

EMNLP 2021 Tutorial

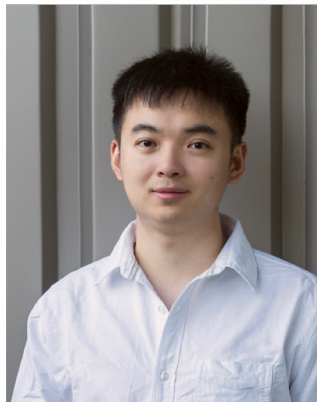
Knowledge-Enriched Natural Language Generation



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Remaining Challenges



- Challenge 1: LM Hallucination and Bias
- Challenge 2: Knowledge Bottleneck
- Challenge 3: Capturing Global Consistency across discourse, tables and graphs
- Challenge 4: Removing Repetitions
- Challenge 5: Urgent Need of Better Evaluation Metrics

Challenge 1: LM Hallucination and Bias



- 30% of abstractive summaries contain unfaithful information by state-of-the-art models (Cao et al, 2018)
- Examples of fabricated answers in movie question answering
 - Q: What did Susie promise to one of the waiters at the Copacabana Club in return for smuggling her into the club for free?
System: Susie promises to **buy one of the men a drink after every act.**
Key: Susie promised him a prime slot for his singing act at the Gaslight Café for 2 weeks. Unfortunately Susie thinks his act is awful but keeps her word even since they had to watch the show from the kitchen.
 - Q: What do Midge and Susie fight over?
System: **Their son.**
Key: With emotions on high, Susie confronts Midge about why she hired Herb. Midge felt Susie does not help and sabotaged her earlier because Susie rushed her on stage. Midge tells her she wants to quit and, after a few insults at each other, walks away.
 - Q: What do Susie and Midge talk about when Midge visits Susie's home?
System: Susie and Midge talk about the upcoming **moon landing.**
Key: Susie confronts Midge about her meeting with Randall and his agent. She tells Midge she does not need a man to help with her set and what she is doing is not stand-up, it's being the annoying party guest. Midge breaks down crying and tells Susie her life has been hard and if Susie wants to be her manager, she has to deal with Midge's personal matters and not run away. After this, Susie comforts Midge.
 - Q: How were some of the Navy Seal members killed back in America?
System: **In a scuffle in France the four members** of the navy were killed.
Key: One was run over by a truck while throwing trash in the sideback. One was shot during a car drive.
- Bias from LM [Wang et al., INLG2018]
 - *"Silvi Jan (born 27 October 1973) is a former Israel. **He** played for Israel women's national football team,..."*
- Potential solutions: filter out popularity bias, incorporate more scenario-specific/domain-specific knowledge

Challenge 2: Knowledge Bottleneck



- Noise from imperfect automatic information extraction and knowledge acquisition methods
 - End-to-end information extraction F-score is only around 75%
- Lacking of effective domain-specific knowledge mining methods
 - Paper generation models trained from biomedical domain don't work for NLP domain
- Need to incorporate more commonsense knowledge and dynamic knowledge
 - Example from KB Description [Wang et al., INLG 2018]:
*"Aleksei Gasilin (born **1 March 1996**) is a ... He made his professional debut in the Russian Second Division in **1992** for ..."*
 - Personification: The attribution of humanlike qualities to something non-human due to lack of common sense knowledge [Modi and Parde, 2019]
- Learning external knowledge in a continuous way (Lifelong learning) [Yu et al., 2021; Mazumder et al., 2018]
- Embed knowledge into pre-trained language model [Cao et al., 2017; Liu et al., 2019; Qin et al., 2021]

Challenge 3: Capturing Global Consistency



- Inconsistency across Discourse
 - *Balanchine's "Mozartiana" (1981) is **one of the best** ballets in the world, but it is also **one of his least interesting**. The first movement, a Tchaikovsky Suite, is **a bit of a mess**, and the second movement is **a little too easy**. The third movement is **too easy**; the fourth, a Gigue, is **too simple**.*
- Inconsistency Analysis from [Modi and Parde, 2019]
 - Contradictions in ideas within the same story
 - Singular/Plural Disagreement
 - Ghost Entities: Some sub-stories make use of a pronoun that has no antecedent at all
 - Point-of-View Inconsistency: The narrative point of view randomly changes within the story
- Inconsistency across Tables/Graphs
 - Current methods are limited to encoding position information
- Potential solutions
 - Develop document-level or corpus-level information extraction methods to capture long-term dependencies
 - Incorporate semantic parsing in encoding and decoding [Huang et al.2020]

- **Input:** *the Senate proposed a tax bill on Tuesday*
- **Output:**
 - Semantic structure:
 - *proposed* <ARG0> *the Senate* <ARG1> *tax bill*
 - Summary:
 - *Senate proposes bill*

Legend:
A Attention over Input Article
S Attention over Generated Semantics

Challenge 4: Repetition



- It has been a mystery why DNN generates so many repetitions [Modi and Parde, 2019]
 - Repetitions within Story: Recurrence of the same sentence(s) within a story
 - Repetitions within Sentence: Recurrence of the same phrase(s) within a substory
 - Repetitive Subject: The sub-stories have the same subject and differ only in the adjective used to describe it
 - Repetitive Sentence Structure: Most sentences start with “the [noun] was/were/is [adjective]”
 - Excessive Paraphrasing: Presence of substories that have similar meanings but are expressed using different words or phrases
- Most solutions try to add controls (through vocabulary selection or hyperparameter control) in beam search decoding, which might generate less important content

