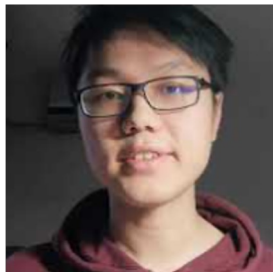


InFillmore: Frame-Guided Language Generation with Bidirectional Context



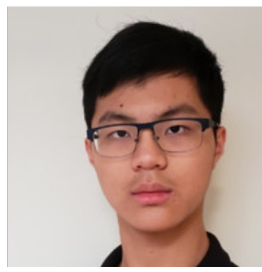
Jiefu Ou



Nathaniel Weir



Anton Belyy



Felix Yu



Ben Van Durme

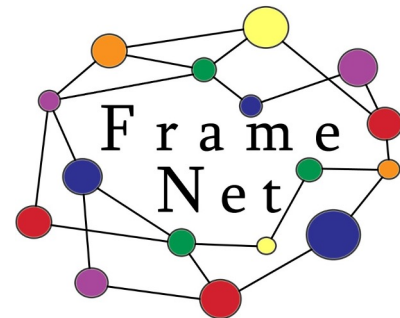


JOHNS HOPKINS
UNIVERSITY

Motivation

- State-of-the-art **text infilling models**: high-quality human-like text generation, core components of **automatic and interactive story generation**.
- Lack of control mechanism: explicitly **control for underlying semantic content**.
- Propose a way for humans (or content planning models) to **specify discrete semantic content** while conditioning on **surrounding textual context**.

FrameNet



Research ← One of 1221 frames

Definition:

A **Researcher** (an individual or a group or institution) attempts to answer a **Question** by means of consulting literature, observation, or conducting experiments in a particular **Field** pertinent to the **Question**. The **Question** may be underspecified in the form of a **Topic**.

Simmons and Nadel did **RESEARCH** pertaining to *Ardea purpurea* and *Egretta garzetta* in 1998

(Core) Frame Elements:

Question [que]

A significant unanswered open proposition which the **Researcher** is attempting to resolve.
When we have **RESEARCHED** why Brazilian mothers have stopped breastfeeding, principal reasons given are 'poor milk' and 'insufficient milk'.

Researcher [res]

Semantic Type: Sentient

The people engaged in a research endeavor.
Before he became an astronaut, **Grunsfeld** did **RESEARCH** in physics.

Topic [top]

A phenomenon or idea involved in a **Question**.
Would you take part in **RESEARCH** on the best place to have a baby?

Lexical Units:

investigate.v, research.n, research.v

Created by JKR on 06/29/2004 10:55:02 PDT Tue

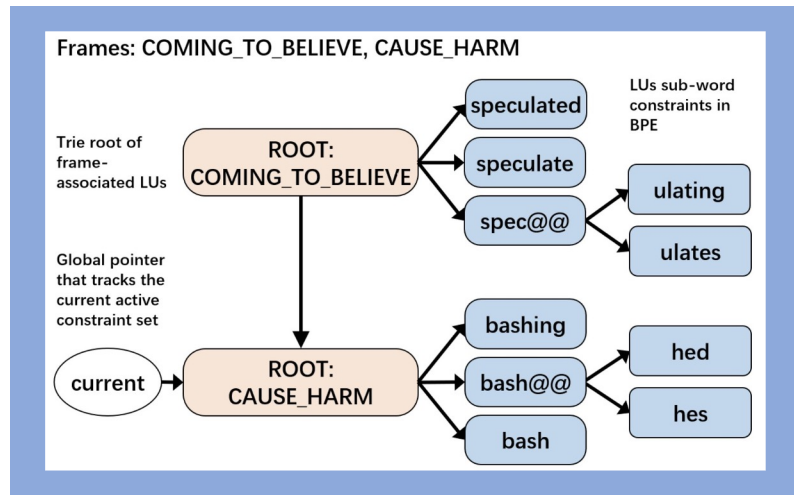
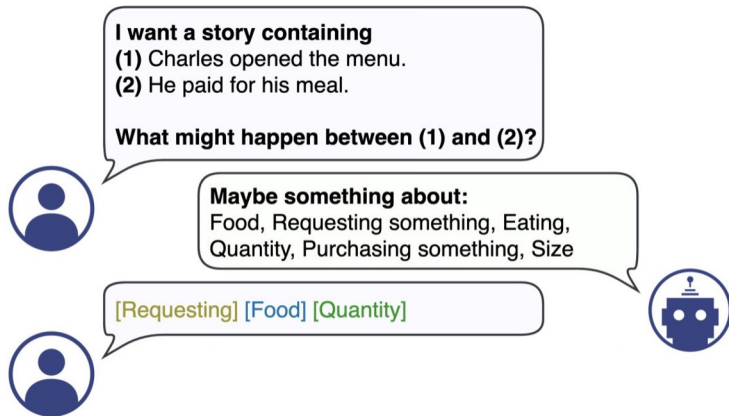
[Lexical Unit](#) [LU Status](#) [Lexical Entry Report](#)

