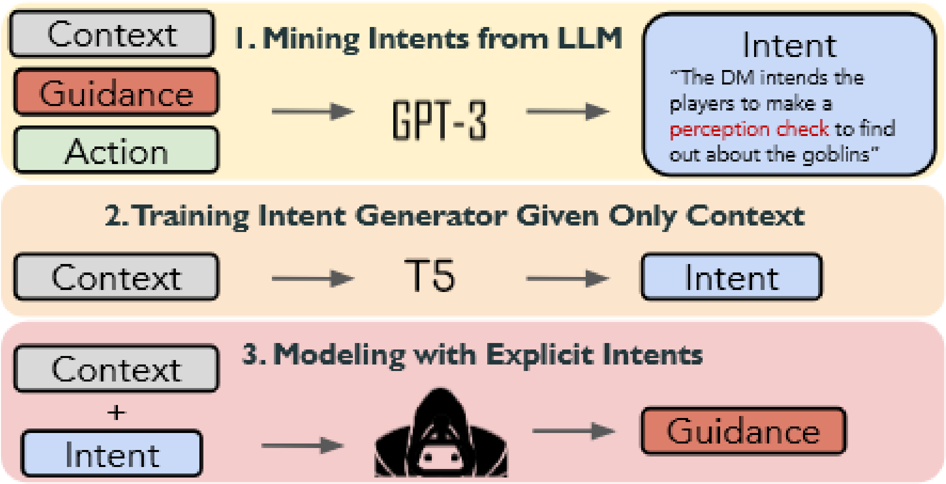

Figure 3: Illustration of intent modeling. We first mine intents from LLM and then train an intent generator to generate intent as additional context to train the DM model.

P. Zhou *et al.*, "I Cast Detect Thoughts: Learning to Converse and Guide with Intents and Theory-of-Mind in Dungeons and Dragons," in *ACL*, 2023. doi: 10.18653/v1/2023.acl-long.624.

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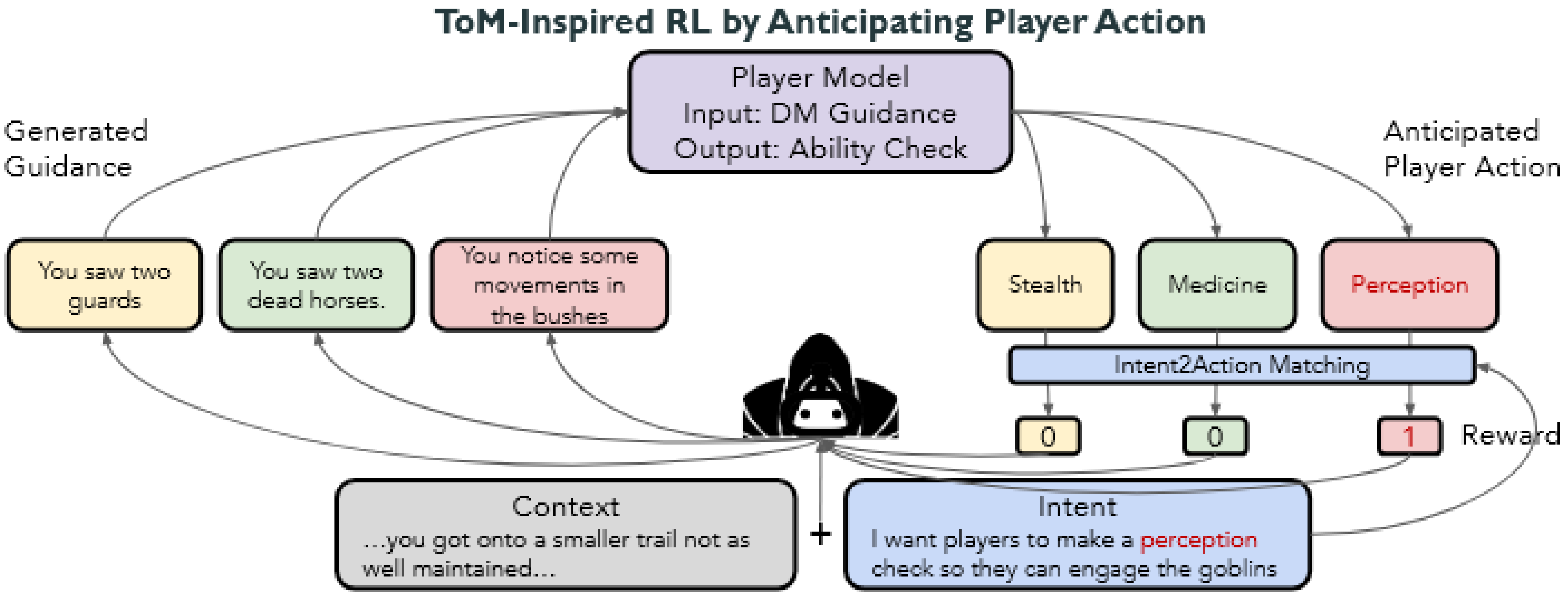

P. Zhou *et al.*, "I Cast Detect Thoughts: Learning to Converse and Guide with Intents and Theory-of-Mind in Dungeons and Dragons," in *ACL*, 2023. doi: 10.18653/v1/2023.acl-long.624.