Repetition Removal Example [Wang et al., ACL2019]

- **Before:** Background: The aim of this study was to compare the efficacy and safety of pain relief in **patients with knee osteoArthritis (OA)**. Methods: This was a prospective cohort study of **patients with knee osteoArthritis (OA)**. The primary endpoint was the proportion of **patients with knee osteoArthritis (OA)**.
- **After:** Background: The aim of this study was to compare the efficacy and safety of pain in patients with knee osteoArthritis (OA). Methods: This was a prospective, multicentre, multi-center, non-interventional, observational, randomized, controlled trial. The primary endpoint was the proportion of the knee and joint symptom of the physical functioning, and to evaluate the relationship between the two groups. Patients were randomly assigned to receive either a single dose of 0.5 mg twice daily (n = 30) or placebo (500 mg/day) for 52 weeks.

Repetition Removal Example [Wang et al., ACL2019]

- **Before:** Background: The aim of this study was to compare the clinical outcome of myocardial infarction (MI) in patients with acute ST segment elevation (MI). Methods: We retrospectively reviewed the clinical records of patients with acute ST segment elevation of **acute ST elevation myocardial infarction (MI)**. Patients with **acute ST elevation myocardial infarction (MI)**, and **acute ST elevation myocardial infarction (MI)**, were included in this study. The primary endpoint was the proportion of patients with acute ST elevation myocardial infarction (MI) and coronary artery disease (CAD).
- **After:** Background The aim of this study was to compare the prevalence of myocardial infarction (MI) in patients with acute ST. Methods : The primary endpoint was the first time of the left anterior descending coronary artery , and to evaluate the clinical utility of Protocol . We performed a retrospective analysis of a prospective, randomized controlled trial. Patients were divided into two groups (n=6). The median follow-up period was defined as the presence of the right ventricle, and the level of cardiac catheterization was evaluated .

Challenge 5: Urgent Need of Better Evaluation Metrics

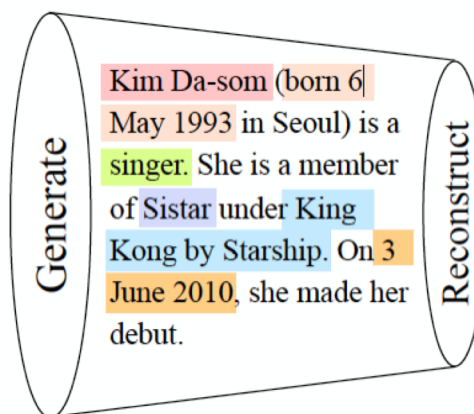
- “Bad” examples with 0 BLEU/ROUGE scores
 - Question: *How Midge’s parent react to the news that Joel has left Midge*
 - Key: Midge’s dad starts to play the piano frantically and later blames Midge for marrying a weak man against his advice.
 - System: Midge’s mother starts crying and whining heavily.
 - Question: Did the CIA know that Russia was dealing weapons out of Aleppo?
 - Key: Yes.
 - System: the intelligence community was aware that the sale of nerve gas was being carried out.
- “Bad” examples from Abductive Reasoning
 - Given beginning: Billy had received good grades on his report card.
 - **TO generate a reason between beginning and ending!**
 - Given ending: He decided as he got home that elephants were his new favorite animal.
 - Ground truth: He went to the zoo later in the day and saw elephants.
 - Generated example:
 - (1) Billy's parents sent him on an African safari for a reward.
 - (2) His mother stopped by the store and bought him a stuffed elephant.

Challenge 5: Urgent Need of Better Evaluation Metrics

• (Potash et al., ACL2018 workshop)

- Potential solution: adding coherence, fact verification and fluency into metrics, in addition to WordNet/embedding based semantic similarity [Potash et al., 2018]
- Knowledge reconstruction metric [Wang et al., 2018]:

Slot Type	Slot Value				
Name	Kim Da-som				
Date of Birth	6 May 1993				
Place of Birth	Gwangju				
Occupation	Singer				
Occupation	Actress				
Genres	K-pop				
Start Active Year	3 June 2010	Start Active Place	Seoul	Start Active Song	PUSH PUSH
Agent	King Kong by Starship				
Associated acts	Sistar				