investigate.v **Finished_Initial** [Lexical entry](#)

research.n **Finished_Initial** [Lexical entry](#)

research.v **Finished_Initial** [Lexical entry](#)

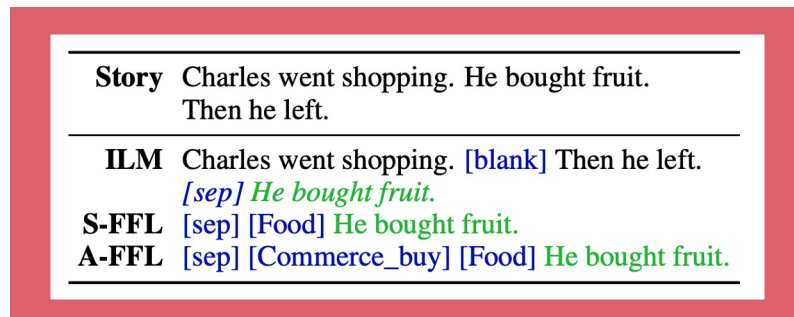
Frame-Guided Generation



We introduce two approaches to FGG:

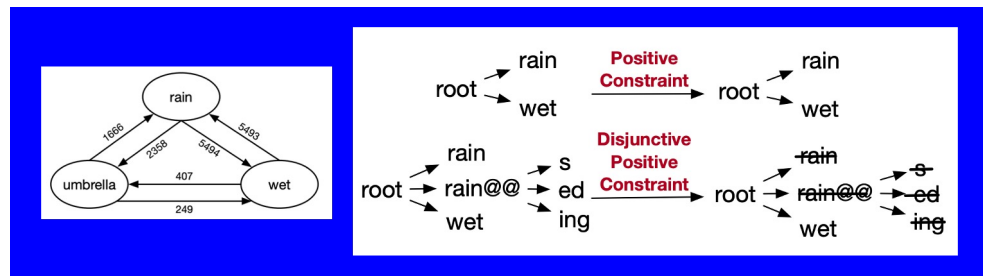
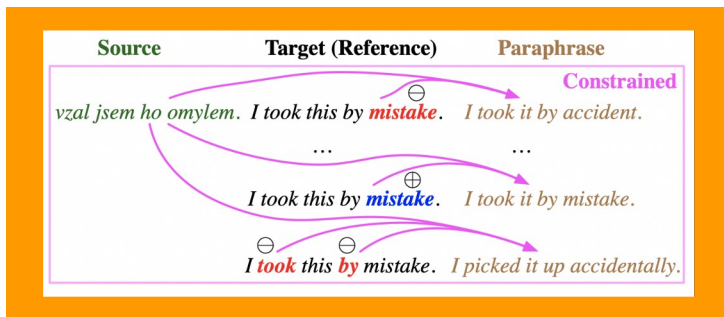
1. Lexically constraining decoding (LCD) to include a frame's lexical units (LUs)
[Bringing] -> {carry, bring, convey, haul,...}

2. Fine-tuning a “framefilling” (FFL) model to generate from control codes that specify frame content



Lexically Constrained Decoding (LCD)

