Towards a GLUCOSE Knowledge Graph

and the power of it's generalization

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BA-Thesis
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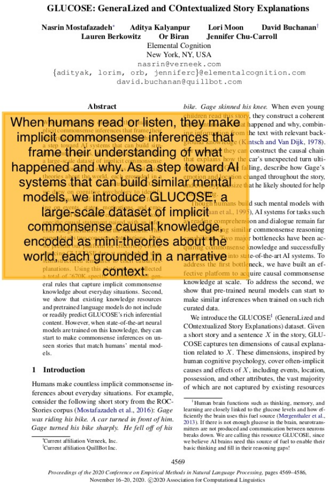
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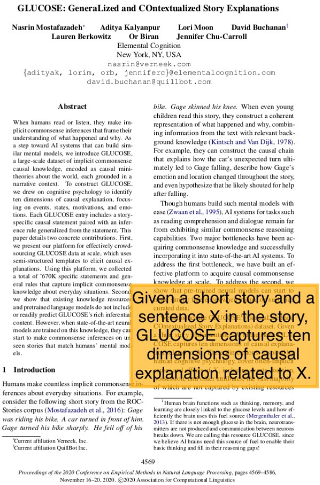

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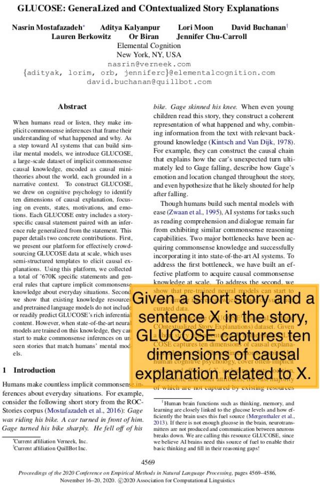

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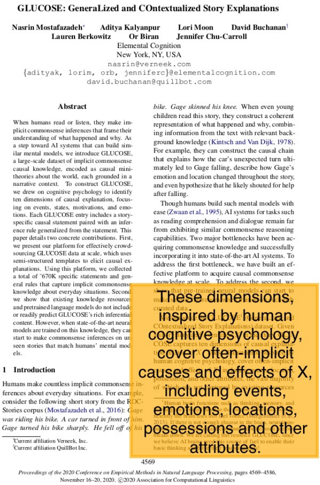

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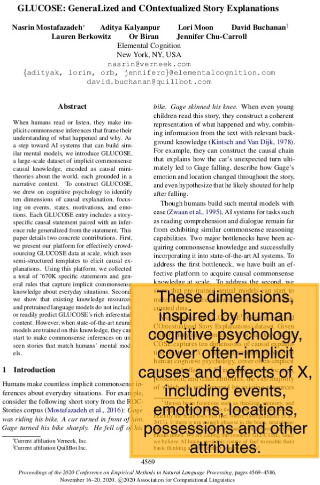

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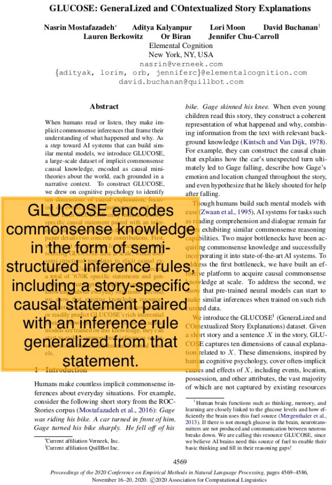

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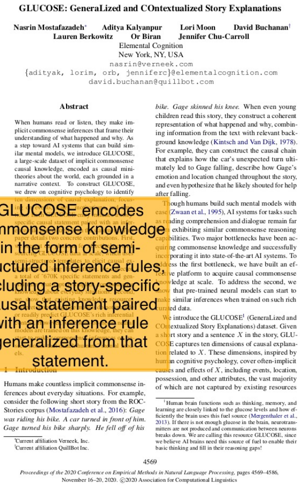
GLUCOSE: GeneraLized and COntextualized Story Explanations

Nasrin Mostafazadeh* Aditya Kalyanpur Lori Moon David Buchanan†
Lauren Berkowitz Or Biran Jennifer Chu-Carroll
Elemental Cognition
New York, NY, USA
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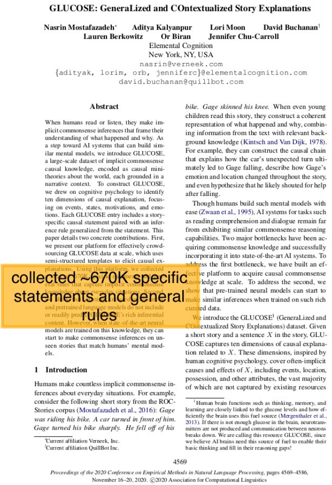

