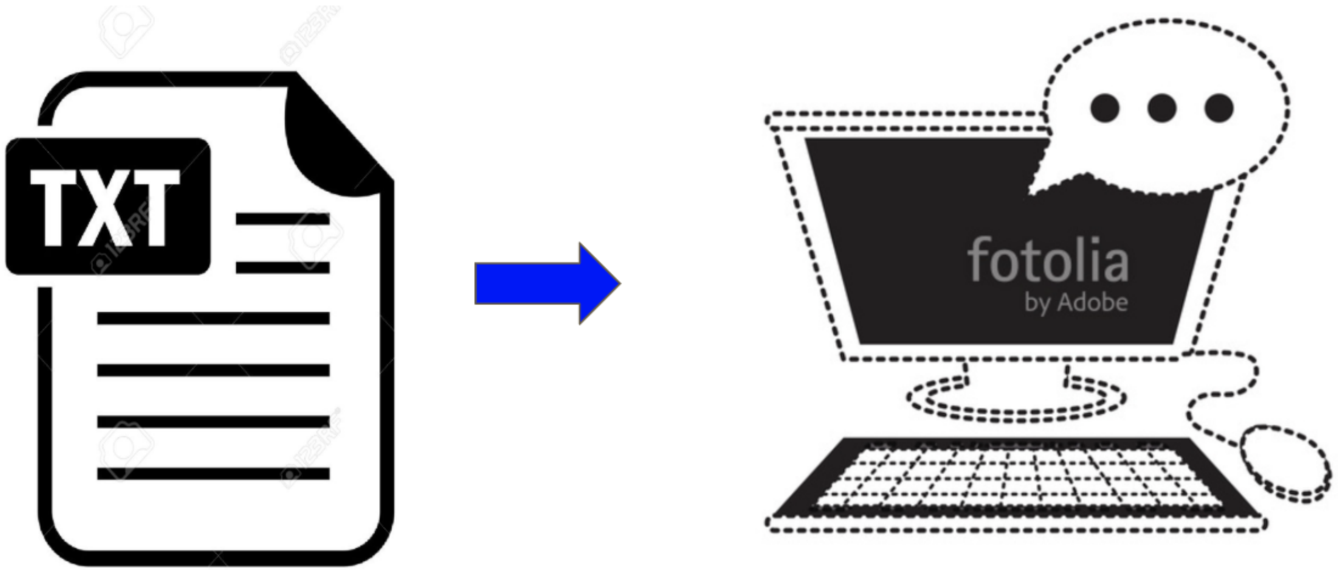
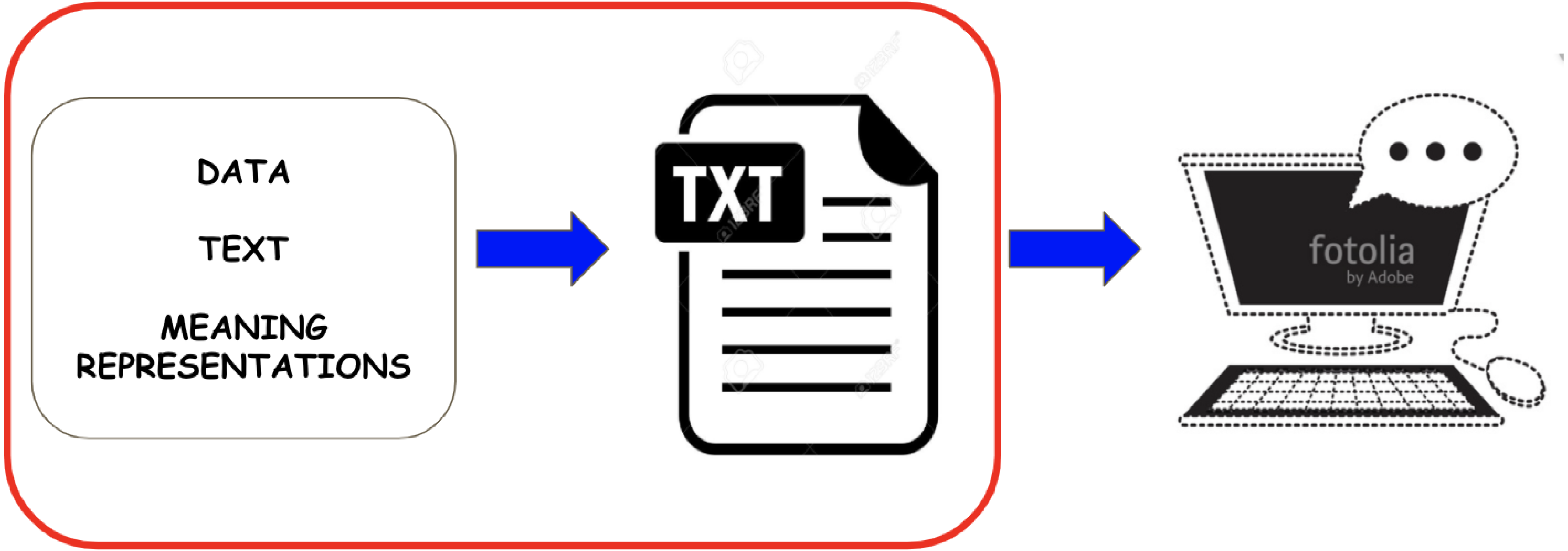
Synthesis



Synthesis and Generation



Natural Language Generation

Claire Gardent

SSW10
Vienna, Austria
22 September 2019

Joint work with

Emilie Colin, PhD Student, Lorraine University, Nancy

Ido Dagan, Bar-Ilan University, Ramat-Gan, Israel

Angela Fan, PhD Student, Lorraine University, Nancy and Facebook AI Research, Paris

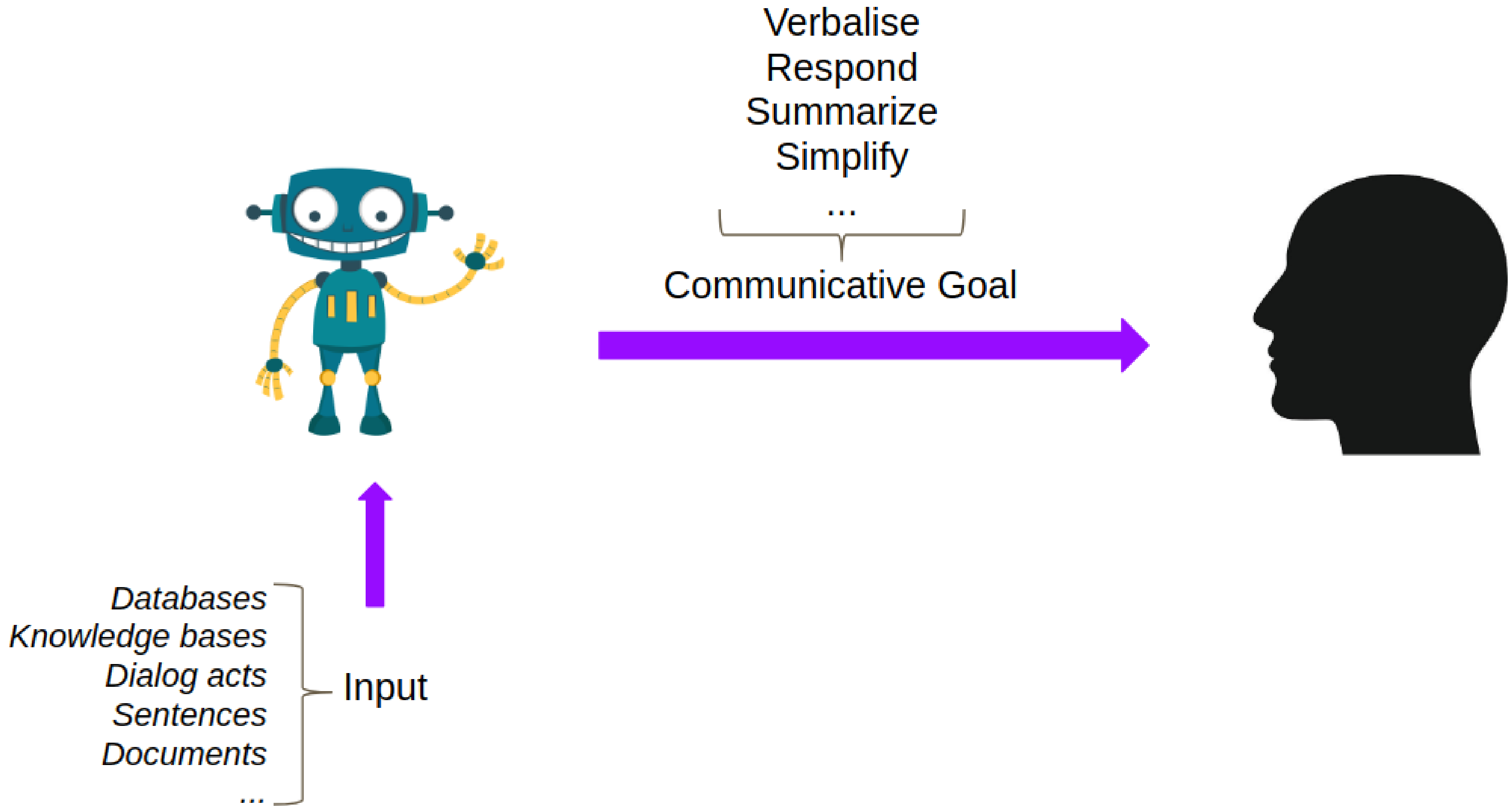
Iryna Gurevych, AIPHES and UKP Lab, Technische Universitat Darmstadt, Germany