- A modification to beam search that forces the inclusion of pre-specified words and phrases in the output.
- Applications: Machine Translation, **Paraphrasing**, **Causal Generation**



Post, Matt, and David Vilar. "Fast Lexically Constrained Decoding with Dynamic Beam Allocation for Neural Machine Translation." *NAACL 2018*

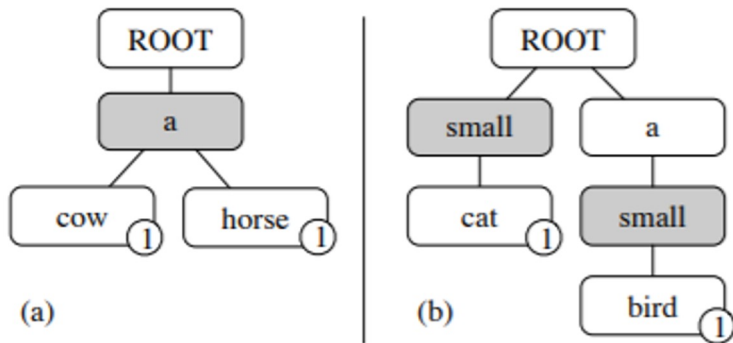
Hu, J. Edward, et al. "ParaBank: Monolingual bitext generation and sentential paraphrasing via lexically-constrained neural machine translation." *AAAI 2019*.

Li, Zhongyang, et al. "Guided Generation of Cause and Effect." *IJCAI 2020*.

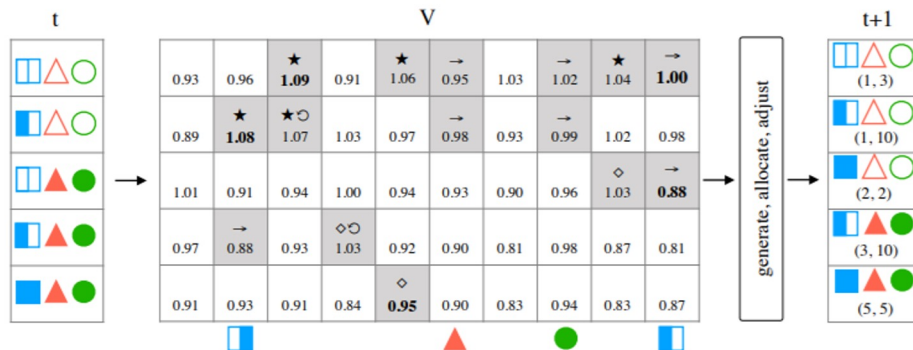
Lexically Constrained Decoding (LCD)

- A modification to beam search that forces the inclusion of pre-specified words and phrases in the output.
- Applications: Machine Translation, Paraphrasing, Casual Generation

Constraints Progress Bookkeeping

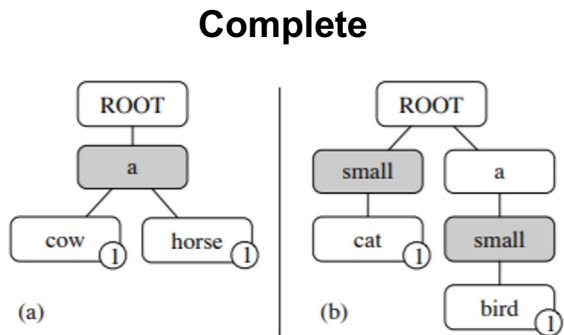


(Dynamic) Beam Allocation

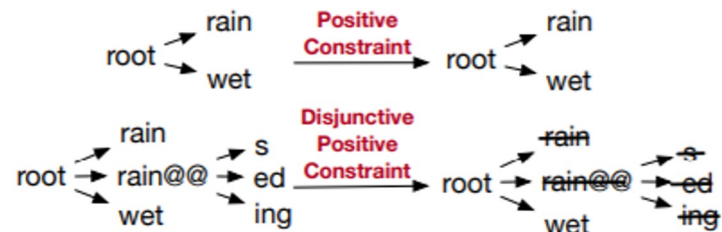


Lexically Constrained Decoding (Cont'd)