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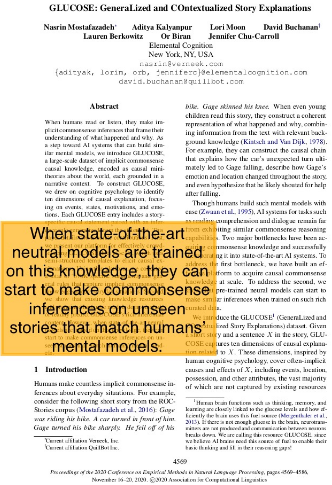

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Key Questions

- What kind of knowledge is contained in the GLUCOSE dataset?
- How can we represent that knowledge?
- What power lies in the generalization of that knowledge?
- Is the generalization an factor of improvement?
- How much generalization is too much?

Table of Contents

4584 Annotated Stories

Each story consists of 5 sentences:

Story Example:

1. Tom always loved the ocean.
2. He would vacation at the beach often.
3. He decided to buy a vacation home.
4. He got one right on the beach.
5. Tom spent a lot of time there.

Given a **Sentence** from a **Story**...

Story Example:

1. Tom always loved the ocean.
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...annotate **Inference Rules** in different **Dimensions**:

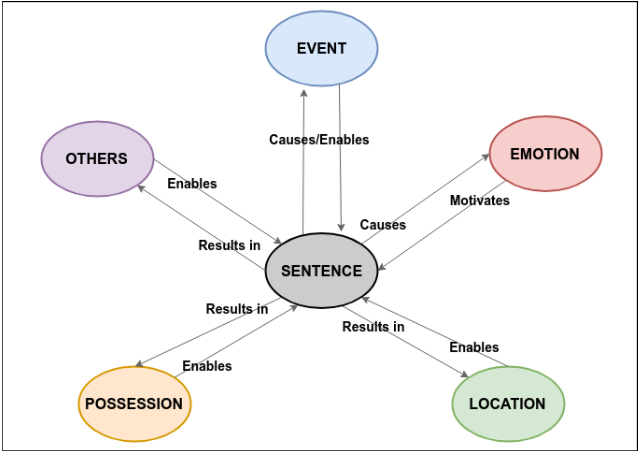

Figure 2: Annotation Dimensions of GLUCOSE Dataset

How does an annotation look like?

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Each annotation has two forms:

Specific Rule:

Tom love(s) the ocean `MOTIVATES` Tom vacations at the beach often

General Rule:

Someone_A love(s) the ocean `MOTIVATES` Someone_A vacations at the beach often

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LOCATION

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Someone_A goes to Somewhere_A	RESULTS IN	Someone_A is at Somewhere_A

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EVENT

Tom would vacation at the beach often	`ENABLES`	Tom decided to buy a vacation home
Someone_A would vacation at Somewhere_A often	`ENABLES`	Someone_A decided to buy Something_A

What Knowledge is in the Data?

- Stories form a **Narrative Context**

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- Annotated **Inference Rules**
  - specific
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  - EMOTION
  - LOCATION
  - POSSESSION
  - OTHERS

What is this Knowledge about?

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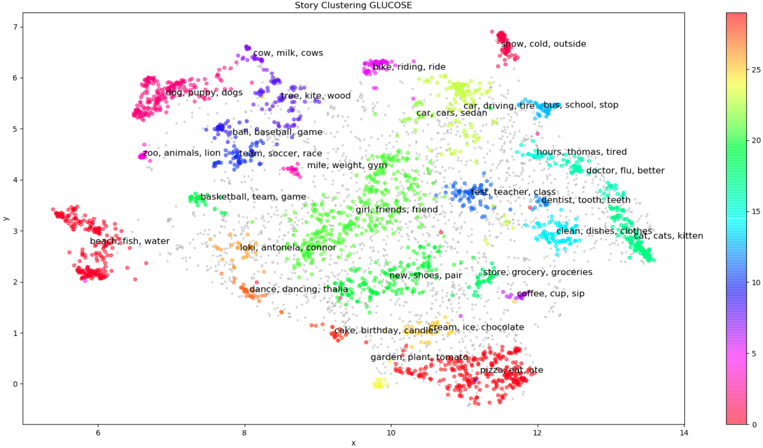