Yevgenyi Puzekov, AIPHES and UKP Lab, Technische Universitat Darmstadt, Germany

Leonardo Ribeiro, AIPHES and UKP Lab, Technische Universitat Darmstadt, Germany

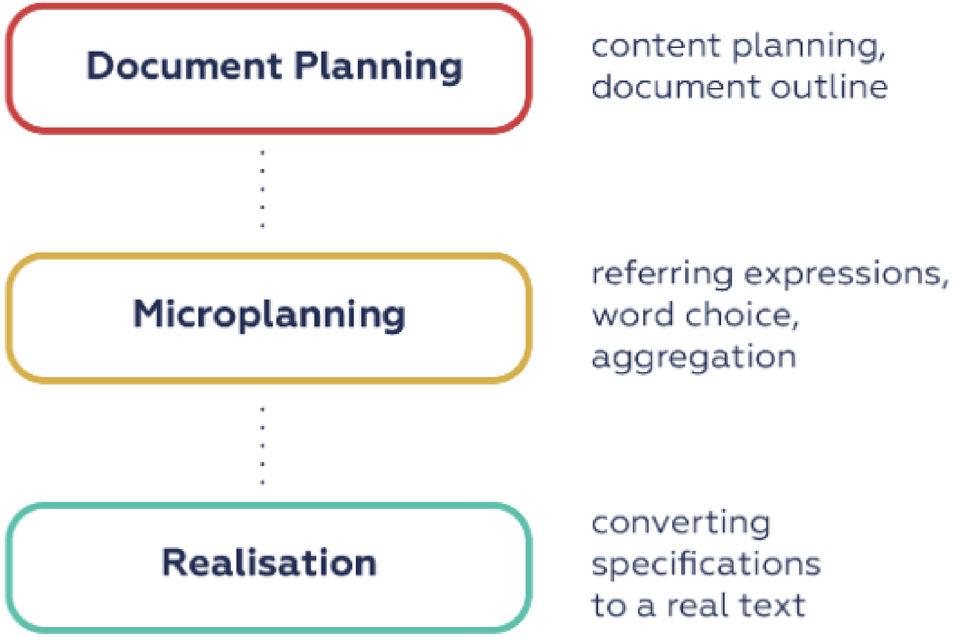
Anastasia Shimorina, PhD Student, Lorraine University, Nancy

NLG: Many Inputs, Many Goals



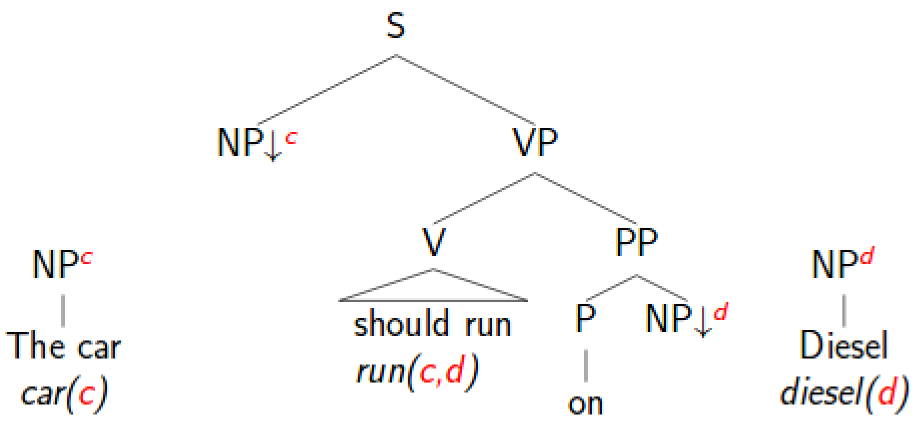
Generating from Data

The NLG Pipeline



Generating from Meaning Representations

Grammar



car(c), run(c,d), diesel(d)

Statistical modules

Language models
To choose between comparable .blue[intermediate results]
the black cat/the cat black

Hypertaggers
To prune the .blue[initial search space]

Rankers
To determine the .blue[best output]

Generating from Text

In 1964 Peter Higgs published his ~~second~~ paper ~~in Physical Review Letters~~ describing Higgs mechanism [which] predicted a new massive spin-zero boson ~~for the first time~~.

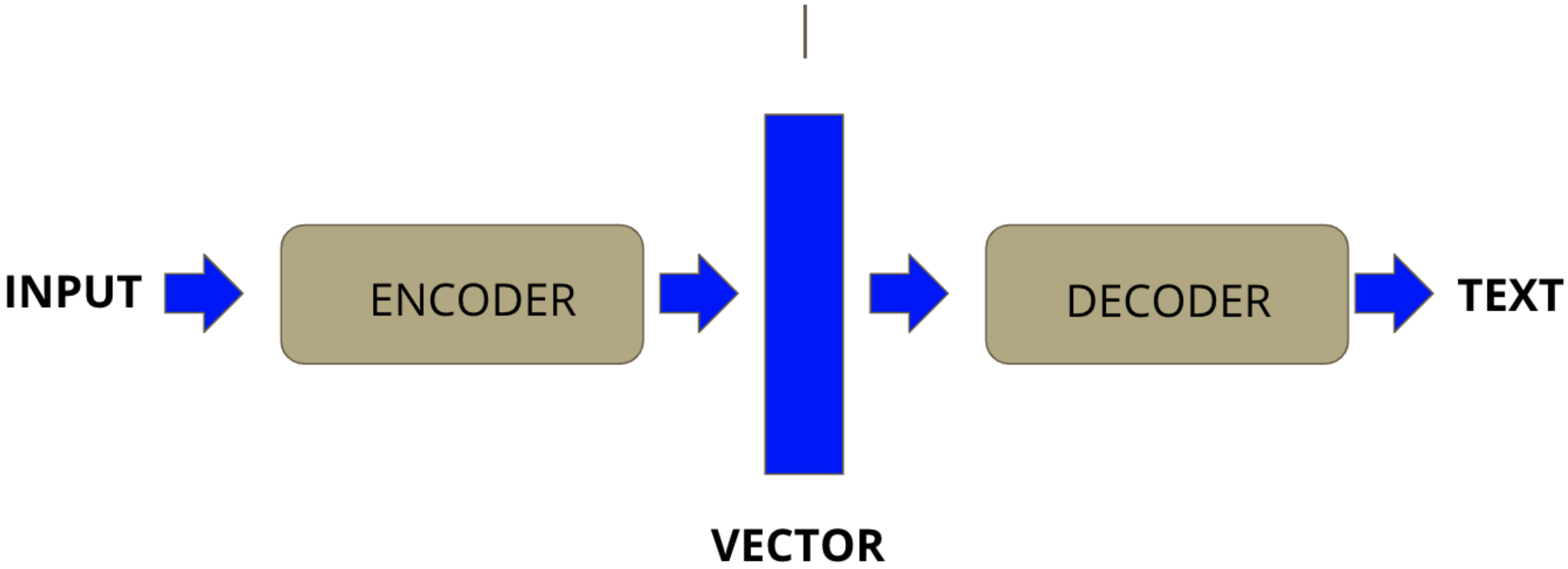
Split Rewrite Reorder Delete

Peter Higgs wrote his paper explaining Higgs mechanism in 1964.

Higgs mechanism predicted a new elementary particle.