- Extending the type of constraints



Single Disjunctive Set

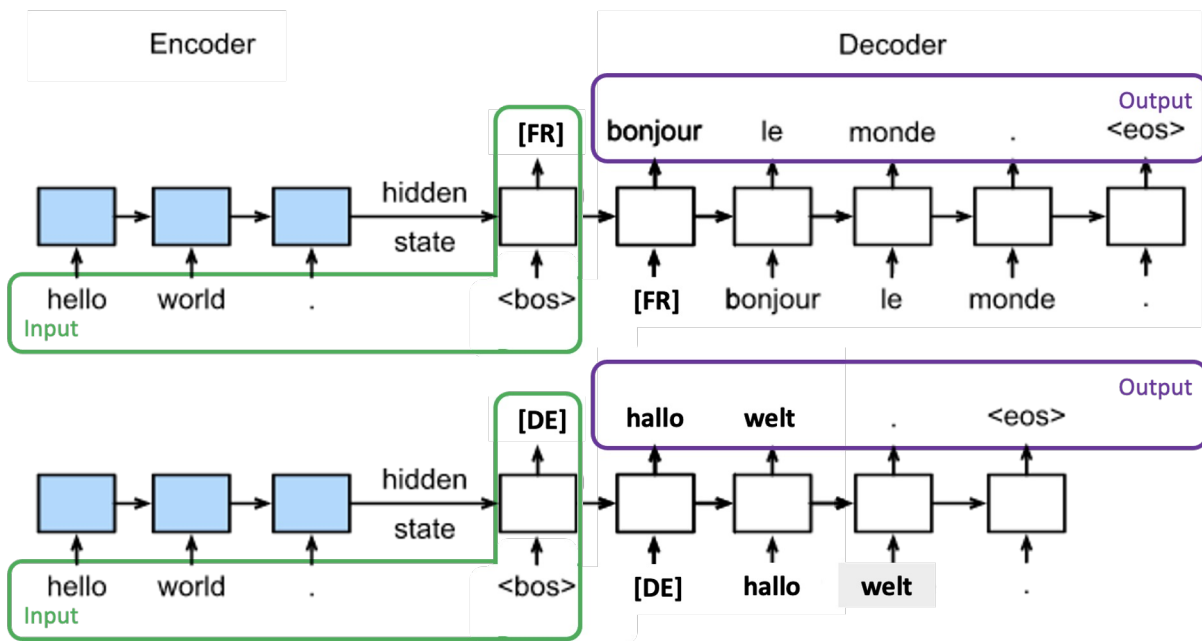


Multiple Disjunctive Sets (Our)

Frames: COMING_TO_BELIEVE, CAUSE_HARM

Fine-tuned “Framefilling” with Control Codes

A **control code** is a special vocabulary token used as a **soft specification content** to a LM



Used previously for

- Multilingual machine translation [1]
- Arbitrary style + content features [2]
- Semantically diverse NLG [3]
- ...and many more

[1] Ha, Thanh-Le, Jan Niehues, and Alex Waibel. "Toward Multilingual Neural Machine Translation with Universal Encoder and Decoder." IWSLT 2016

[2] Keskar, Nitish Shirish, et al. "Ctrl: A conditional transformer language model for controllable generation." 2019.

[3] Weir, Nathaniel, João Sedoc, and Benjamin Van Durme. "COD3S: Diverse Generation with Discrete Semantic Signatures." EMNLP 2020.

Fine-tuned “Framefilling” with Control Codes

We add frame IDs as control codes to an “Infilling Language Model” fine-tuned for bidirectional-context generation

Original Story:

- (1) Charles opened the menu.
- (2) He *ordered* a *few* dishes.
- (3) The *waiter* brought him the food.
- (4) He paid for his meal.