Figure 3: Story Clustering of GLUCOSE with minimal cluster size 15

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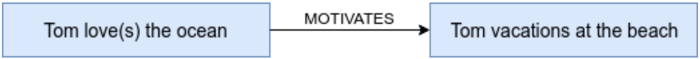
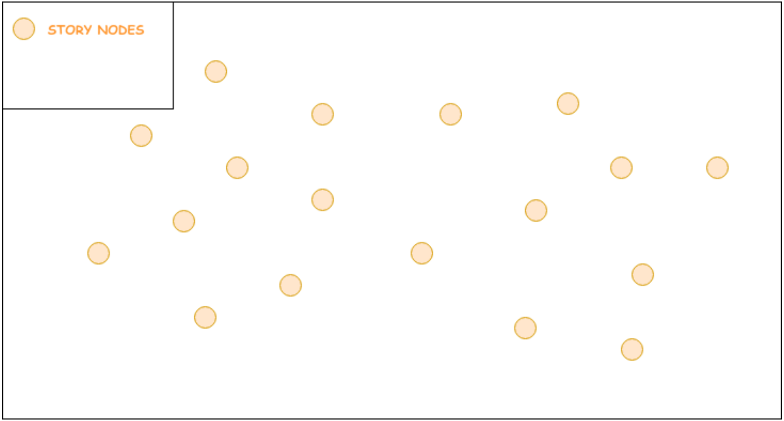


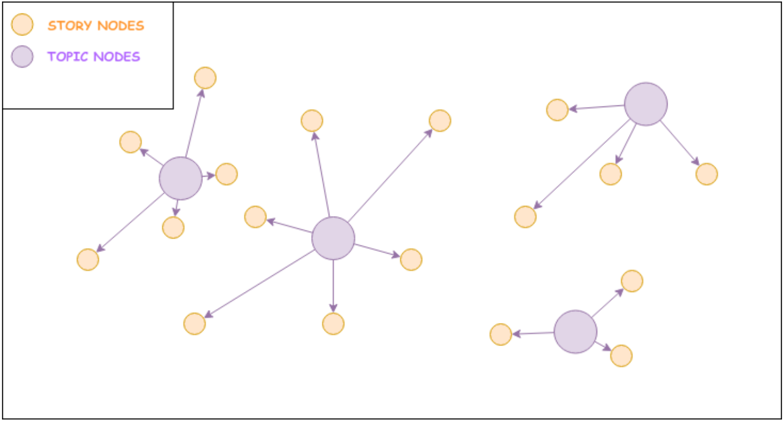
Graph Building Part 1: Knowledge in the Stories

Imagine every story was a node...



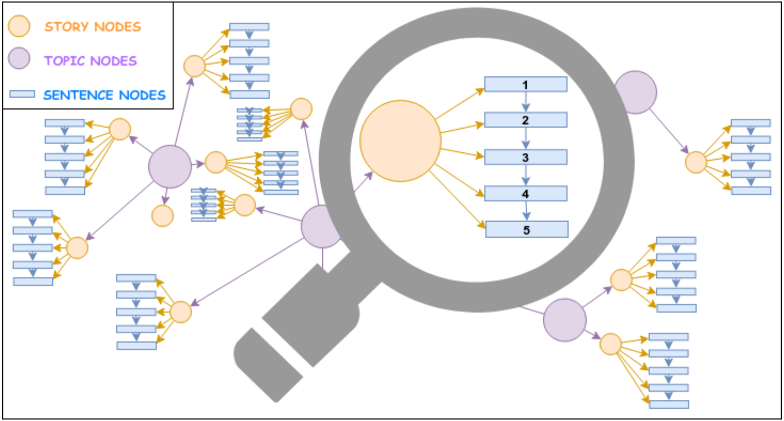
Graph Building Part 1: Knowledge in the Stories