Neural NLG

A Single UnifyingFramework



Adapting the Encoder-Decoder Framework to the various NLG Tasks

Encoding

Training Data

Encoding

Modelling Graph-Structured Input

Graphs rather than sequence

Local + Global Encoding

Scaling

Encoding Large Quantities of Text

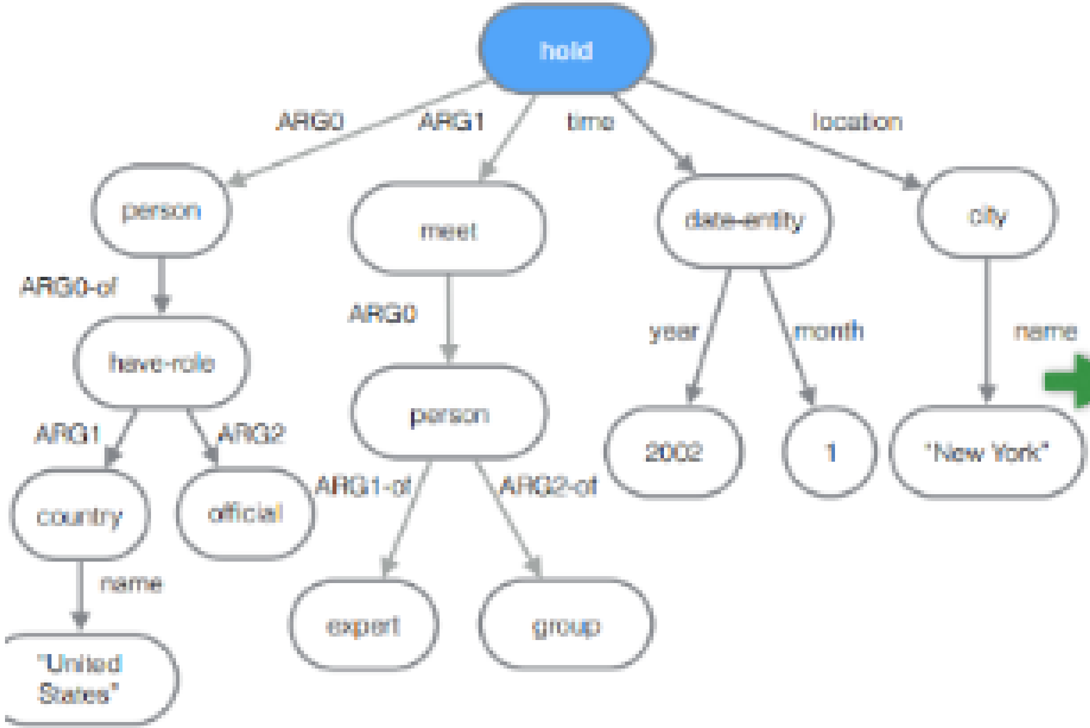
Generalising

Delexicalisation

Encoding

Modelling Graph-Structured Input (MR)

Generation from AMR 2017 Challenge




```
hold
    :ARG0 (person
            :ARG0-of (have-role
                :ARG1 United_States
                :ARG2 official)
          )
    :ARG1 (meet
            :ARG0 (person
                :ARG1-of expert
                :ARG2-of group)
          )
    :time (date-entity 2002 1)
    :location New_York
```

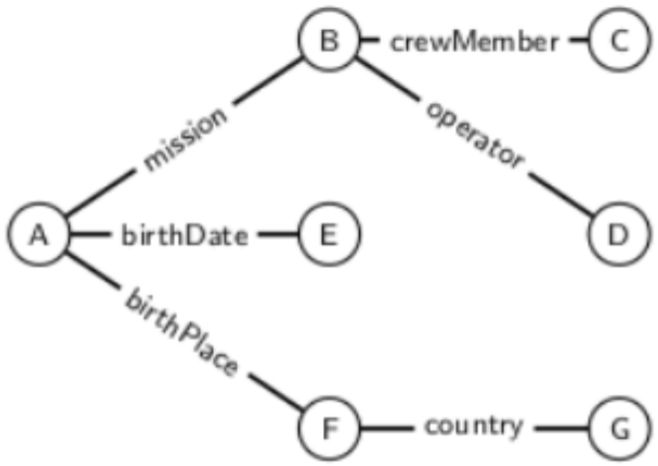
US officials held an expert group meeting in January 2002 in New York .

Generating from Sets of RDF Triples

The WebNLG Challenge 2017

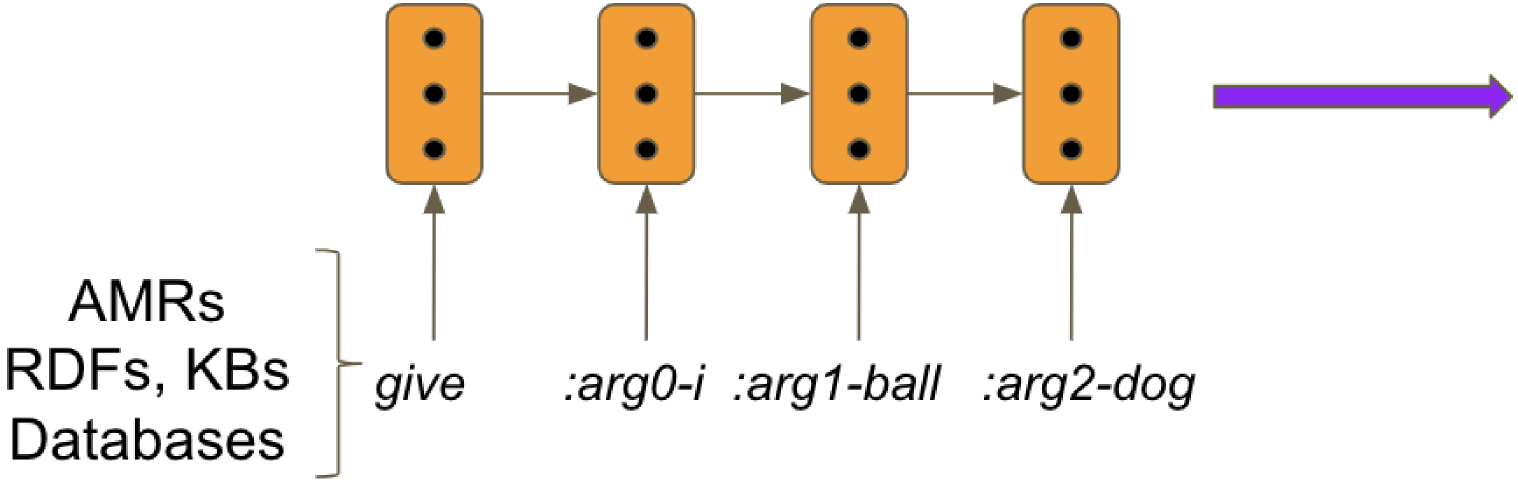
(John_E_Blaha *birthDate* 1942_08_26)
(John_E_Blaha *birthPlace* San_Antonio)
(John_E_Blaha *occupation* Fighter_pilot)

“John E Blaha, born in San Antonio on 1942-08-26, worked as a fighter pilot.”



Graph Structure as a Sequence

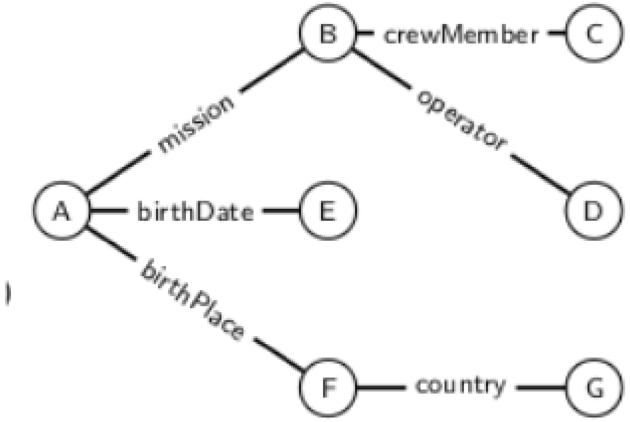
Early approaches to MR- or Data-to-Text generation encode the input structure as a sequence.