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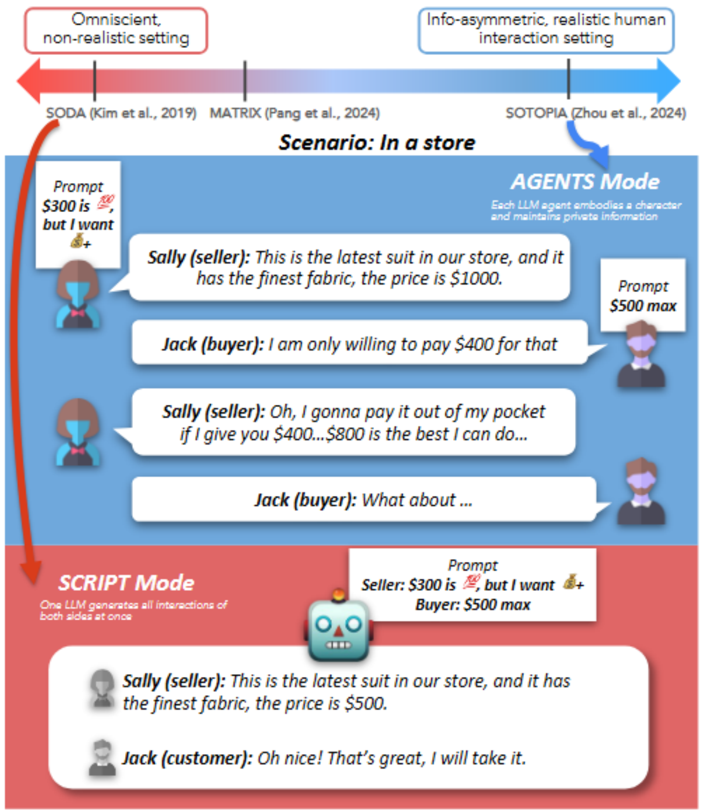


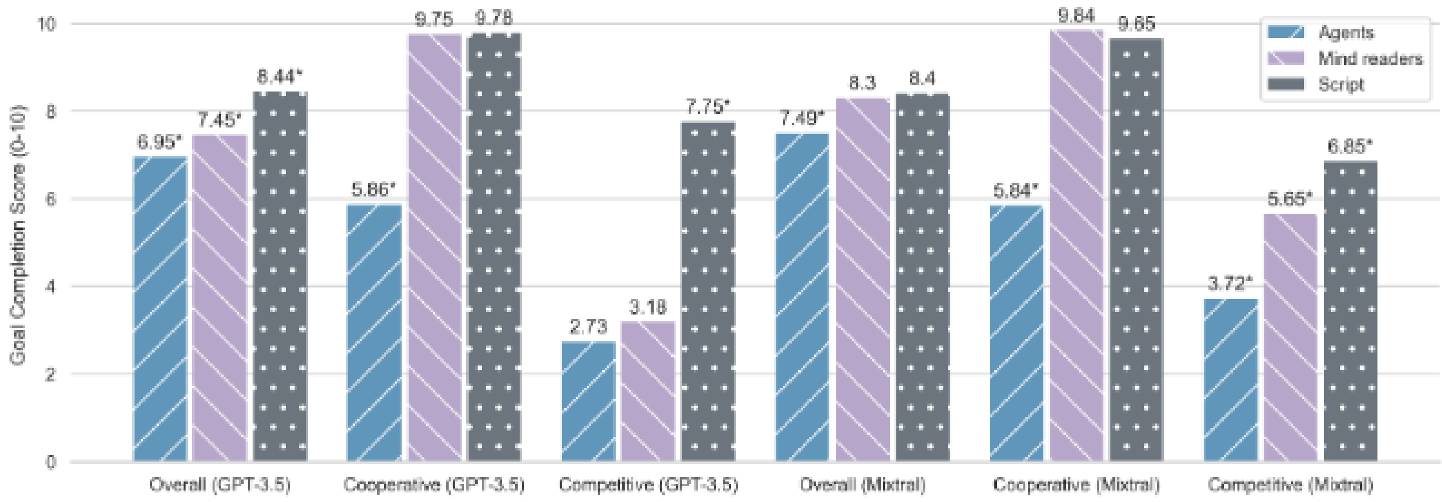


Figure 2: Average goal completion score of models across different modes in various settings. Overall contains all the scenarios, and the other two contains representative scenarios from the cooperative and competitive scenarios. We perform pairwise t-test, and * denotes the score is statistical significantly different from the other two modes in this setting ($p < 0.001$).