Every STORY NODE is connected to one TOPIC NODE



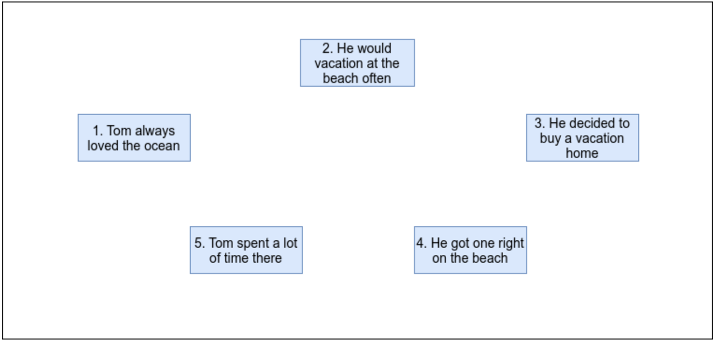
Graph Building Part 1: Knowledge in the Stories

Every STORY NODE points to five SENTENCE NODES



Graph Building Part 2: Knowledge in the Specific Rules

Imagine every sentence was a node...



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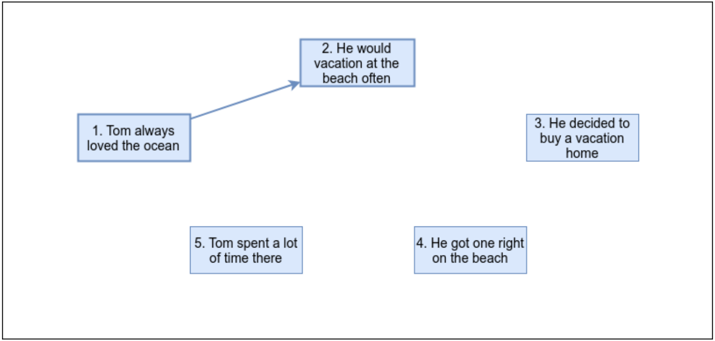

EMOTION

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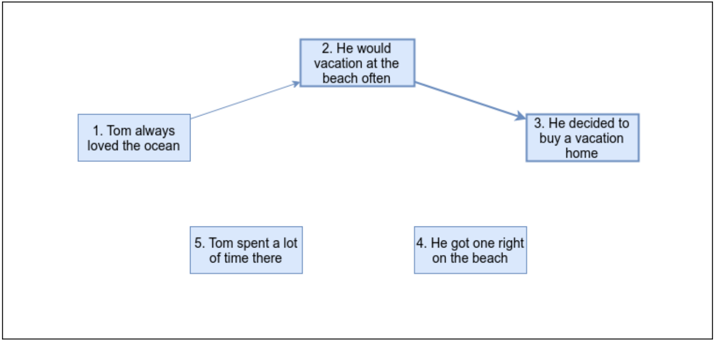

EVENT

Tom would vacation at the beach often `ENABLES` Tom decided to buy a vacation home

Graph Building Part 2: Knowledge in the Specific Rules

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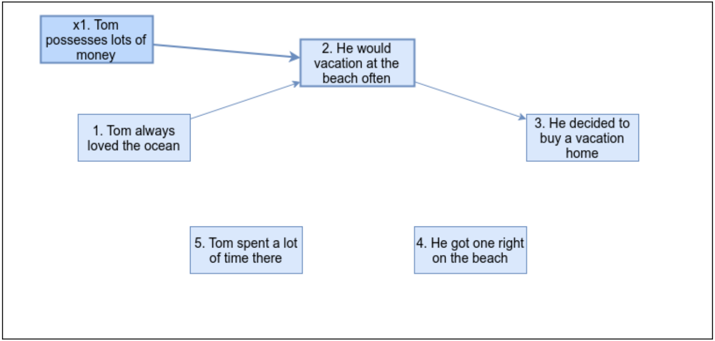

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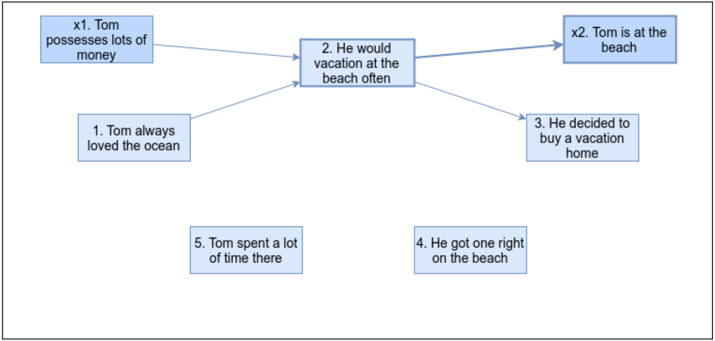
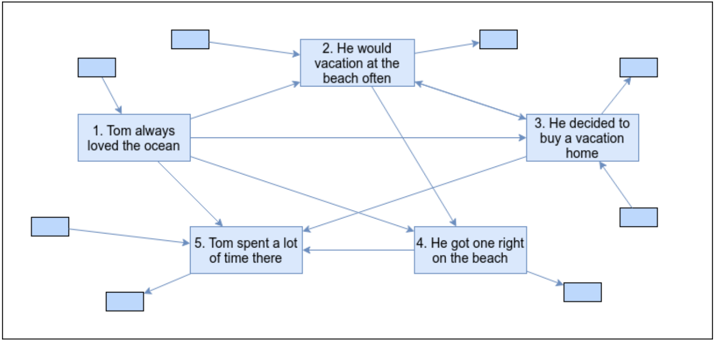