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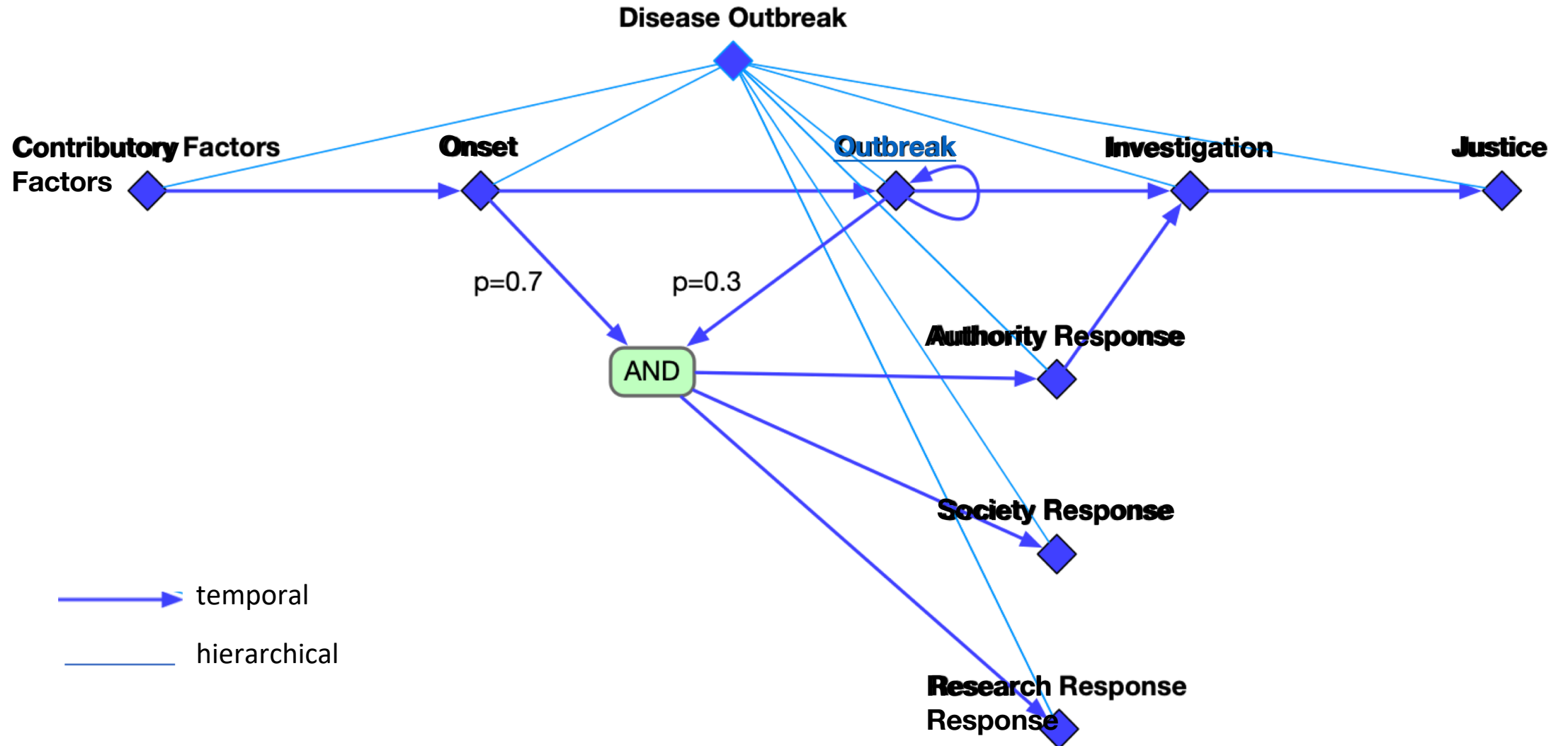
Anom.	Example	Scores
Good Story, Low Score	we went to a halloween party . there were a lot of interesting things to see . we saw a lot of cool things . we saw a lot of old buildings . the christmas tree was the best part of the day . (AREL)	CIDEr: 4.27, BLEU-4: 0.00, BLEU-3: 15.79, BLEU-2: 29.76, BLEU-1: 50.95, ROUGE-L: 24.43, METEOR: 24.42
	the couple was excited to be on vacation . they were going to the mountains . they went down the road . they saw a beautiful church . they had a nice dinner . (GLACNet)	CIDEr: 0.62
Bad Story, High Score	the group of friends decided to go on a trip . they saw many interesting things . they stopped at a local restaurant . they had a great time . they ended up buying a new car . (GLACNet)	METEOR: 19.52, Bleu-4: 0.00, Bleu-3: 8.93, Bleu-2: 16.00, ROUGE-L: 22.55
	i went to a wedding last week . i had to take a picture of this beautiful flower . this is a picture of a woman . the flowers were so beautiful . the flowers were so beautiful . (AREL)	CIDEr: 20.90, Bleu-1: 71.79, Bleu-2: 43.47, METEOR: 33.98