X. Zhou, Z. Su, T. Eisape, H. Kim, and M. Sap, "Is this the real life? Is this just fantasy? The Misleading Success of Simulating Social Interactions With LLMs," in *EMNLP*, 2024. https://aclanthology.org/2024.emnlp-main.1208/

Goals

Self: guard	**Partner:** archer	**Self:** swimmer	**Partner:** turtles
Persona:	I guard the castle. I guard the king. I would kill to protect the royal family	**Persona:**	I am a huge fan of deep sea exploration, but I take any chance I can get to go for a swim...
Setting:	The armory, Inside Tower. The near top of the tower 6 feet before the very top. Where the watchers keep their eye...	**Setting:**	Bank, Swamp This is a grassy area that surrounds much of the swamp. It's a plain field with some trees nearby along...
$\mathbf{U}_0^{\text{player}}$	This is the armory! The king keeps the best weapons here. Take a look -	$\mathbf{U}_0^{\text{player}}$	Just keep taking good care of your beautiful little turtle family! Your species is quite unique and I love to see you about when I go for a swim.
$\mathbf{U}_0^{\text{env}}$	Hello, I need to get into the palace to see the king. I think he might like to see these weapons.	$\mathbf{U}_0^{\text{env}}$	Well, thank you for that. Do you happen to know where my other turtle friend is? You haven't captured any turtles have you?
$\mathbf{A}_0^{\text{env}}$	get weapon	$\mathbf{A}_0^{\text{env}}$	hug swimmer

Table 2: Example 1-step episodes where after the Topic RL agent's utterance $\mathbf{U}_0^{\text{player}}$ the environment agent's response action $\mathbf{A}_0^{\text{env}}$ was equal to the RL agent's goal g. Our RL agent both makes natural utterances given the situation, and that elicit the desired goal.

S. Prabhumoye *et al.*, "I love your chain mail! Making knights smile in a fantasy game world: Open-domain goal-oriented dialogue agents," in *Wordplay: When Language Meets Games Workshop,* 2020. https://wordplay-workshop.github.io/wordplay2020/pdfs/4.pdf

Goals

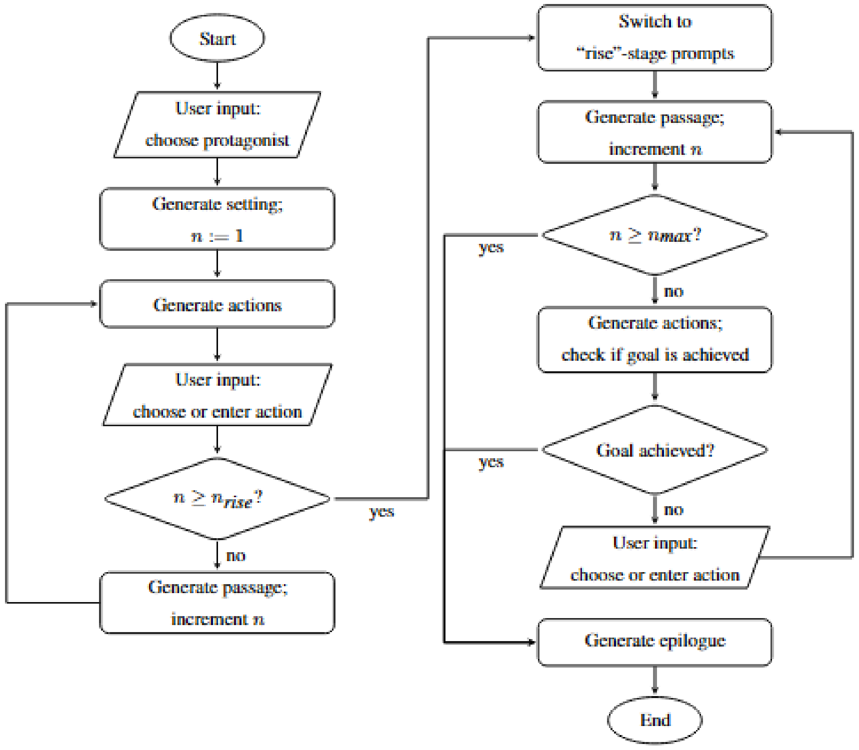


Figure 4: Story generation workflow. The left-hand side corresponds to the "low" stage of the story, the right-hand side to the "rise" stage.