LOCATION

Tom vacations to the beach `RESULTS IN` Tom is at the beach

Graph Building Part 2: Knowledge in the Specific Rules

deriving relations between SENTENCE NODES from specific rules



But what about GENERALIZATION?

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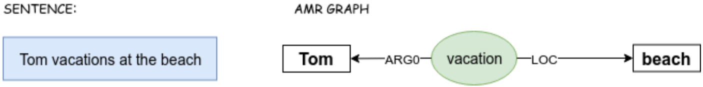

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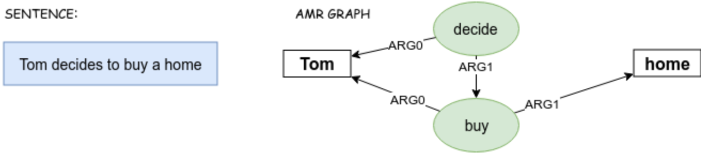
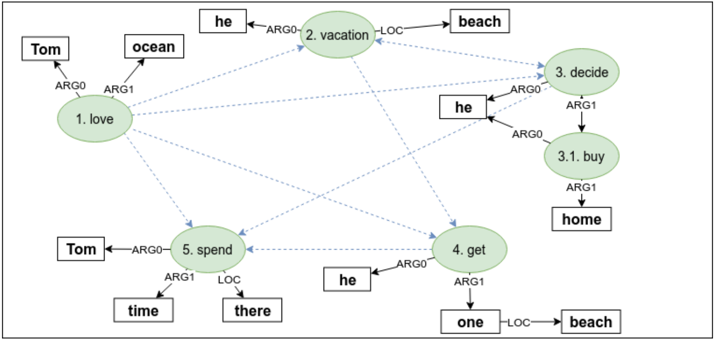


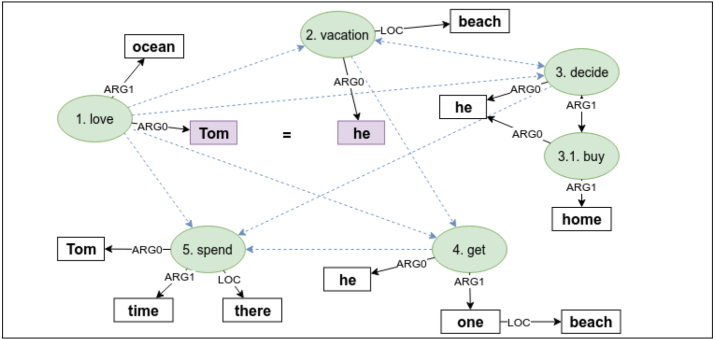
Graph Building Part 3: Knowledge in the General Rules

Imagine every SENTENCE NODE was an AMR GRAPH...



Graph Building Part 3: Knowledge in the General Rules

deriving relations between CONCEPT NODES from general rules



EMOTION

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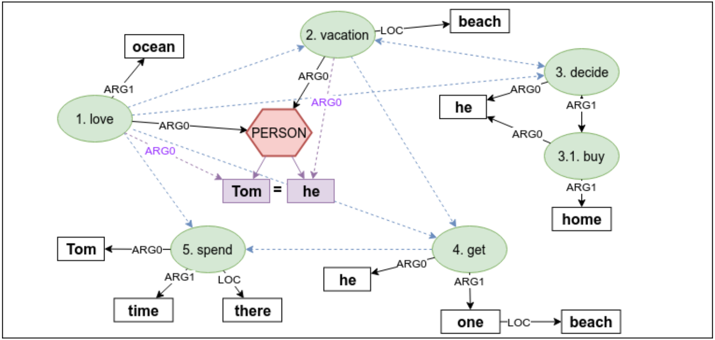
Graph Building Part 3: Knowledge in the General Rules