Future Directions

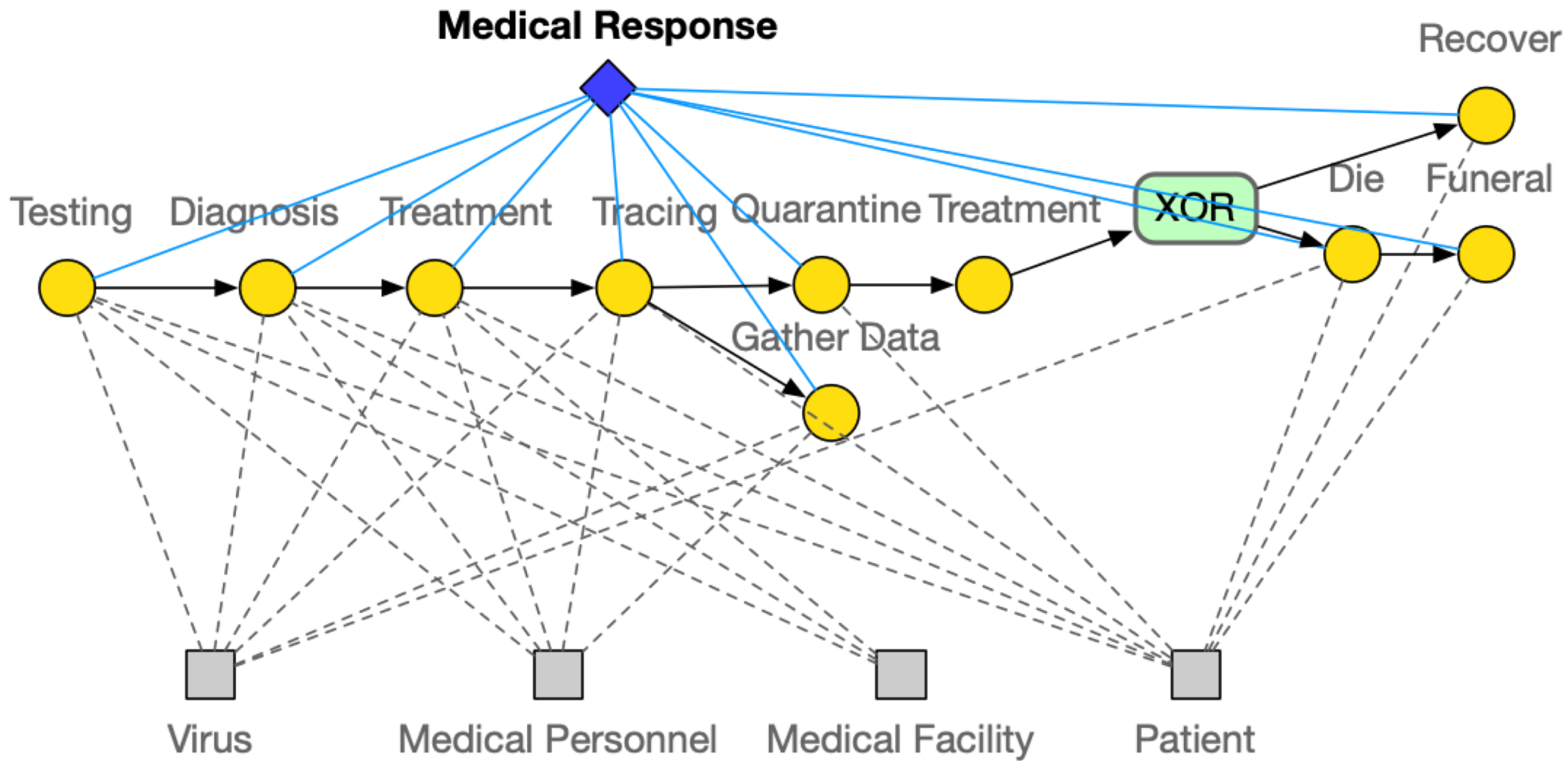


- Direction 1: Background Knowledge Guided NLG
 - Joint Knowledge and Text Representations
 - Dynamic knowledge acquisition and encoding
- Direction 2: Multimedia Guided NLG
- Direction 3: Extract and then Generate
- Direction 4: Multi-view Summarization
- Direction 5: Using Knowledge-Enhanced NLG for Training Data Generation or Augmentation
 - Misinformation Detection
- Direction 6: Using Knowledge-Enhanced NLG for other NLP tasks
 - Information Extraction
 - Taxonomy Completion
 - Entity Linking

Direction 1: Background Knowledge Guided NLG



Direction 1: Background Knowledge Guided NLG



Direction 1: Background Knowledge Guided NLG

GRU

yesterday i went grocery shopping . i did n't know anything all the items in my cart , so that it was ready to pick up up . i got my items off , and found it to the front of the store . i was on narita shopping cart because i had less than twenty of them . i grabbed my cart and went to the cashier . i paid for the items , then i gave the cashier my money and my bag , checked my bags up , and the other items in my hand bag . i am glad i 'm flying for my plane and go through security .

Neural Checklist

yesterday i wanted to go grocery shopping . when i went to the front of the store , i went to the grocery store and drove to the front of the store . i went to the cashier and drove to the front desk .

Random Event Order

yesterday i went grocery shopping . i grabbed a shopping cart and put the items on the list . i put my items in the cart and drove to the store . i drove to the grocery store and went to the grocery store . i made a list of all the items i would need . i put my items on the cart and headed to the store . when i entered the store , i grabbed a shopping cart and walked inside . i put the cart away in the cart .

Agenda: evoking→take shop cart→put conveyor→get groceries→go grocery→move section→make list→check off→put conveyor→leave→enter→take shop cart→enter→return shop cart→story ends

Full

yesterday i went grocery shopping . i made a list of my list and drove to the grocery store . when i entered the store , i grabbed a shopping cart and pushed the cart down to the meat aisle . i got all my items , and crossed items on my list . i went to the checkout register and paid for my groceries . i put my groceries in my cart and left .