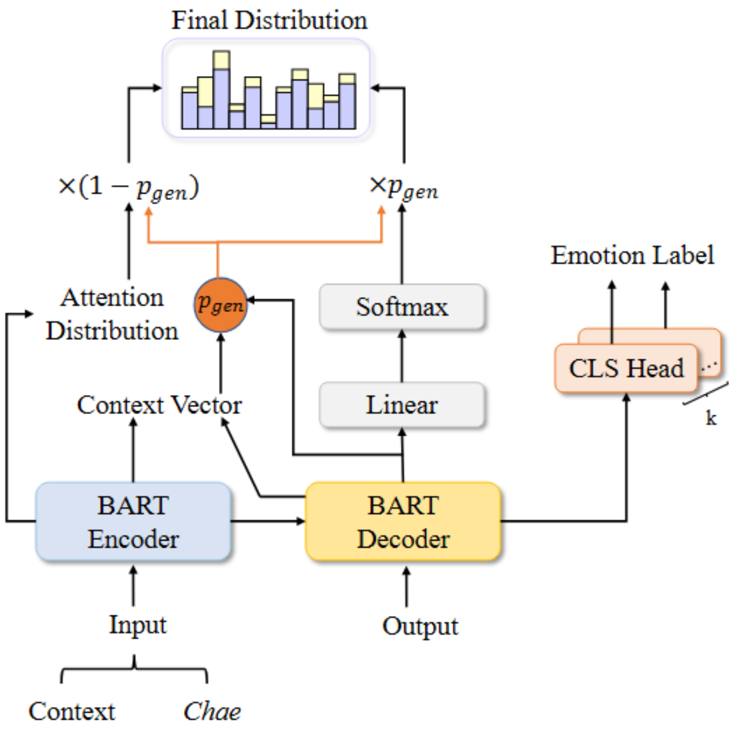
```
You are a language model for writing WHOLESOME
children's fairy tales suitable for six-year-olds
[...] The protagonist of the fairy tale is {name}.
Their goal is to {goal}.
The child will submit an action undertaken by the
protagonist, and you will write the next plot point
of the story [...]
Your answers develop the plot and logically follow
from the protagonist's actions. However, the
protagonist always faces challenges and NEVER
reaches their goal [...]
```

```
You are a language model for writing WHOLESOME
children's fairy tales suitable for six-year-olds
[...] The protagonist of the fairy tale is {name}.
Their goal is to {goal}.
The child will submit an action undertaken by the
protagonist, and you will write the next plot point
of the story. [...]
Your answers develop the plot, logically follow
from the protagonist's action, and bring them
closer to their goal [...]
```

Figure 2: System prompt templates for passages in the "low" (left) and "rise" (right) stages of the story. Placeholders for story-specific information are highlighted in red

M. Ermolaeva, A. Shakhmatova, A. Nepomnyashchikh, and A. Fenogenova, "How to tame your plotline: A framework for goal-driven interactive fairy tale generation," in *Workshop on Narrative Understanding (WNU)*, 2024. https://aclanthology.org/2024.wnu-1.2

Emotions

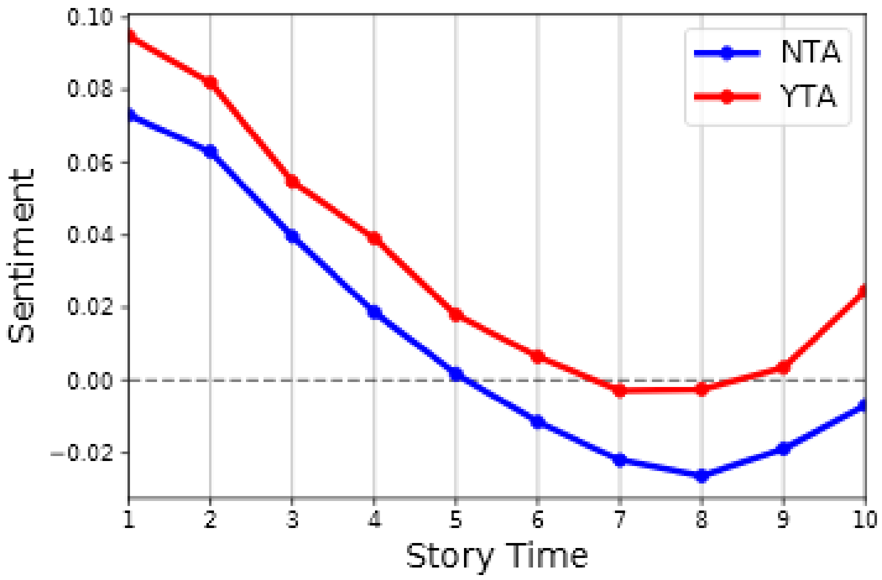


Context	A polite thief was making robberies in the small town.
Chae1	⟨SEP⟩ ⟨soc⟩ People ⟨soa⟩ ⟨no_action⟩ ⟨soe⟩ fear ⟨SEP⟩ ⟨soc⟩ **Man** ⟨soa⟩ to catch the thief ⟨soe⟩ **anger**
Result1	One day, a **man** walked up to him and **asked him to stop** .
Chae2	⟨SEP⟩ ⟨soc⟩ People ⟨soa⟩ ⟨no_action⟩ ⟨soe⟩ fear ⟨SEP⟩ ⟨soc⟩ **Man** ⟨soa⟩ ⟨no_action⟩ ⟨soe⟩ **joy**
Result2	The **man** who was supposed to stop him was a **nice man** .
Chae3	⟨SEP⟩ ⟨soc⟩ People ⟨soa⟩ ⟨no_action⟩ ⟨soe⟩ fear ⟨SEP⟩ ⟨soc⟩ **Tom** ⟨soa⟩ **to catch the thief** ⟨soe⟩ **anger**
Result3	**Tom** decided to investigate and **caught the thief** .
Chae4	⟨SEP⟩ ⟨soc⟩ **People** ⟨soa⟩ **call the police** ⟨soe⟩ **fear** ⟨SEP⟩ ⟨soc⟩ **Tom** ⟨soa⟩ **call the police** ⟨soe⟩ **anger**
Result4	**Tom** **called the police** and **they** **told him** to **call the police** .