generalizing CONCEPT NODES with Gap Fillers



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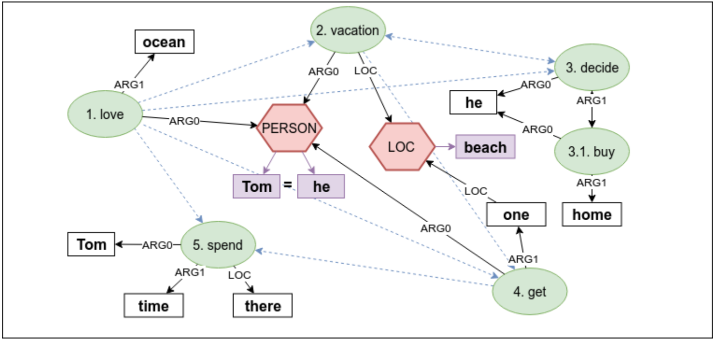
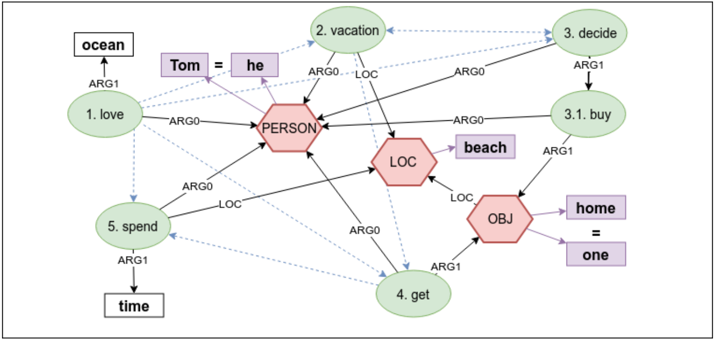


EVENT

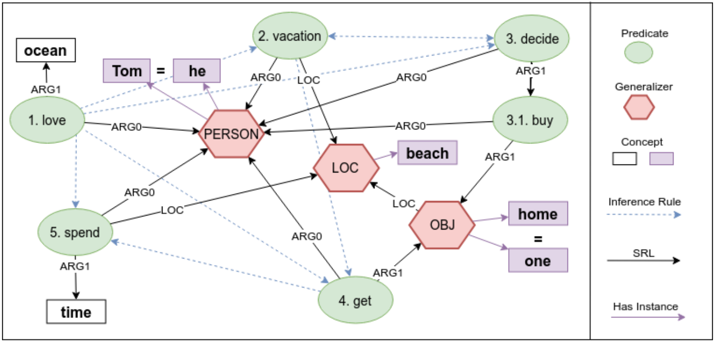
Tom would vacation at the beach often	ENABLES	Tom got a home at the beach
Someone_A would vacation at Somewhere_A often	ENABLES	Someone_A got a home at Somewhere_A

Graph Building Part 3: Knowledge in the General Rules

do that for every rule

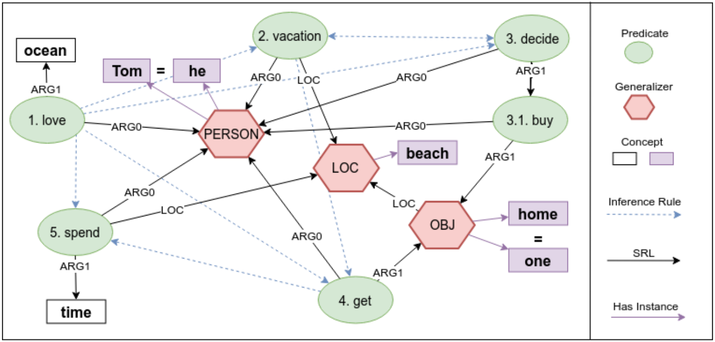


Graph Building Part 3: Knowledge in the General Rules



Graph Building Part 3: Knowledge in the General Rules

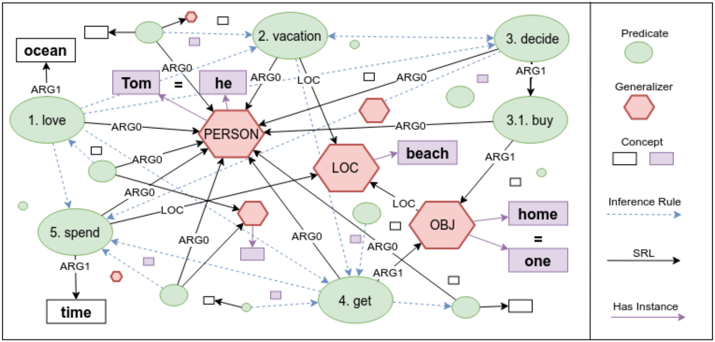
but what about...?