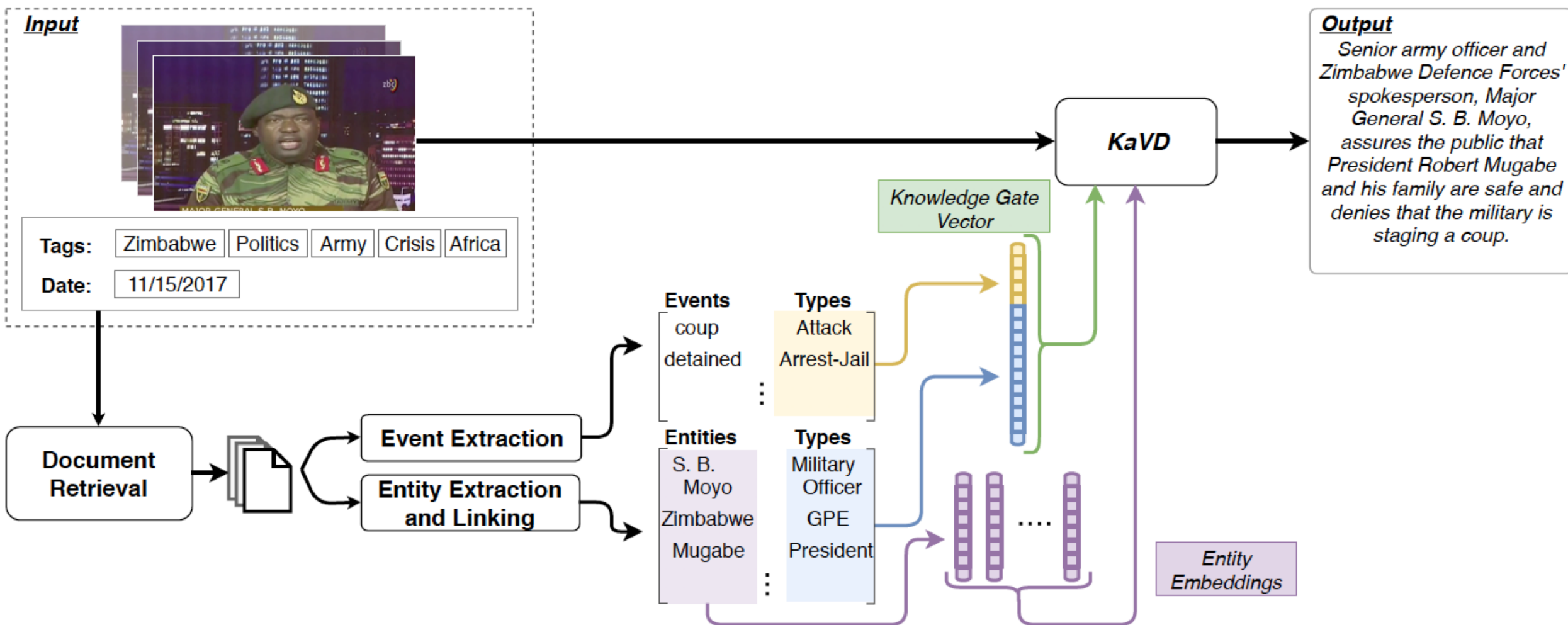
Agenda: evoking→make list→go to store→enter→take cart→move along sections→take grocery→check list→go to checkout→pay→pack grocery→leave→story ends

Human Author

yesterday i went grocery shopping . i took my grocery list with me , along with some reusable shopping bags . my grocery list has all the items i want to buy on it . i selected a shopping cart from in front of the store , and went inside . i put my reusable bags in the cart . i looked at my list and started in the produce section . i put different vegetables and fruits into my cart . next i wheeled my cart to the cereal aisle and took a box of cereal . i went through the store aisle by aisle and selected my groceries . each aisle is organized by types of food and non-food items . one aisle has dried pasta , canned tomatoes , rice , and sauce . i selected a few boxes of pasta and some rice . another aisle carries plastic wrap , trash bags , and aluminum foil . as i went through the store , i kept looking at my list to see what i needed next . when i added each item to my cart , i crossed it off my list . my last stop was the dairy aisle where i got milk and eggs . when i had all the groceries i wanted , i went to the cash register and stood in line . when it was my turn , i put each item on the conveyor belt and the cashier scanned each one . a bagger put all of the groceries into my reusable bags . i paid , and then the cashier gave me a receipt . i loaded the bags of groceries into the trunk of my car and drove home .

Direction 2: Multimedia Guided NLG

- (Whitehead et al., EMNLP17)



Direction 3: Extract and then Generate (Sharma et al., 2019)

Input Article

Prime Minister Bertie Ahern of Ireland called Sunday for a general election on May 24. Mr. Ahern and his centrist party have governed in a coalition government since 1997. . Under Irish law, which requires legislative elections every five years, Mr. Ahern had to call elections by midsummer. On Sunday, he said he would base his campaign for reelection on his work to strengthen the economy and efforts to revive Northern Ireland's stalled peace process this year. Political analysts said they expected Mr. Ahern's work in Northern Ireland to be an asset . . .

Entity Mention Cluster

{Prime Minister Bertie Ahern, Mr. Ahern, he, he, his, Mr. Ahern's}
 {Ireland, Northern Ireland, Northern Ireland's}

Output Summary

prime min bertie ahern of ireland calls for general election on may 0. ahern and his centrist party, have governed in coalition government since 0. ... ahern says he would base his campaign for re-election on his work to strengthen economy and his efforts to revive northern ireland's stalled peace process.