Problems with Graph Linearization

- Local dependencies available in the input turned into long-range dependencies
- RNNs often have trouble modeling long-range dependencies

D2T Generation (Data = RDF)

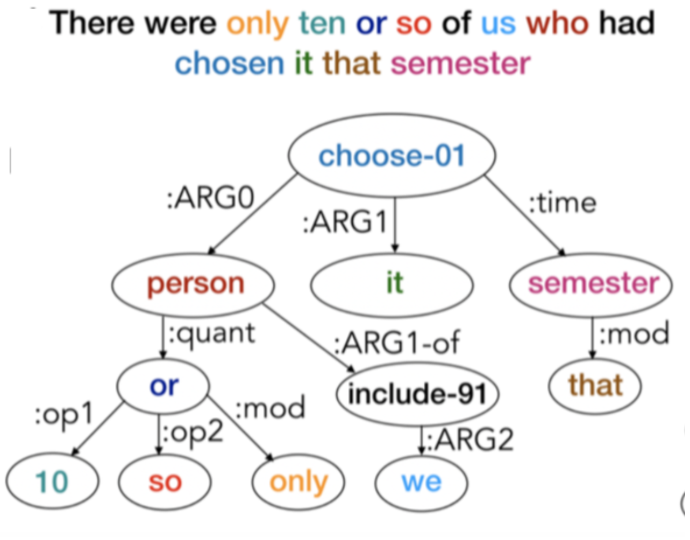


LINEARISATION

Alan_Bean **mission** Apollo_12 Apollo_12 **crewMember** Peter_Conrad Apollo_12 **operator** Nasa Alan_Bean birthDate 1932-03-15 Alan_Bean birthPlace Wheeler_Texas Wheeler_Texas country USA

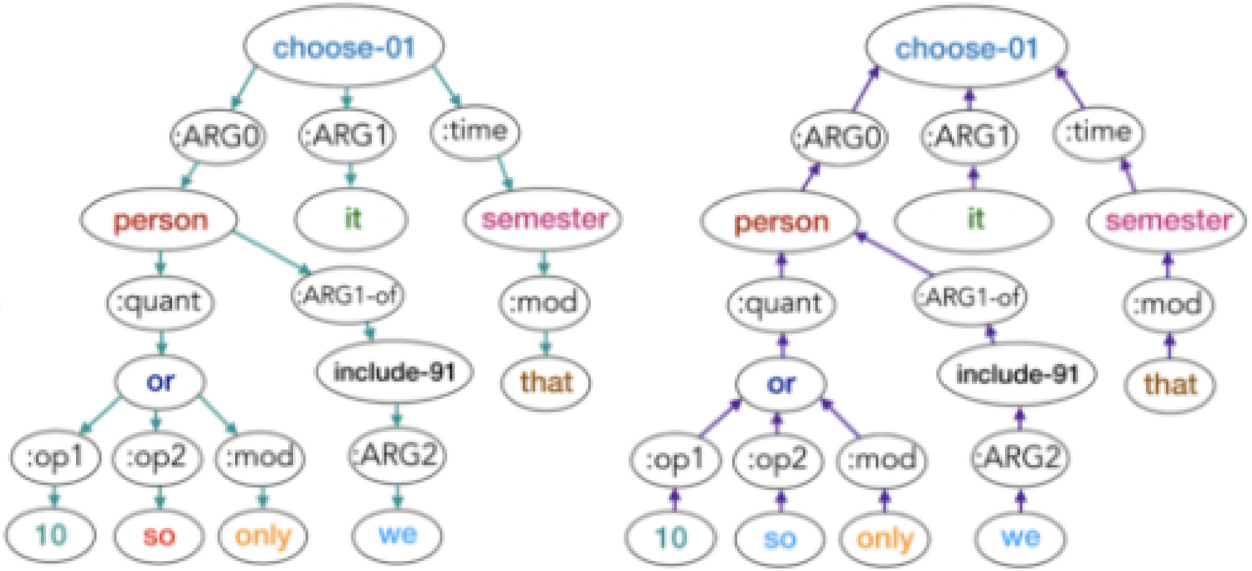
NLG with Graph Encoders

- (Damonte and Cohen, 2019): Graph Convolutional Networks
- (Song et al., 2018): Graph LSTM
- (Becker et al., 2018): GRU LSTM



Dual Top-Down and Bottom-Up Graph Encoding

Ribeiro, Gardent, Gurevitch (EMNLP 2019)



Results

Cao & Clark 2019

- Delexicalisation
- Added Syntactic Information

Damonte et al. 2019

- Delexicalisation

Model	**BLEU**	**METEOR**
	LDC2015E86	
Konstas et al. (2017)	22.00	-
Song et al. (2018)	23.28	30.10
Cao et al. (2019)	23.50	-
Damonte et al.(2019)	24.40	23.60
Guo et al. (2019)	**25.70**	-
`S2S`	22.55 ± 0.17	29.90 ± 0.31
`G2S-GIN`	22.93 ± 0.20	29.72 ± 0.09
`G2S-GAT`	23.42 ± 0.16	29.87 ± 0.14
`G2S-GGNN`	24.32 ± 0.16	**30.53** ± 0.30
	LDC2017T10	
Back et al. (2018)	23.30	-
Song et al. (2018)	24.86	31.56
Damonte et al.(2019)	24.54	24.07
Cao et al. (2019)	26.80	-
Guo et al. (2019)	27.60	-
`S2S`	22.73 ± 0.18	30.15 ± 0.14
`G2S-GIN`	26.90 ± 0.19	32.62 ± 0.04
`G2S-GAT`	26.72 ± 0.20	32.52 ± 0.02
`G2S-GGNN`	**27.87** ± 0.15	**33.21** ± 0.15

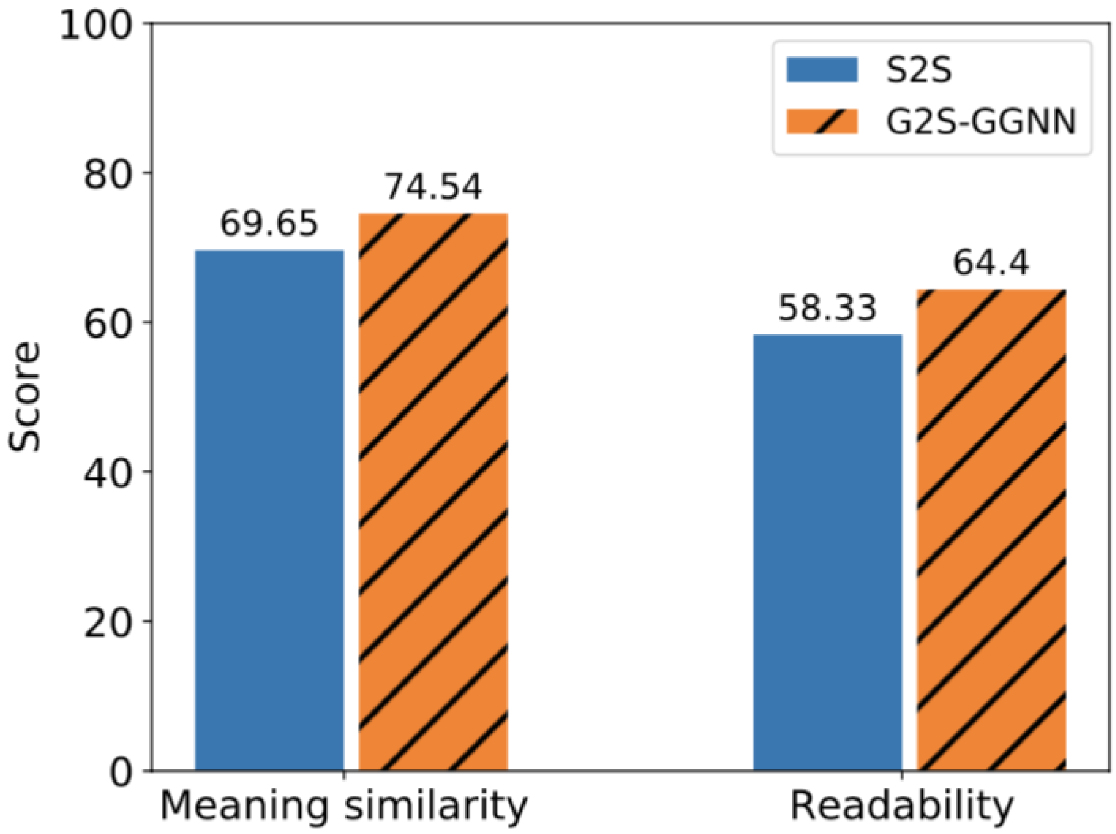
Semantic Adequacy

Does the reference entails the generated sentence and vice versa ?