POSSESSION

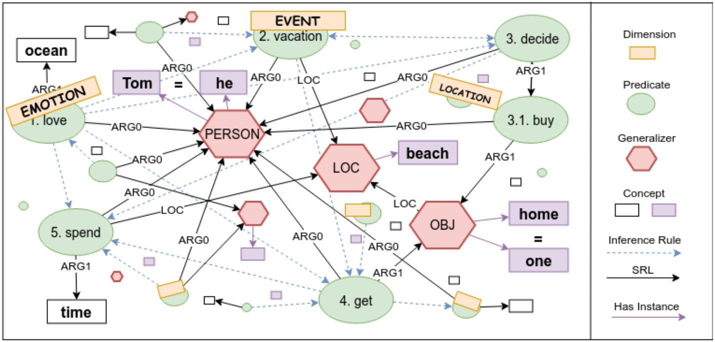
Tom possess(es) lots of money	ENABLES	Tom vacations at the beach often
Someone_A possess(es) lots of money	ENABLES	Someone_A vacations often

Graph Building Part 3: Knowledge in the General Rules

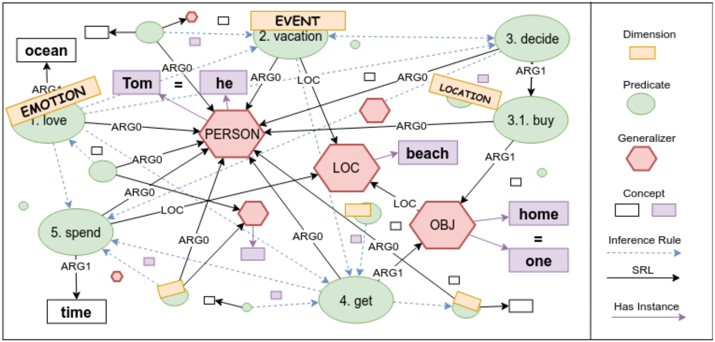


Graph Building Part 3: Knowledge in the General Rules

and don't forget the dimensions label...

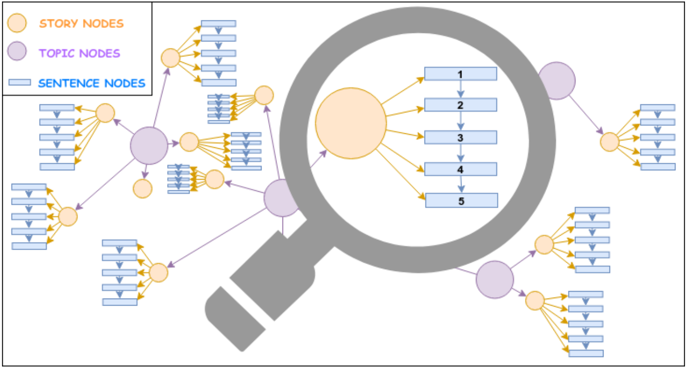


Graph Building Part 3: Knowledge in the General Rules

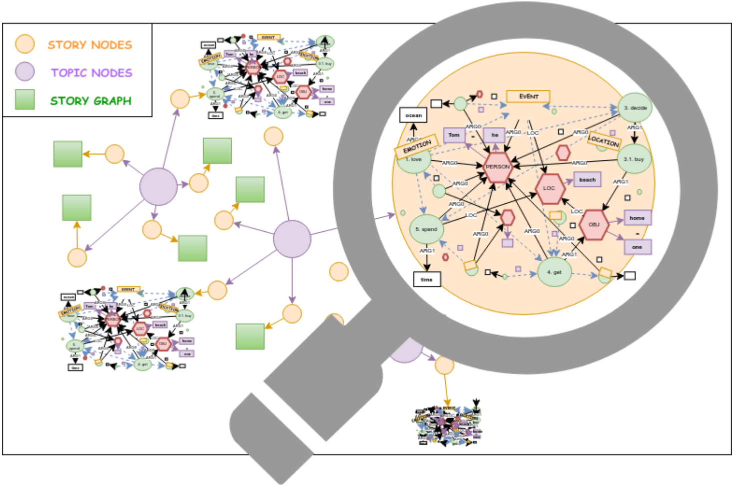


Now we built one semi-structured graph per story based on annotated semi-structured rules.