Table 6: Case study of controllability.

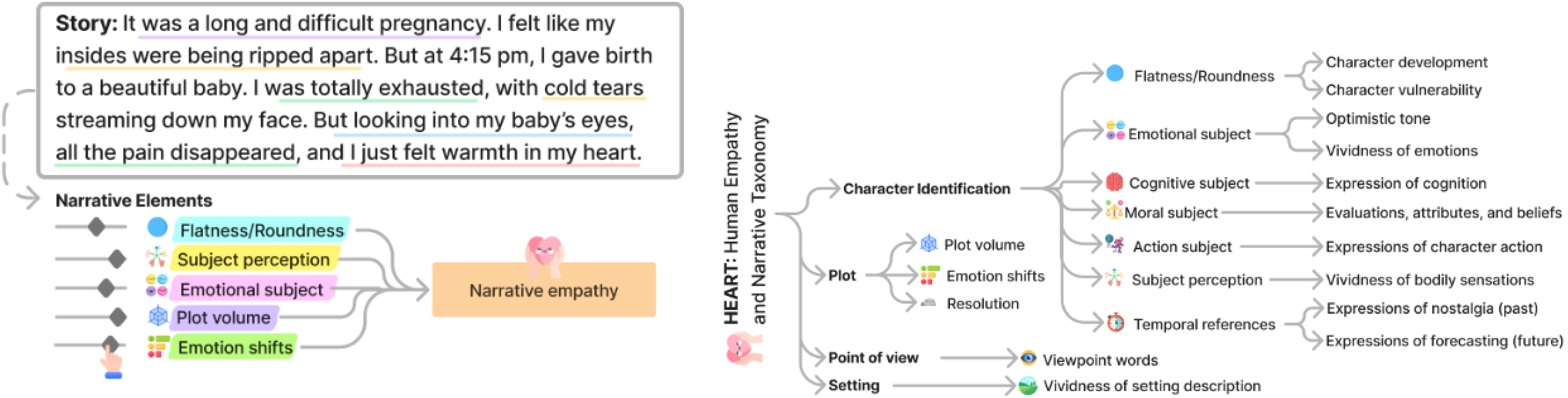
X. Wang, H. Jiang, Z. Wei, and S. Zhou, “CHAE: Fine-Grained Controllable Story Generation with Characters, Actions and Emotions,” in *COLING*, 2022.
https://aclanthology.org/2022.coling-1.559/

Emotions



(b) Emotional Story Arc. Average VADER sentiment across 10 equally-sized sentence-level chunks. Positive values are positive sentiment, negative values are negative sentiment.