	REF ⇒ GEN		
Model	**ENT**	**CON**	**NEU**
S2S	38.45	11.17	50.38
G2S-GIN	49.78	9.80	40.42
G2S-GAT	49.48	8.09	42.43
G2S-GGNN	51.32	8.82	39.86
	GEN ⇒ REF		
Model	**ENT**	**CON**	**NEU**
S2S	73.79	12.75	13.46
G2S-GIN	76.27	10.65	13.08
G2S-GAT	77.54	8.54	13.92
G2S-GGNN	77.64	9.64	12.72

Human Evaluation

Semantic adequacy and readability



Encoding

Combining Local and Global Information

Local + Global Encoding of AMR nodes

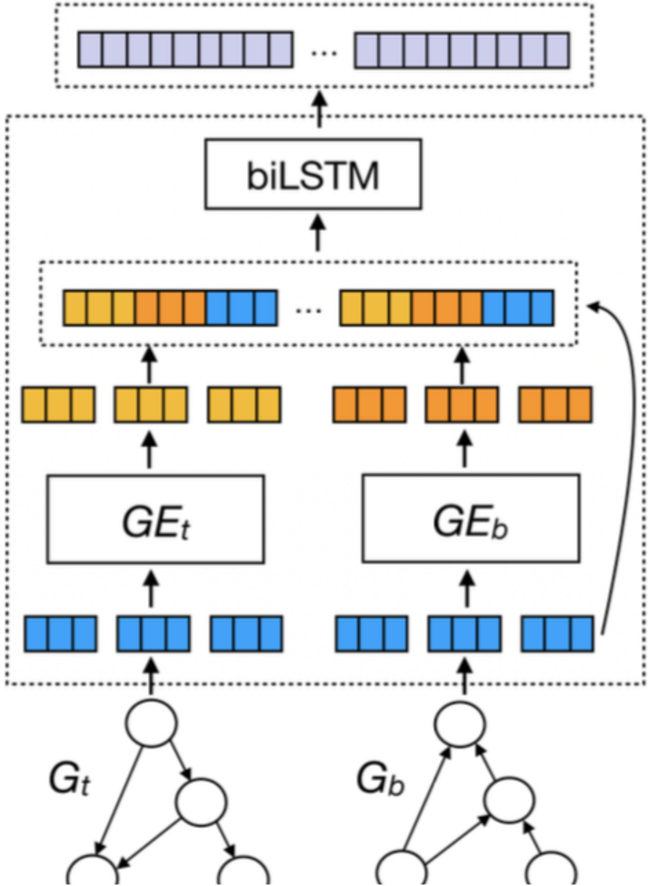
Ribeiro, Gardent, Gurevych (EMNLP 2019)

Local

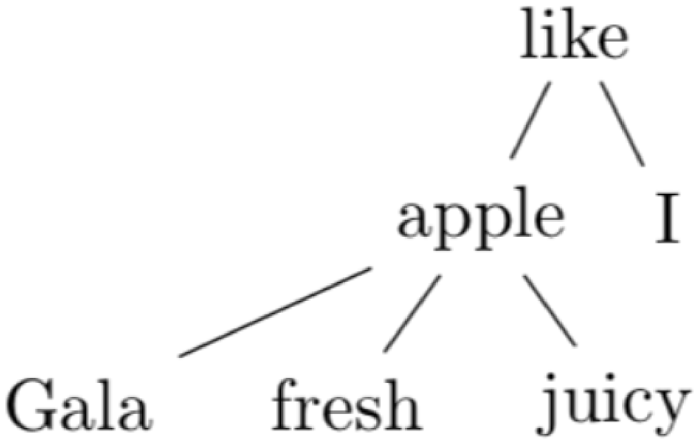
- Node Embeddings (h_t, h_b)
- Label embedding (h_l)

Global

- bi-LSTM Encoding of the whole graph



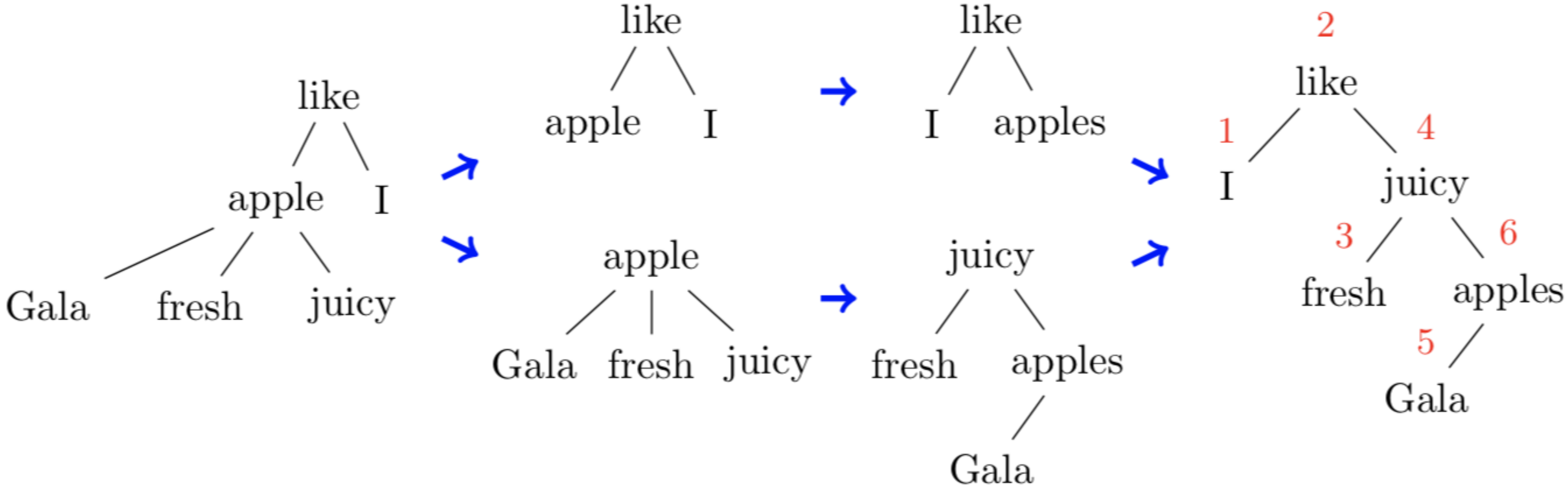
Unordered, Lemmatized Dependency Tree $\Rightarrow$ Sentence



I like fresh juicy Gala apples

Unordered, Lemmatized Dependency Tree $\Rightarrow$ Sentence

Puzikov, Gardent, Dagan, Gurevych (INLG 2019)



Local + Global Encoding of Dependency Tree Nodes

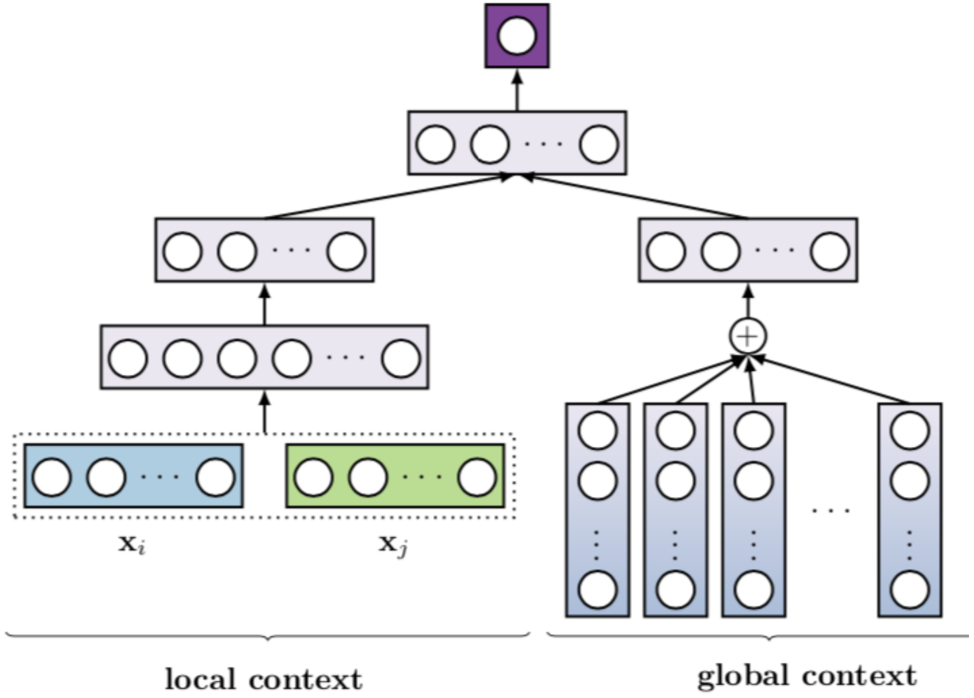
Puzikov, Gardent, Dagan, Gurevych (INLG 2019)