Do you remember...?



Do you remember...?



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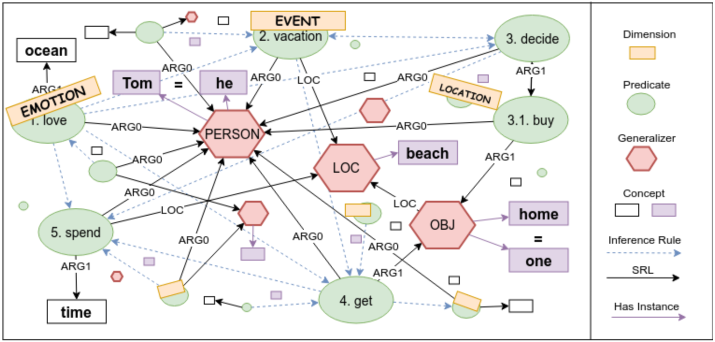
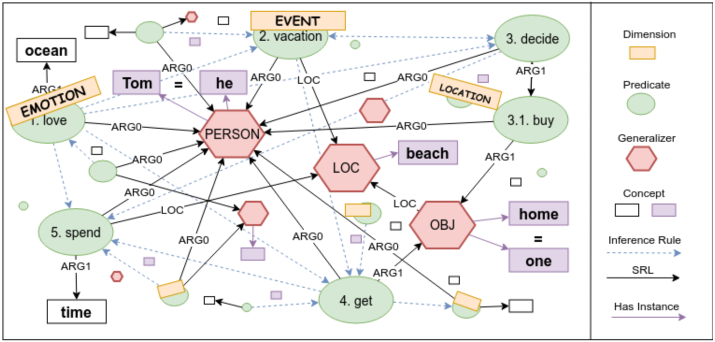


deduct a...

1. fully instanciated graph
2. highly generalized graph
3. intermediate graph

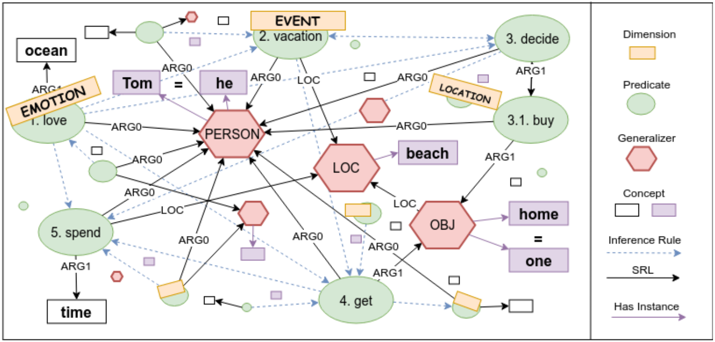
What now?



given these representations, how many times can a rule be applied?

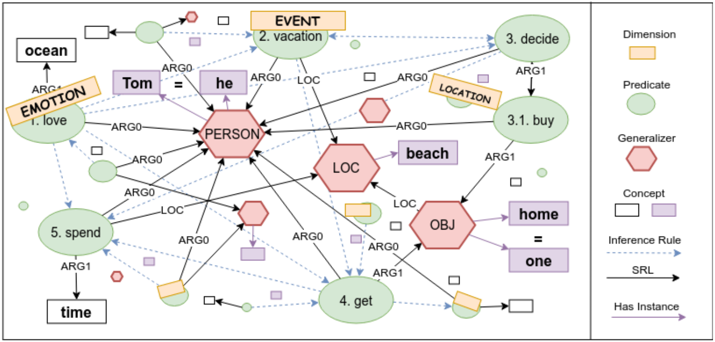
1. Tom love(s) the ocean MOTIVATES Tom vacations at the beach
2. PERS_A love(s) OBJ_A MOTIVATES PERS_A vacations at LOC_A
3. PERS_A love(s) the ocean MOTIVATES PERS_A vacations at the beach

What now?



- how much generalization is a knowledge gain?
- how much generalization is too much?

What now?



- on what and how many concepts can a general rule be applied?
- are there certain patterns depending on topics?
- are there certain patterns depending on dimensions?

THANK YOU FOR YOUR ATTENTION