Emotions

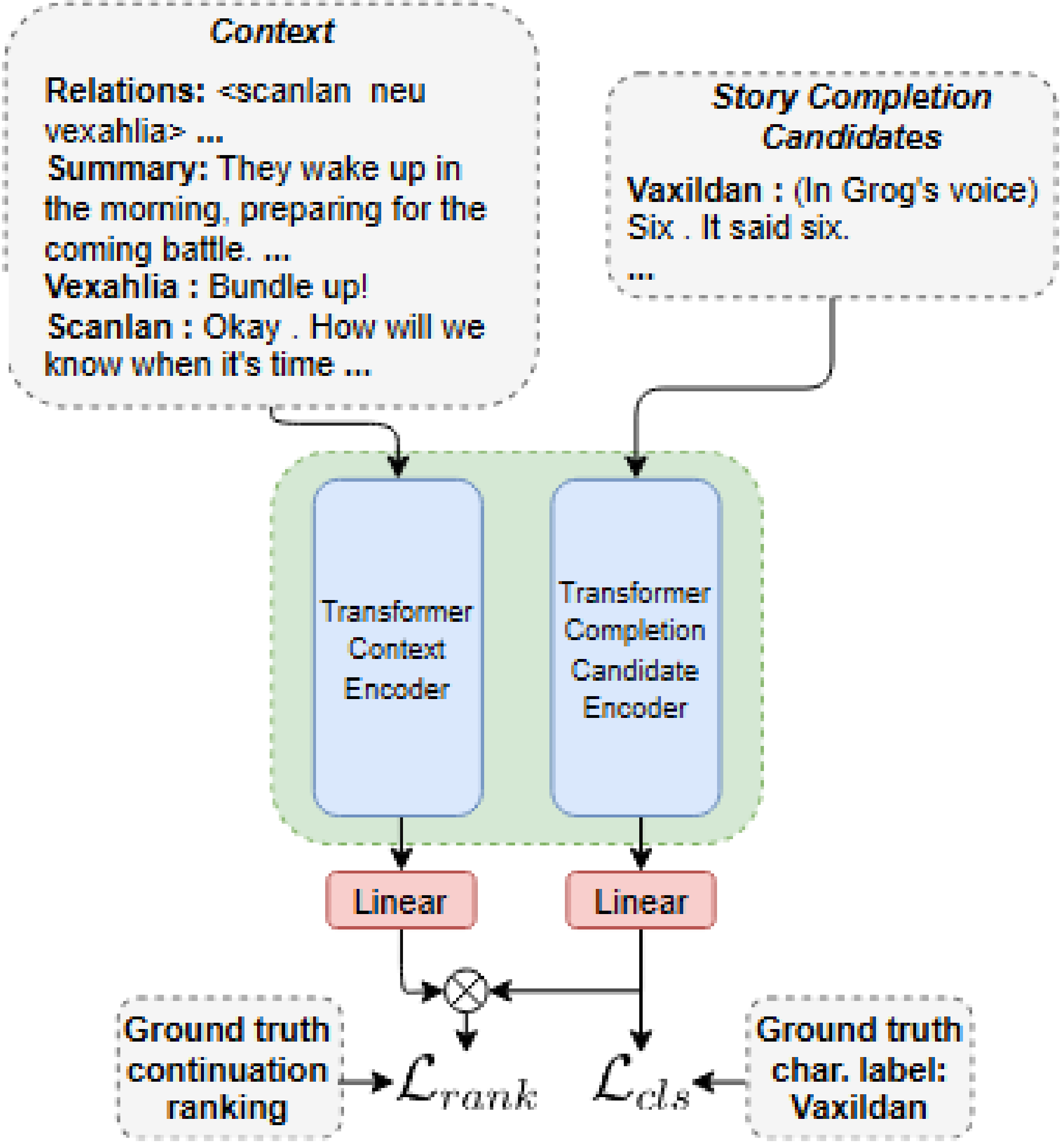


J. Shen, J. Mire, H. W. Park, C. Breazeal, and M. Sap, "HEART-felt Narratives: Tracing Empathy and Narrative Style in Personal Stories with LLMs," in *EMNLP*, 2024. https://aclanthology.org/2024.emnlp-main.59/.

Relationships

Relations	⟨ Scanlan, neutral, Vexahlia ⟩, ⟨ Keyleth, positive, Scanlan⟩, ⟨ Grog, negative, Vexhalia⟩, ⟨ Scanlan, positive, Vaxildan ⟩ ...
Summary	They wake up in the morning, preparing for the coming battle. Scanlan turns them all into Ravenites with light clothing. The sleet storm is starting. ...
Vexahlia:	Bundle up!
Scanlan:	Okay. How will we know when it's time for me to release? We have to wait for Tooma to go report.
Vexahlia:	Is Vorugal back? He's back.
Scanlan:	I assume.
Vexahlia:	Do we see Larkin around?
DM:	No, you do not see Larkin around.
Scanlan:	Vax , do you want to go look?
Vaxildan:	For Larkin?
Scanlan:	No Larkin. *I attempt to see see if Tooma is coming.* I don't want to release this thing before Tooma is there reporting to Vorugal.
Vaxildan:	(Grog voice) Six. It said six.

Table 1: A sample from CRD3 extended, showing: pairwise character relationships; historical context via the summary; and current character interactions in the form of dialogue, *first-person* (green), and second-person (blue) narration. DM refers to the Dungeon Master who provides arbitration and additional context to players.



Relationships

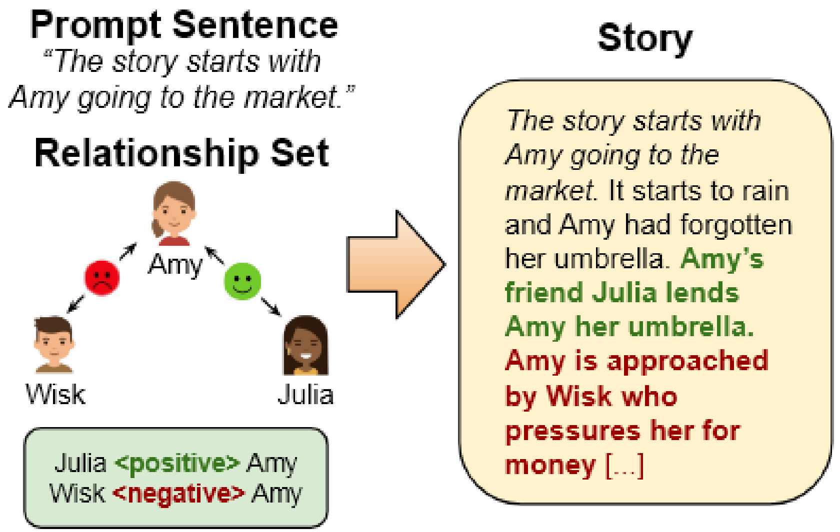


Figure 1: Example of relationship-driven story generation task: given a set of relationships and a prompt sentence, the goal is to generate a story continuing the prompt sentence and reflecting the input relationships. Positive and negative relationships are highlighted.