Local

- Dense feature representations of the two nodes
- Head node, Child node

Global

- All nodes of the subtree dominated by the head node
- Weighted sum of their feature representations



	BLEU	EDIST	NIST
BinLin	24.92	35.91	9.55
+ data enrichment	48.47	62.04	10.72
+ new encoder	50.67	64.05	10.82

Encoding at Scale

Graph Encoding of Text

Encoding Large Quantities of Text

Question-Answering on Free Form Web Text

- ELI5 Dataset
- Query = NL question
- TASK: Generate answer from question + web text (200K words)

Multi-Document Summarisation

- Wikisum Dataset
- Query = WKP article title
- TASK: Generate lead paragraph from title + web text (200K words)

Question: Why consumers are still so terrified of genetically modified organisms (GMOs), yet there is little debate in the scientific community of whether they are safe or not. (Scientists are for GMOs)

Beginning of Web Search: The controversial safety of gmos and the skepticism of the use of gmos College paper Writing Service URL_0. diamond chemicals plc the merseyside. appendix f research question for. antisocial personality disorder affects family relations and interactions. The controversial safety of gmos and the skepticism of the use of gmos. Gmo facts what is a gmo genetically modified organisms the safety of gmos is unknown poll: skepticism of genetically modified foods abc news abc news network, 19 june 2015 web fernandez-cornejo, jorge, and seth james wechsler. The controversy over gmos, particularly in food continues: scientists are split pros and cons of gmo's september 28 and environmentalists and consumer groups remain unconvinced about the safety of gmos. The controversy around genetically modified foods on the surface, food evolution is a resetting of the controversial conversation around genetically modified organisms (gmos) we just ask people by a show of hands to tell us are they concerned about gmos for their own safety or the. When gmos are the movie star can documentaries on controversial science be entertaining and the message is that gmo food is safe to eat and that naysayers are. Genetically modified organisms (gmos) the top five anti-gmo tropes gmos are genetically modified organisms the evidence on gmo safety by ramez naam. Genetically modified organisms what are gmos with the use of gm technology, pure and safe equivalents can be produced using gmos and industrial scale. Here's a bullet-point summation of what nathanael johnson learned about gmos in 2013 20 gmo questions: animal, vegetable, controversy by pretty darn safe. The controversy surrounding genetically modified organisms what do we tolerate as far as detrimental this would be a profound service to scientific skepticism with regards to gmos current gmos are safe to eat- however [...]

Target Answer: There is little difference in essence between what is called GMO now and the techniques we have been using to domesticate and cultivate the food in the past. Its an arbitrary line that's been drawn in the sand and people fail to realize this often. That being said I think it is more then wrong the patenting of crops and again even more then wrong to genetically modify crops to not have viable seeds so that seed-washing can't be used to grow the next crop. So the real god damned issues are being masked and lost by this retarded polemic between GMO and more conventional genetic modification of organisms.

How to encode 200K words and generate from it ?

Previous Work

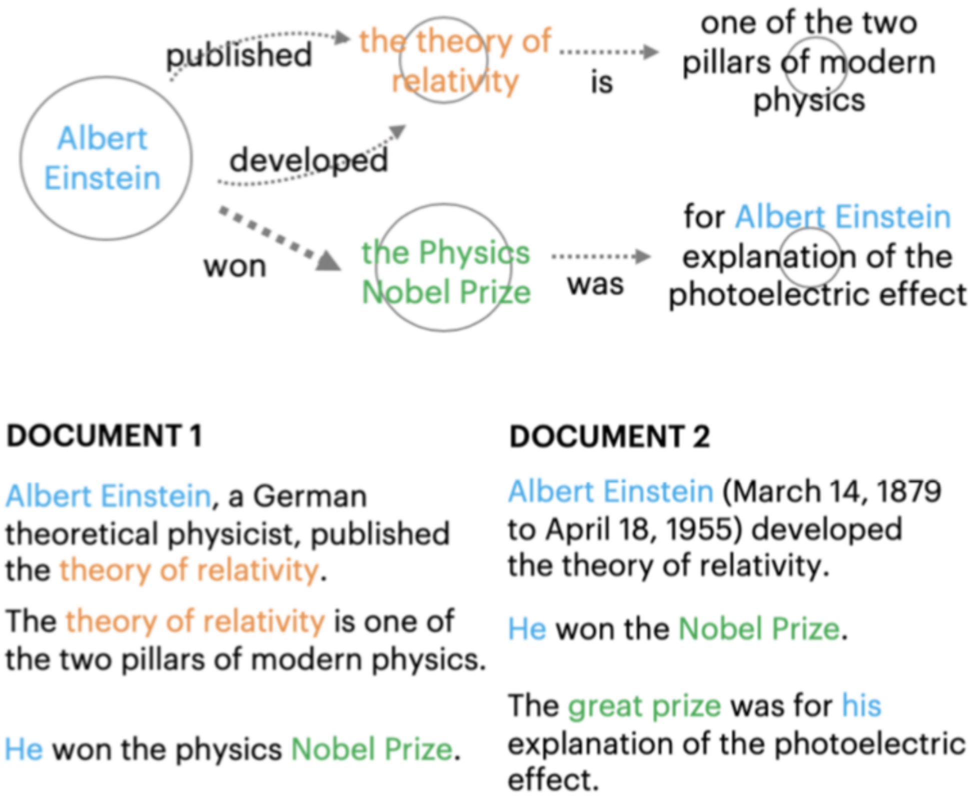
- TF-IDF-based information extraction
- Limits the input information to a few thousand words

Knowledge Graphs

- Convert text to a graph
- Scales to 200K words

Non Neural Graph Encoding of Text: 200K ⇒ 10K Tokens

Q: Explain the theory of relativity



Constructing the Knowledge Graph

GRAPH CONSTRUCTION STEPS

QUERY: Can someone finally explain the theory of general relativity?

DOCUMENT SENTENCES with GRAPH OPERATIONS

1 Albert Einstein, a German theoretical physicist, published the theory of relativity.

ADDED TO GRAPH

2 The theory of relativity is one of the two pillars of modern physics.

MERGE OPERATION:
theory of relativity
EXISTS AS A NODE
NODE WEIGHT + 1

3 He won the physics Nobel Prize.

COREFERENCE:
he and Albert Einstein

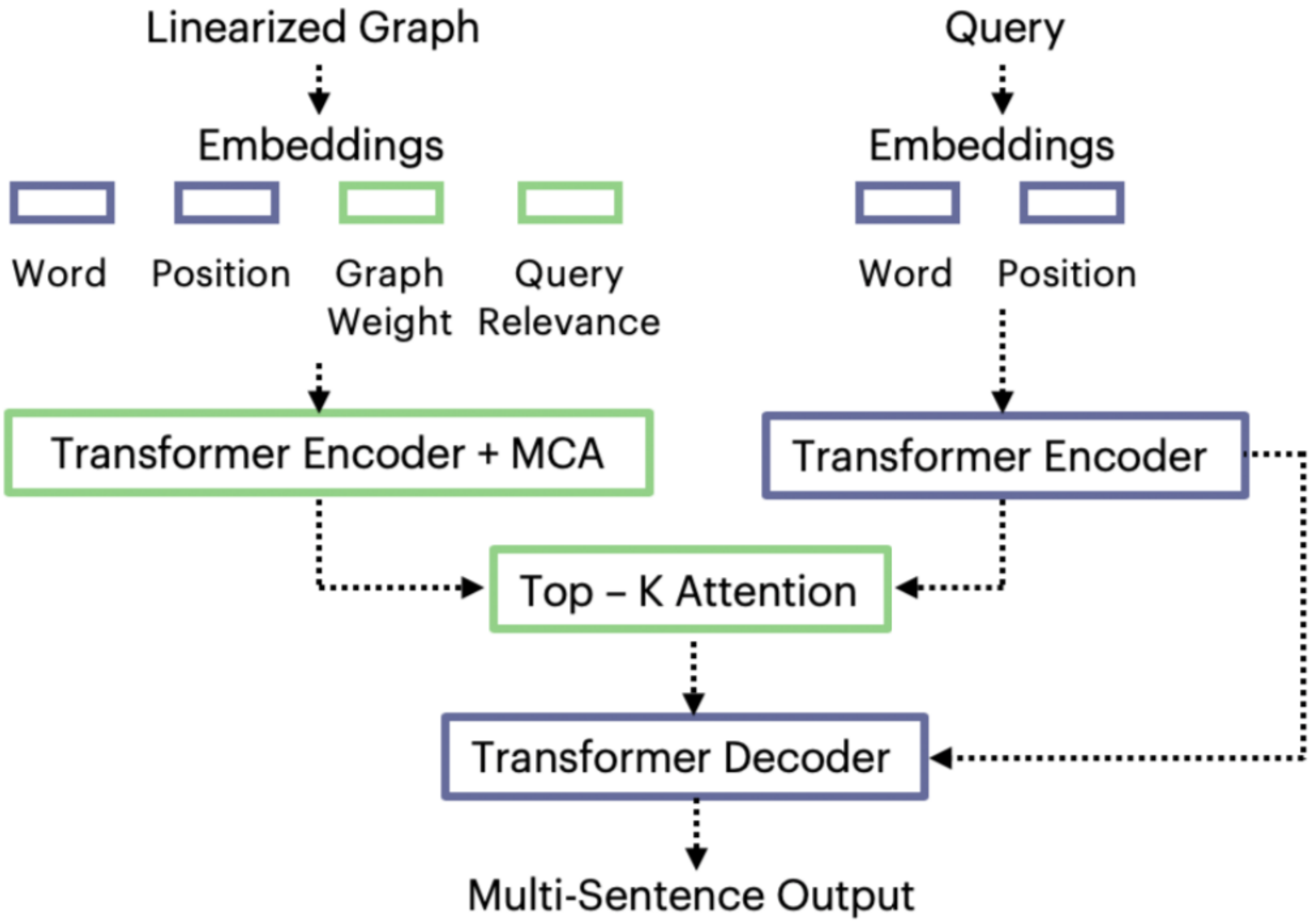
MERGE OPERATION:
Albert Einstein
EXISTS AS A NODE
NODE WEIGHT + 1