Entity-aware Content Selector

Extracted Sentences

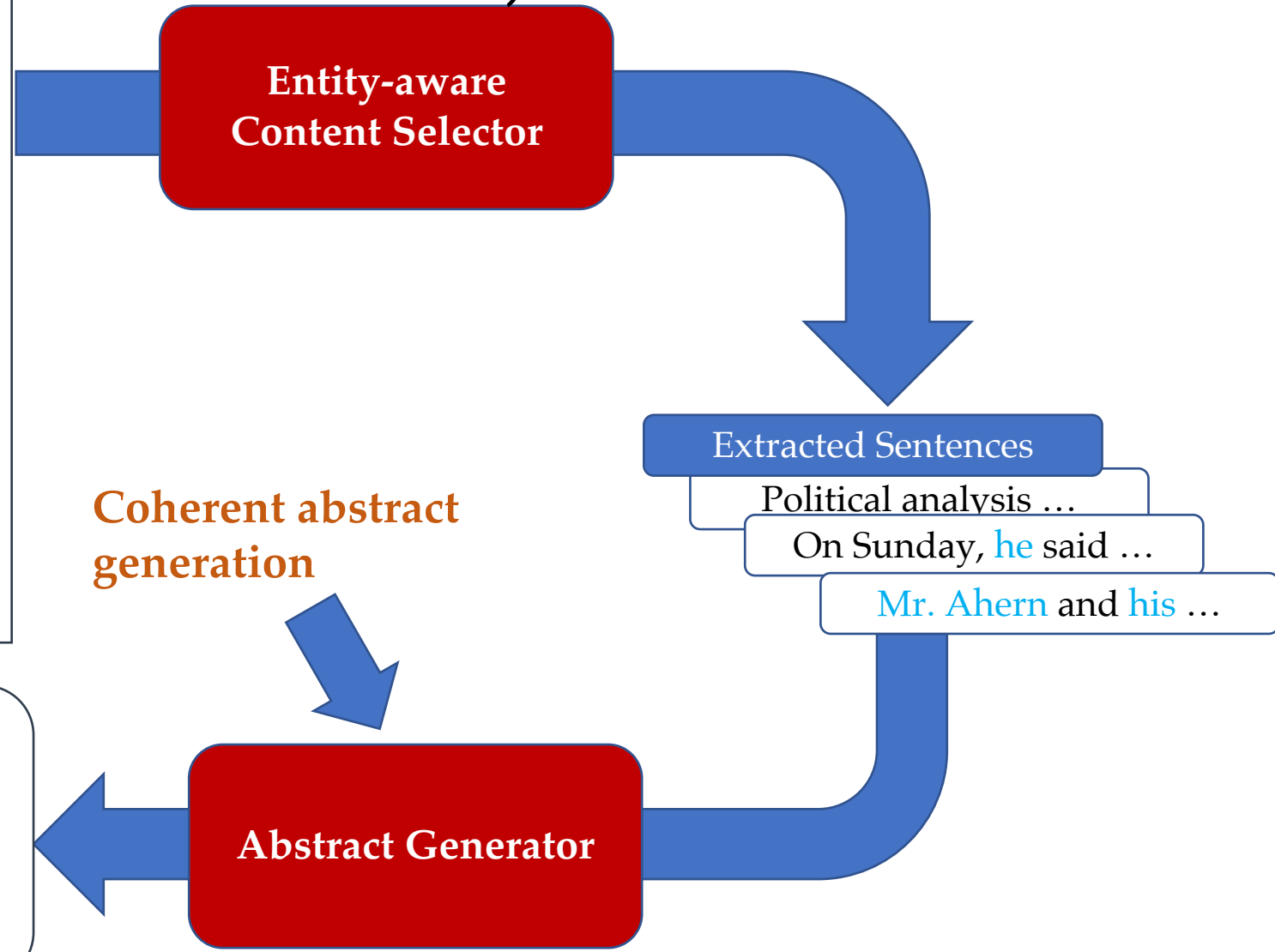
Political analysis ...

On Sunday, he said ...



Mr. Ahern and his ...

Coherent abstract generation

Abstract Generator



Direction 4: Multi-View Summarization

Claims:	<i>Arrested protesters should be released.</i>		Claims:	<i>The protests are not necessary.</i>			
	<i>Carrie Lam should resign.</i>			<i>Violent protesters should be arrested.</i>			
Profile:	<i>Birth Place: Hong Kong</i>	<i>Age: below 30</i>	Profile:	<i>Birth Place: not Hong Kong</i>	<i>Age: Above 50</i>		
	<i>Education: above college</i>	<i>Participate in protest? No</i>		<i>Education: Below secondary school</i>	<i>Participate in protest? No</i>		
Premises		Evidence		Premises		Evidence	
<i>Extradition Law will weaken autonomy and judicial independence.</i>		Police violently attacked protesters.		<i>Protests on Extradition Law amendment are not necessary.</i>		The target of Extradition Law is only on felon criminals.	
		Government ignored requests from protesters about revoking the amendment.				The Law is not proposed by the Beijing government.	
<i>Beijing government will undermine certain freedoms.</i>		N/A		<i>Most of the protests are violent.</i>		Protesters blocked traffic.	
							
							

Direction 5: Using Knowledge-Enhanced NLG for Training Data Generation or Augmentation [Fung et al., ACL2021]



- Fake News Generation o Train Misinformation Detectors

With Cross-media Manipulation Constraints

Article Image



Manipulated KG

```
<team, Manufacture.Artifact_Artifact.Artifact_Manufacturer, Zambia Fiji>  
<Zambia Fiji, Manufacture.Artifact_Manufacturer, men> ...  
<bicycle> <hospital> ...
```