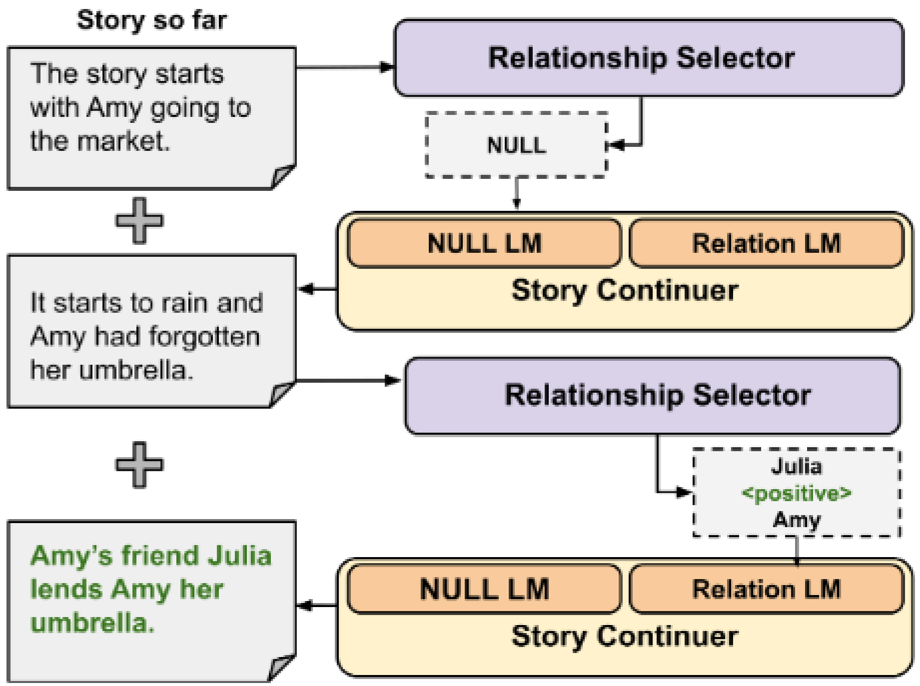


Figure 2: Proposed model RELIST illustrated. RELIST has two components, the relationship selector and the story continuer, which jointly generate the story.

A. Rao Vijjini, F. Brahman, and S. Chaturvedi, "Towards Inter-character Relationship-driven Story Generation," in *EMNLP*, 2022. doi: 10.18653/v1/2022.emnlp-main.613.

Relationships

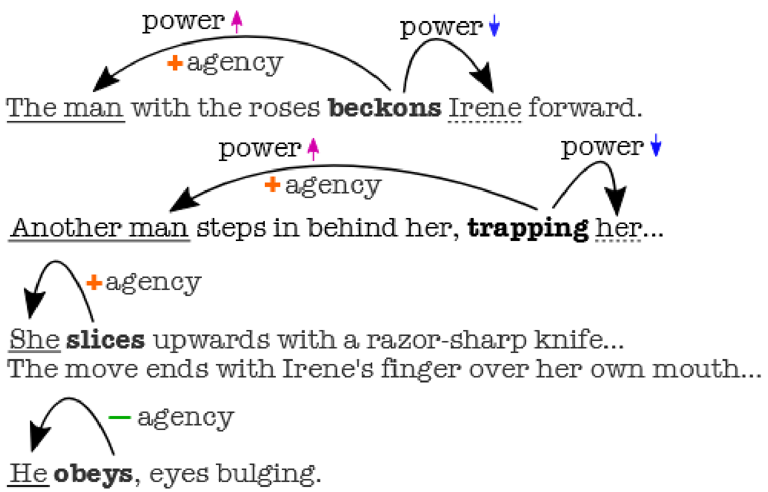
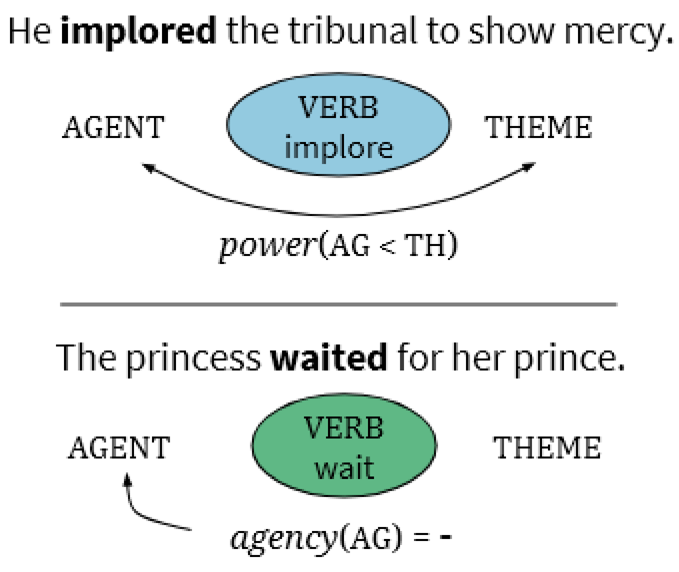
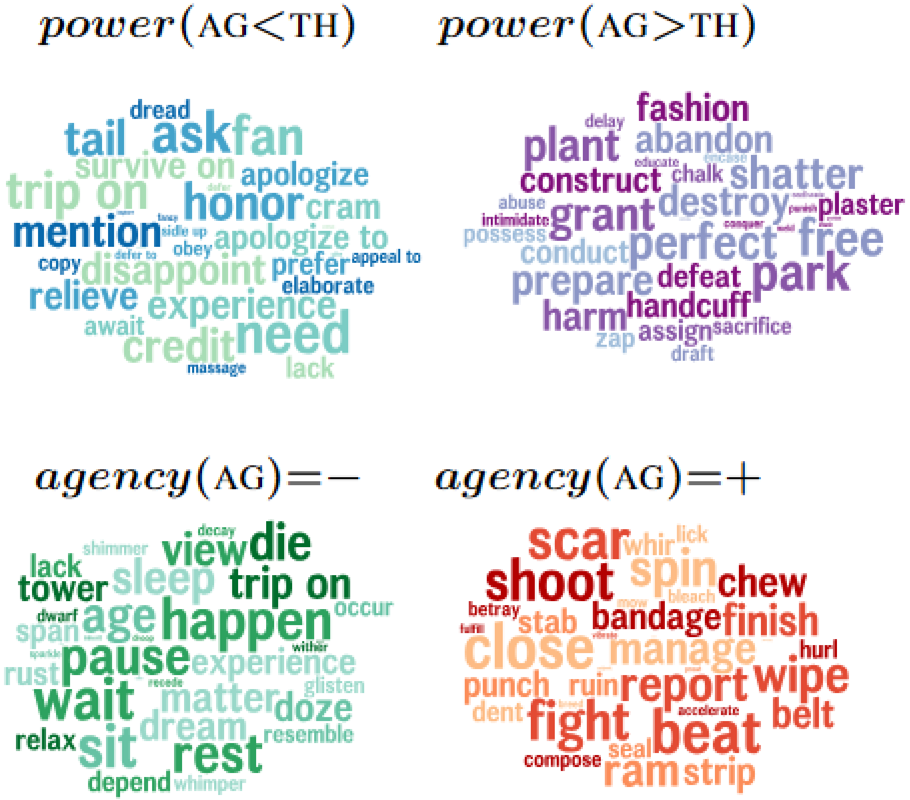