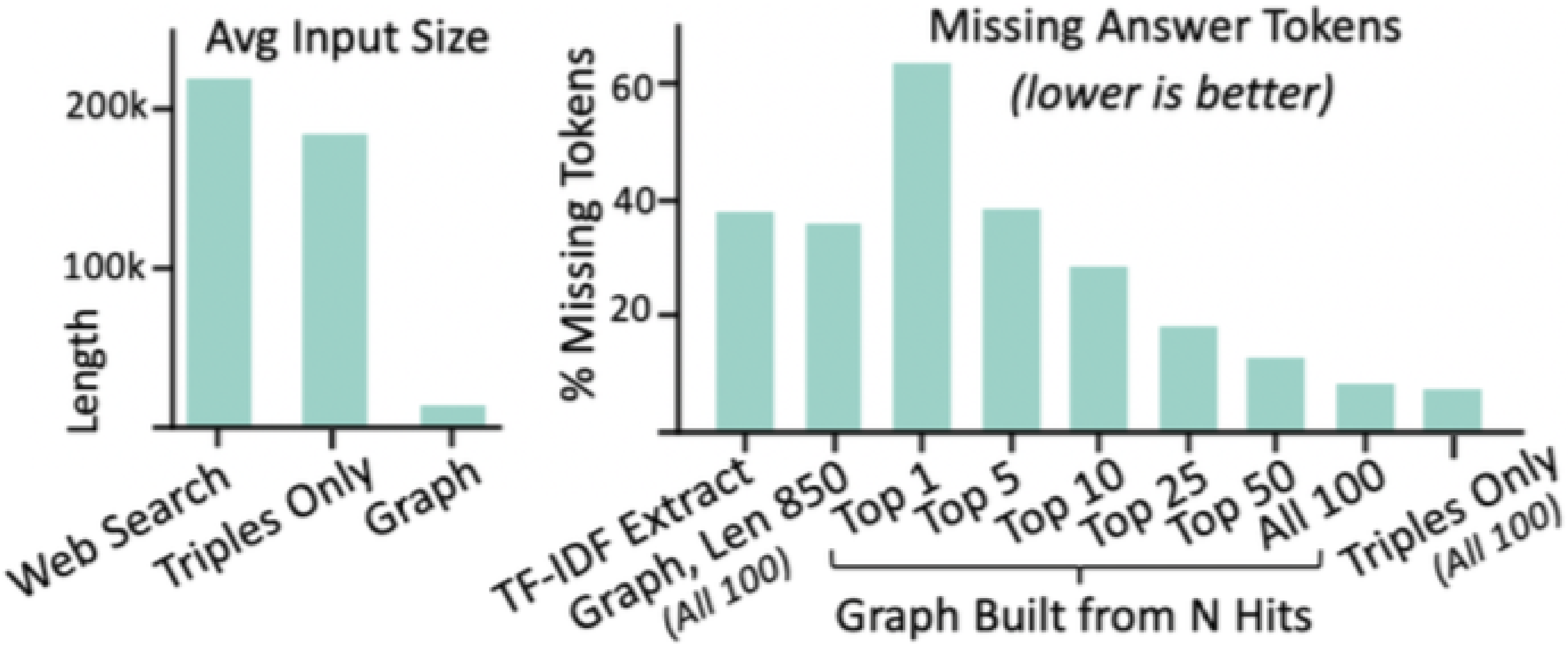
4 Puppies are very cute.

FILTER OPERATION:
low TF-IDF overlap with query
NOT ADDED TO GRAPH

Rich Node Embeddings

WORD EMBEDDING	<sub>	Albert	Einstein	<obj>	the	theory	of	relativity	<pred>	published	<s>	developed	<obj>	the	Physics	Nobel	Prize	<s>	won
POSITION EMBEDDING	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
GRAPH WEIGHT EMBEDDING	0	4	4	0	2	2	2	2	0	1	0	1	0	3	3	3	3	0	2
QUERY RELEVANCE EMBEDDING	0	1	1	0	1	1	1	1	0	1	0	2	0	1	1	1	1	0	1


Linearized Graph
Embeddings
Word
Position
Graph Weight
Query Relevance
Query
Embeddings
Word
Position
Transformer Encoder + MCA
Transformer Encoder
Top – K Attention
Transformer Decoder
Multi-Sentence Output



The input is reduced by an order of magnitude

The TF-IDF Extraction from (Fan et al., 2019) is missing 38% of tokens.

The graph constructed on all 100 web search results is only missing 8.7% of tokens, but has around 10K words.

Results

Eli5

Model	Input Length	ROUGE 1	2	L
Q + D to A*, TF-IDF	avg 850	28.3	5.1	22.8
Q + D to A, MMR	avg 850	28.1	5.0	22.9
Multi-task*	avg 850	28.9	5.4	23.1
Multi-task Triples	850	29.0	5.2	23.2
Multi-task Top20 Trip.	avg 570	28.8	5.3	23.2
Q + D to A Graph	850	28.8	5.3	23.3
Multi-task Graph	850	29.5	5.6	23.6
+ Top-100 Attention	850	29.7	5.7	23.8
+ E-MCA	11K	30.0	5.8	24.0

WikiSum

Model	Input Len	ROUGE-L
T + D to P*	500	34.2
Language Model + D-MCA*	11K	36.2
T + D to P	500	33.8
Multi-task	500	34.4
Multi-task Graph	500	34.9
+ Top-100 Attention	500	35.2
+ E-MCA	11K	36.5

Question: Why is touching microfiber towels such an uncomfortable feeling?

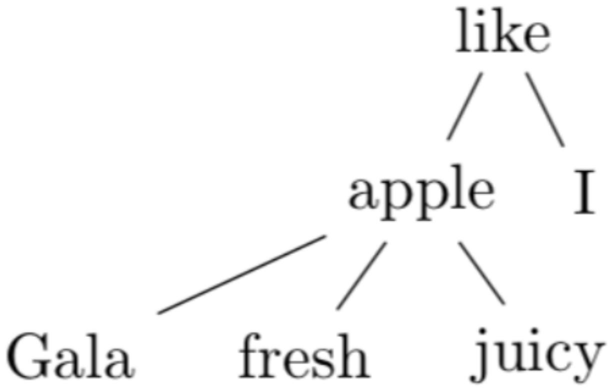
True Answer: Do you mean the kind of cloths used to clean glasses and lenses? I've never noticed any uncomfortable feeling myself, but I do find touching certain cleaning cloths can be quite uncomfortable. There's a brand called "e - cloth" which market themselves as not needing any cleaning supplies. Basically the threads have tiny little hooks and barbs in them, so dragging them over skin makes you feel like it 's catching against you.