Generated Article

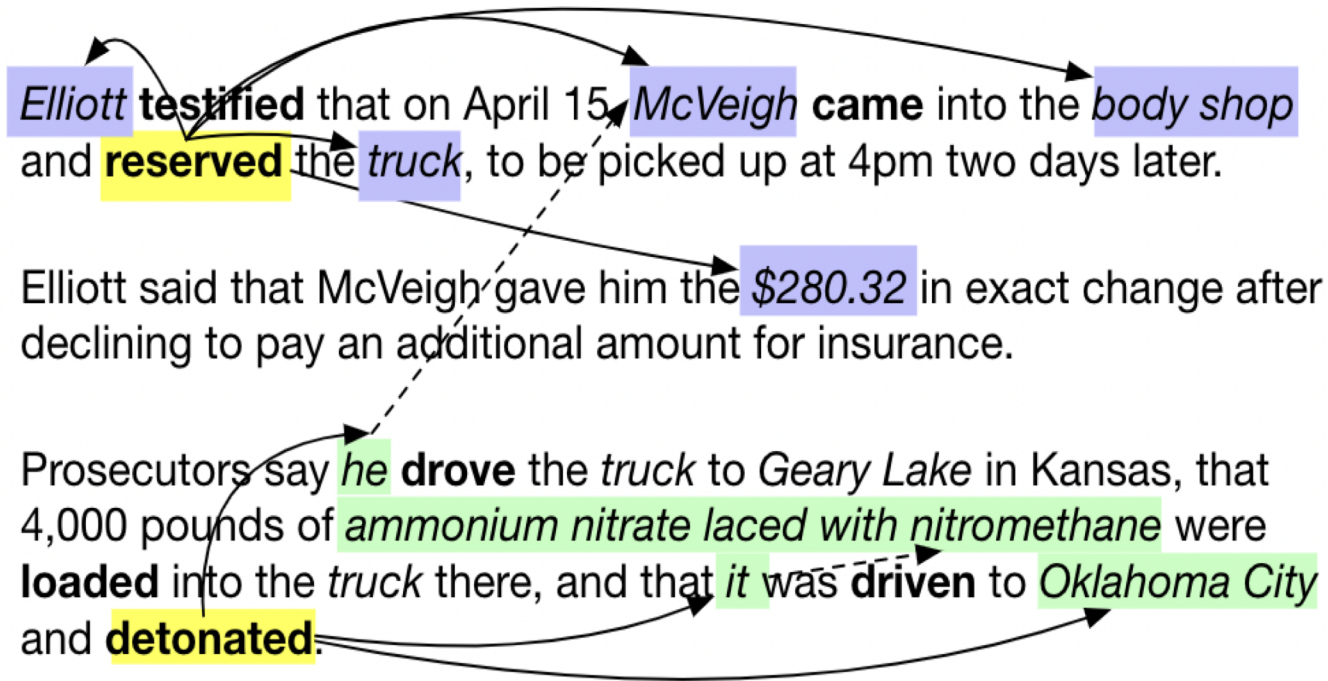
A team of two Californians living in **Fiji** is trying to build the world's smallest and most affordable bicycle. They are using bamboo as the frame for their bicycles. The team is made up of 25 young men who met at a university in the Pacific island nation of **Fiji**. They're using their...

- Knowledge Graph manipulations:
- **Entity swapping** – Swapping entity that has same type and similar embedding (so they are harder to tell apart)
- **Addition of new relation or event** – Randomly select relation / event argument roles and append a new entity to the relation / event
- **Subgraph replacement** – Select a subgraph of the news article from an entity and replace it with a subgraph from another news article
- Generate a fake news article that aligns with manipulated KG's by finetuning a BARTlarge language model (Lewis et al., 2020) on our training set + copy mechanism (Post and Vilar, 2018)

Direction 6: Using Knowledge-Enhanced NLG for other NLP tasks



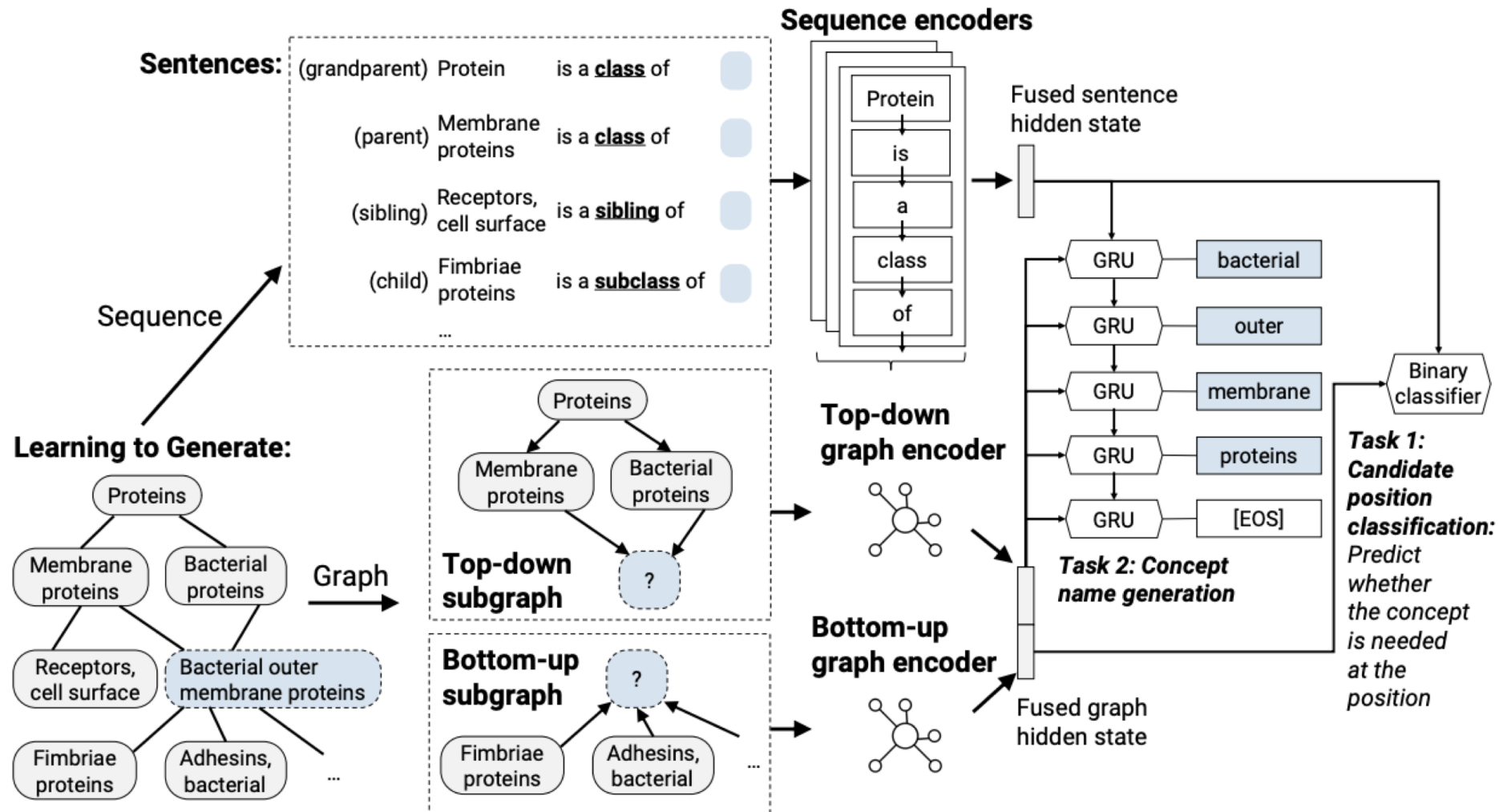
- Use Conditioned NLG for Document-level Event Extraction [Li et al., NAACL2021]
- Is there any limitation during inference? Can we extract events from a wider context?
 - document-level IE, corpus-level IE.