Figure 1: An excerpt from a box-office hit, *Sherlock Holmes* (2009). **Bolded** words are the predicates, solid underlined phrases are the agent of the verb, and dash underlined words are the theme. The full example with additional nuanced discussion is available in Figure 6 in the appendix.



Formal Definition



Labels

M. Sap, M. C. Prasettio, A. Holtzman, H. Rashkin, and Y. Choi, "Connotation Frames of Power and Agency in Modern Films," in *EMNLP*, 2017. doi: 10.18653/v1/D17-1247.

Relationships

```
Megan PROPOSE friend_have_lunch Meredith
Lester PROPOSE friend_chat Robert
Suzette PROPOSE friend_chat Silvy
Betty PROPOSE friend_weekend_out Clark
Meredith PROPOSE mate_watch_tv Lester
Clark REJECT-PROPOSAL friend_weekend_out Betty
Lester REJECT-PROPOSAL mate_watch_tv Meredith
Meredith ACCEPT-PROPOSAL friend_have_lunch Megan
Lester affinity with Meredith 87
Violet PROPOSE friend_chat Megan
Clark affinity with Betty 67
Robert REJECT-PROPOSAL friend_chat Lester
Meredith affinity with Megan 72
Silvy ACCEPT-PROPOSAL friend_chat Suzette
Robert affinity with Lester 72
Betty affinity with Clark 50
(...)
```

```
PLOT-PROJECTION 0
    ProposeActivity {activity=friend_weekend_out, proposee=Clark, proposer=Betty}
PLOT-PROJECTION 1
    ProposedActivityAccepted    {activity=friend_weekend_out, proposee=Clark, proposer=Betty}
    AffinityChange  {triggerer=Clark, perceiver=Betty, impact=76}
    AffinityChange  {triggerer=Betty, perceiver=Clark, impact=51-->54}
PLOT-PROJECTION 2
    ProposeActivity {activity=mate_go_to_cinema, proposee=Mary, proposer=Clark}
PLOT-PROJECTION 3
    ProposedActivityRejected    {activity=mate_go_to_cinema, proposee=Mary, proposer=Clark}
    AffinityChange  {triggerer=Mary, perceiver=Clark, impact=95}
    AffinityChange  {triggerer=Clark, perceiver=Mary, impact=84}
    (...)
```

P. Gervás and G. Méndez, "Pruning Worlds into Stories: Affective Interactions as Fitness Function," in *Artificial Intelligence in Music, Sound, Art and Design*, 2024. doi: 10.1007/978-3-031-56992-0_12.

Knowledge Check

1. Do you think a system can be made that encompasses all of these attributes using today's technology?
2. How would you start making a system like this? (e.g., Would it be LLM-based? Simulation-based? Planning-based?)
3. Would you need all of these to make a "good" story?
4. What about a "realistic" one?