Generation: The microfiber is made up of a bunch of tiny fibers that are attached to them. When you touch them, the fibers that make up the microfiber are attracted to each other. When they touch, they're attracted to the other end of the fiber, which is what makes them feel uncomfortable.

Encoding

Delexicalisation

Unordered, Lemmatized Dependency Tree $\Rightarrow$ Sentence



I like fresh juicy Gala apples

Intuition

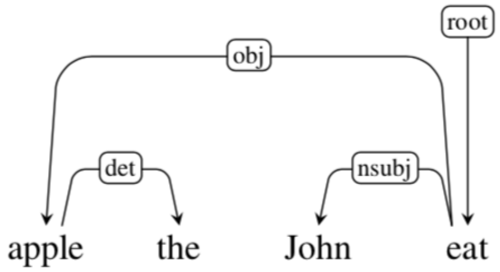
Word ordering mainly depends on syntax

E.g., in English, the subject generally precedes the verb

- Abstracts away from specific words
- Reduces data sparsity
- Permits handling rare/unknown words

Delexicalising

Shimorina, Gardent (EMNLP 2019)



Linearised, Delexicalised Tree

id1:verb:root:0 id2:noun:obj:1 id3:det:det:2 J
id4:pnoun:nsubj

Target Delexicalised Sequence

id4:pnoun:nsubj id1:verb:root:0 id3:det:det:2 J
id2:noun:obj:1

Output

John eat the apple

Results

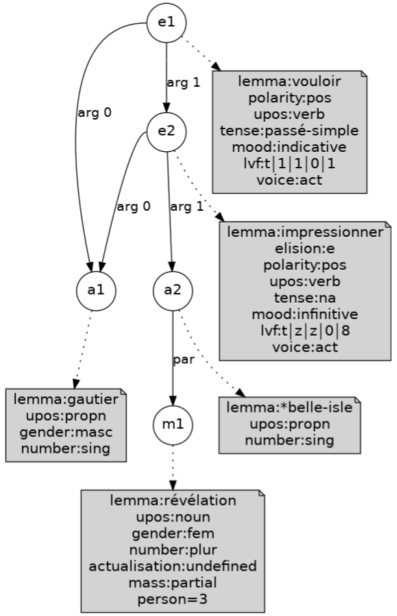
	ar	cs	en	es	fi	fr	it	nl	pt	ru
BL	29.6±1.39	48±0.7	53.57±0.15	46.5±0.78	27.2±0.4	46.4±0.5	49.07±0.9	36.6±0.7	44.3±0.26	58.1±0.46
WO	34.9±0.2	57.97±0.06	59.1±0.36	52.33±0.31	43.1±0.53	50.0±0.0	53.17±0.5	47.03±0.59	51.77±0.32	64.73±0.23
Δ	+5.3	+9.97	+5.53	+5.83	+15.9	+3.6	+4.1	+10.43	+7.47	+6.63

- BLEU score on lemmatised data
- Mean and Standard Deviation on 3 runs
- All results are statistically significant ($p < 0.05$)
- Baseline
  Lexicalised Input

AMRs ⇒ Sentence

Colin, Gardent (INLG 2019)

- Factored, S2S Model with Attention
- Concatenation of 18 embeddings
- Each embedding represent a feature type (POS tag, gender, number etc.)



Lemma linearization:

```
( vouloir|pos|verb|ps|... arg_0
      gautier|propn|masc|sg )
( vouloir|pos|verb|ps|... arg_1
      impressionner|e|pos|verb|... )
( impressionner|e|pos|verb|... arg_0
      gautier|propn|masc|sg )
( impressionner|e|pos|verb|... arg_1
      *belle-isle|propn|sg )
par ( *belle-isle|propn|sg <
      révélation|noun|fem|plur|... )
```

Anonymized linearization:

```
( e1|pos|verb|ps|... arg_0
      a1|propn|masc|sg )
( e1 arg_1|pos|verb|ps|[...]
      e2|e|pos|verb|... )
( e2|e|pos|verb|... arg_0
      a1|propn|masc|sg )
( e2|e|pos|verb|... arg_1
      a2|propn|sg )
par ( a2|propn|sg <
      m1|noun|fem|plur|... )
```

Gautier voulut impressionner Belles-Isle par des révélations.
(Gautier wanted to impress Belles-Isle by some revelations)

Results

Model	BLEU-4	C-R	FW-F1
BL	64.35	0.59	0.906
Dual (Test:Non Anon.)	66.55	0.62	0.910
Anonymised	66.87	0.87	0.933
Dual (Test:Anon.)	68.31	0.87	0.937

- BLEU score on lemmatised data
- Baseline: Lexicalised Input
- Recall (C-R) and F1 on function words
  How well does the model reconstruct function words ?

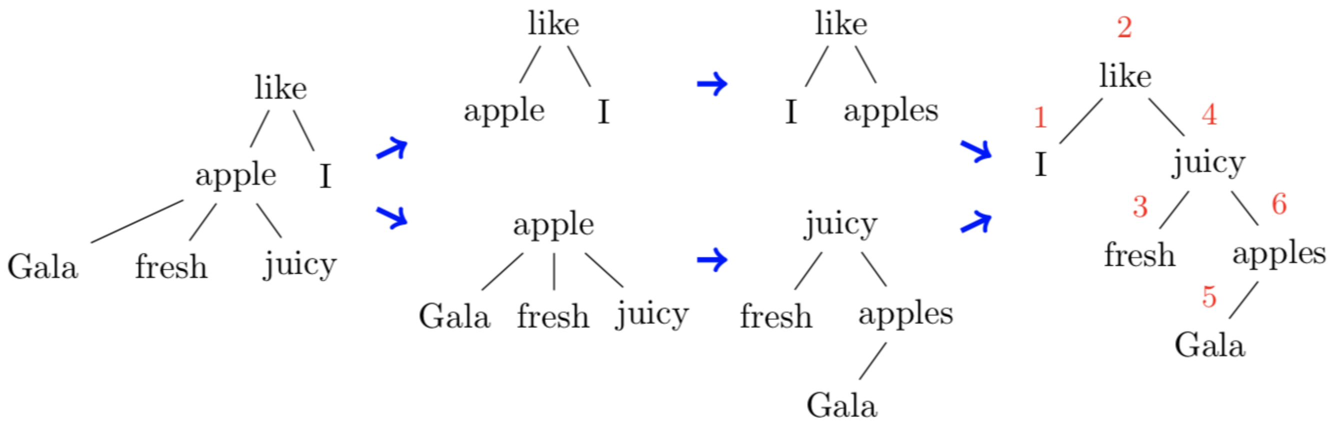
Data

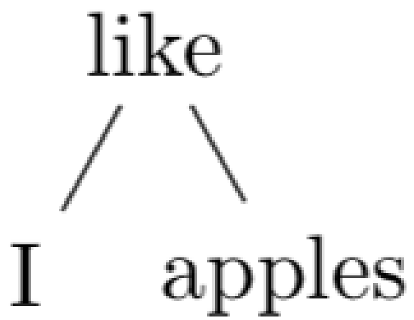
Better Data

Word Ordering

- Convert input dependency into binary tree
- Use Multi-Layer Perceptron to

  predict the relative order of head and child node





Training Example

("like","I","left")

Position of Child wrt Head

Added Training Example

("I","like","right")

Position of Head wrt Child

Results

Dual Head/Child, Child/Head encoding improves performance

	BLEU	**EDIST**	**NIST**
BINLIN	24.92	35.91	9.55
+ data enrichment	48.47	62.04	10.72

Data

More Data

Results

Model	External	BLEU
Konstas et al. (2017)	200K	27.40
Song et al. (2018)	200K	28.20
Guo et al. (2019)	200K	31.60
G2S-GGNN	200K	**32.23**

Additional Training Data

- 200K Gigaword sentences parsed with JAMR (Flanigan et al., 2016)

Pre-training and Fine-tuning

- After each epoch of pretraining on the Gigaword data, the model is fine tuned on the LDC2015E86 dataset

Further Key Issues

Multilingual Generation

- Surface Realisation Shared Task (10 languages, MR2T)
- From data and text ?

Interpretability

- Modular Approaches

Generalising vs. Memorising

- Better test sets

Further Key Issues

Multilingual Generation

- Surface Realisation Shared Task (10 languages, MR2T)
- From data and text ?

Interpretability

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- Better test sets

NLG and Speech Synthesis

- Joint models ?

Questions ?