Splice and
reorder for
infilling



Infilling Language Model (ILM; Donahue et al. 2020):

Charles opened the menu. [blank]. [blank]. He paid for his meal. [sep] He ordered a few dishes. [answer] the water brought him the food. [answer]

Add frame
control
codes



“Framefilling” Language Model (FFL; ours):

Charles opened the menu. [blank]. [blank]. He paid for his meal. [sep]
[Requesting] [Food] [Quantity] He ordered a few dishes. [answer]
[Bringing] [Profession] the water brought him the food. [answer]

Evaluation Task: Story Cloze with ROCStories

Story

Ari spends \$20 a day on pickles.
He decides to make his own to save money.
He puts the pickles in brine.
[blank]
Ari opens the jar to find perfect pickles.

Gold

Ari waits 2 weeks for his pickles to get sour.

ILM Baseline

He puts the pickles in a jar.

FFL

Single Frame: [Transition_to_State]

He ends up with a jar full of pickles. He **gets** the pickles and puts them in jars.

ILM+LCD

Multiple Frames: [Cardinal_Numbers] [Transition_to_State]

He ends up with 5 jars of pickles. He puts **one** in the jar and opens it to **get** a drink.

All Frames: [Cardinal_Numbers] [Measure_duration]
[Transition_to_State][Chemical-sense_description]

He waits for a week for the pickles to get sour.





He **waits** for the pickles to thaw out of the jar to thaw **one day** he **gets** the pickles and eats them **delicious**.

Automatic Evaluation

Fidelity ↑	Recall			Perfect Recall		
	# Frames	Single	Multi	All	Multi	All
ILM (no guidance)	.169	.166	.165	.091	.026	
ILM + LCD	.584	.595	.610	.418	.232	
ILM + LCD-ord	–	.598	.626	.427	.255	
FFL	.518	.559	.640	.381	.259	
FFL (rand sample)	.461	.511	.601	.338	.224	
FFL-ord	–	.585	.669	.415	.298	

FFL and **LCD** are substantially better at capturing the underlying gold semantic content compared to the unconstrained **ILM**

Human Evaluation

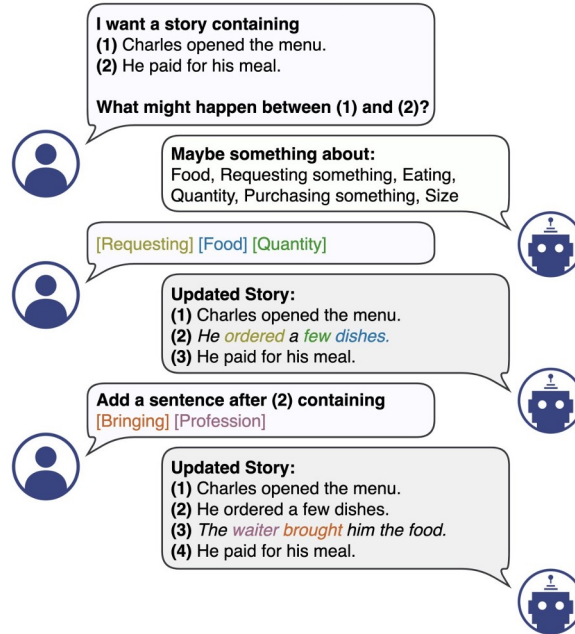
Confusion rate (%) \uparrow	# Frames			Average rank (1..10) \downarrow	# Frames		
	Single	Multi	All		Single	Multi	All
ILM (no guidance)	41	41	41	ILM (no guidance)	5.48	5.48	5.48
ILM+LCD 	35	31*	20*	ILM+LCD 	5.85*	6.38*	7.50*
FFL 	33*	39	38	FFL 	5.88*	5.57	5.11
FFL-ordered	33*	38	37	FFL-ordered	5.88*	5.53	5.02*

- Most **FFL** variants are competitive with **ILM** on generation quality

Conclusions

- We introduce the frame-guided generation framework that uses FrameNet frames to guide semantic content in an infilling model.
- We propose two extensions to an infilling model to efficiently utilize frame-semantic information during text generation.
- Experiments on the story cloze task show that both our extensions enable high semantic frame fidelity with competitive generation quality.

Thank you!



<https://nlp.jhu.edu/demos/infillmore>