Direction 6: Using Knowledge-Enhanced NLG for other NLP tasks



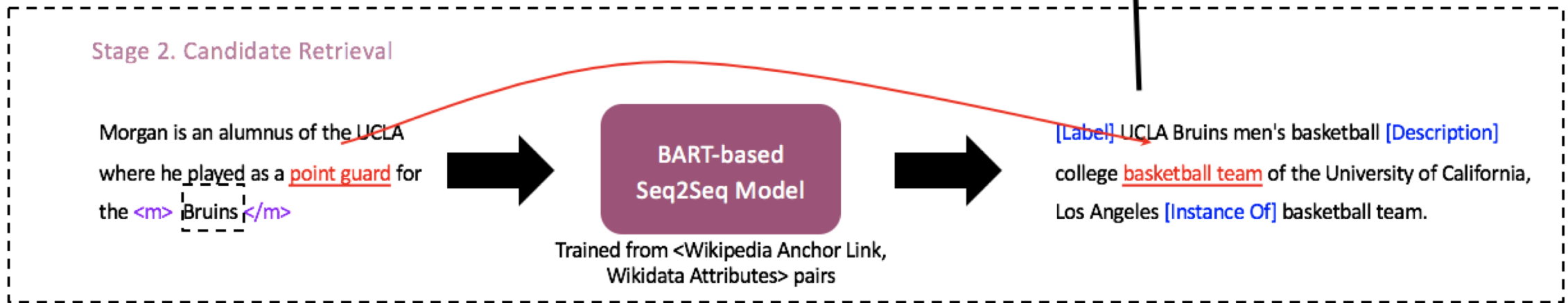
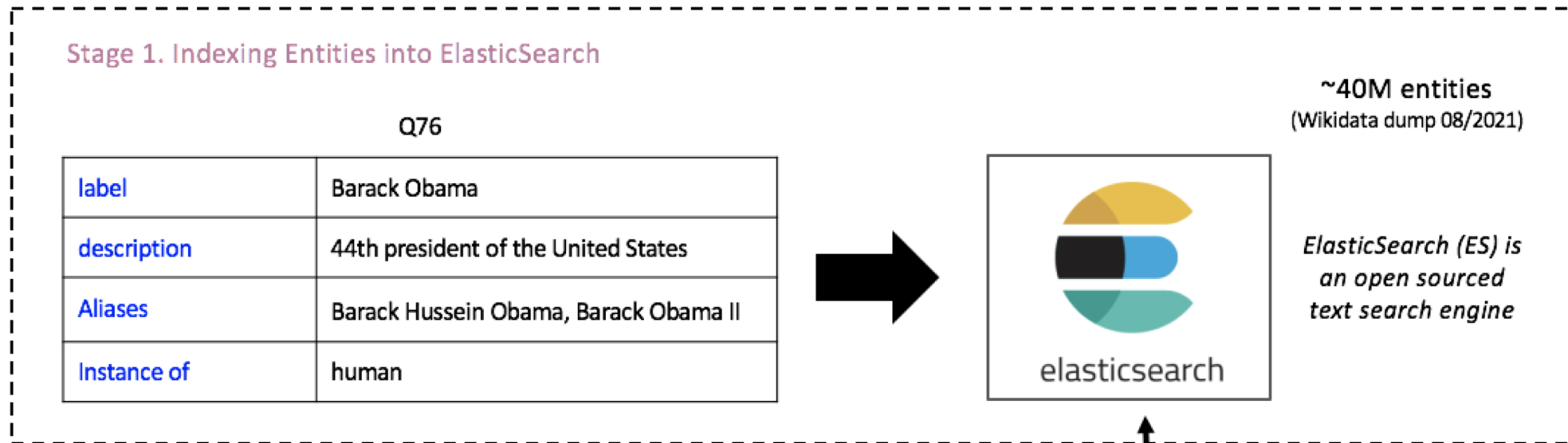
- Use Conditioned NLG for Taxonomy Construction [Zeng et al., 2021]



Direction 6: Using Knowledge-Enhanced NLG for other NLP tasks



- Use Conditioned NLG for Entity Linking [Lai et al., submission]



Thank You!