Examining Language Models

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Interactive *Natural Language* Technology for eXplainable Artificial Intelligence

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Outline

RDF-to-Text Generation

- Detecting omissions
- Analysing the source of omissions

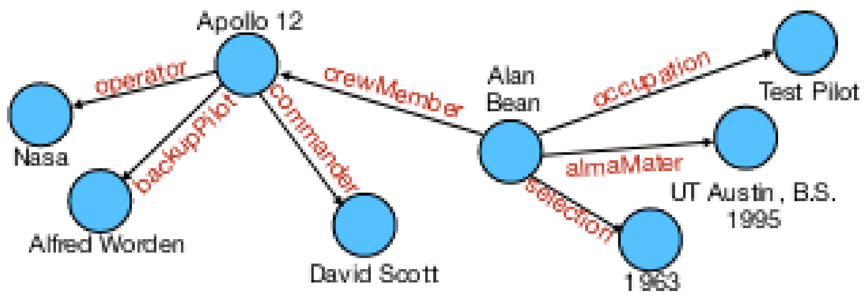
Knowledge-Based Dialog

- Analysing Coherence and Cohesion

RDF-to-Text Generation

Converting Knowledge Graphs to Text

Example



$\Downarrow$

Alan Bean graduated from UT Austin in 1955 with a Bachelor of Science degree. He was hired by NASA in 1963 and served as a test pilot. Apollo 12's backup pilot was Alfred Worden and was commanded by David Scot

Detecting Omissions

Omissions

```
Lady_Anne_Monson | birthPlace | Darlington
Lady_Anne_Monson | birthDate | 1726-01-01
Lady_Anne_Monson | deathDate | 1776-02-18
Lady_Anne_Monson | birthPlace | Kingdom_of_England
Lady_Anne_Monson | residence | India
```

Born in the ***Kingdom of England*** in ***1726-01-01*** , and living in ***India*** , on the 18th of July, 1776, the country is the birth place of Joh Davutoglu.

Omissions are entities with no corresponding mentions

Detecting Omissions

Given a graph and a text, mentions are detected using:

- An Entity Linker
    - returns a list of (RDF entity, mention) pairs
    - pairs whose entity is not in the input graph are filtered out
- Approximate string matching
    - mentions = all n-grams with small edit distance to some input entity
- Pronoun resolution
    - resolve and matched to input entities
- A Date parser

This yields a list of (entity, mentions) pairs

For each input entity, we keep the mention with lowest edit distance

Entity-based semantic Adequacy

$$ESA = \frac{count(InputEntitiesDetected)}{count(InputEntities)}$$

```
Lady_Anne_Monson | birthPlace | Darlington
Lady_Anne_Monson | birthDate | 1726-01-01
Lady_Anne_Monson | deathDate | 1776-02-18
Lady_Anne_Monson | birthPlace | Kingdom_of_England
Lady_Anne_Monson | residence | India
```

$$ESA_I = 0.5$$

*Born in the **Kingdom of England** in **1726-01-01** , and living in **India**, on the 18th of July, 1776, the country is the birth place of Joh Davutoglu.*

6 RDF Entities in the input

3 RDF entities detected in the generated text

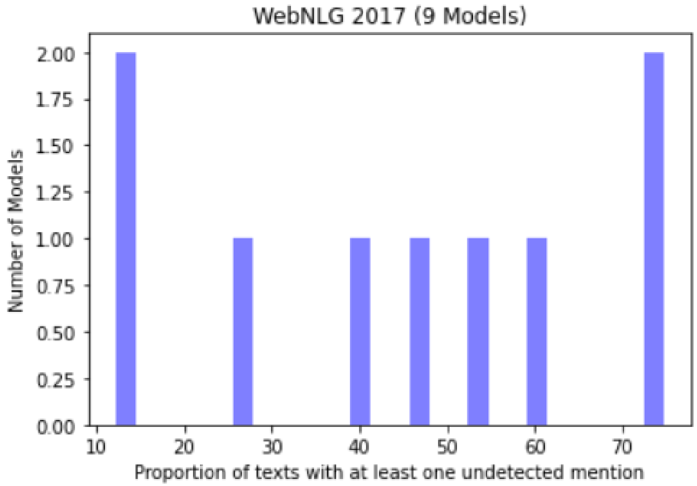
Corpus Level Omission Metrics

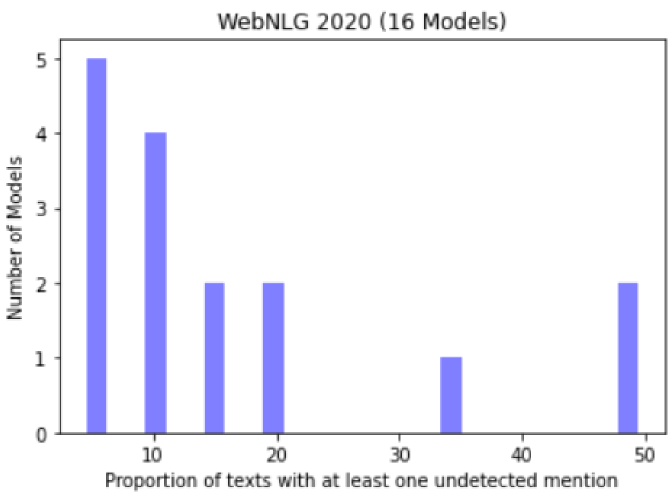
How well does a ***model*** handle a ***corpus*** ?

ESA_C = Average ESA score on corpus

$$ESI_C^n = \frac{count(Text\ with\ at\ least\ n\ Undetected\ Entity)}{\mathrm{count}(Text)}$$

Evaluating RDF-to-Text Generation Models



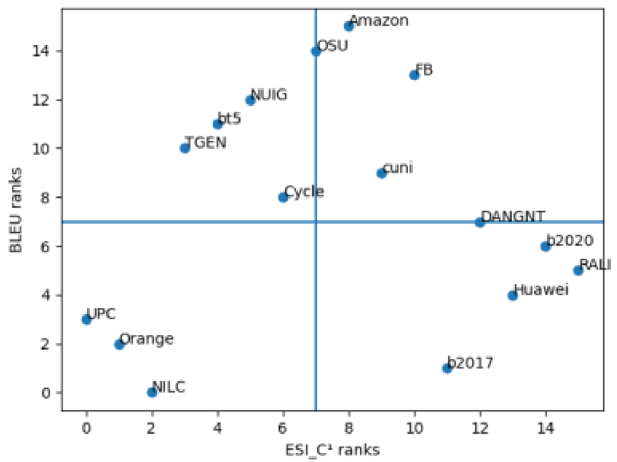


25 models from the WebNLG 2017 and 2020 challenges.

- 2017: ***10 to 77% of the generated texts fail to mention at least one entity*** depending on the model
- 2020: The top 5 models omit one entity or more 5% of the time

BLEU Score and Semantic Entity Based Semantic Adequacy

WebNLG 2020 Models are ranked with respect to BLEU and ESI_C^1 score



A High BLEU does not garantee that all entities are mentioned

From the 8 models with highest BLEU rank

- only three are also among the 8 models with highest ESI C 1 rank (Amazon, FB and cuni-ufal).
- the other five (OSU, CycleGT, NUIG, TGen, bt5) have a high BLEU but an ESI score ranging between 10 and 22%. On average they fail to mention at least one of the input entities 10 to 22% of the time.

Correlation with Human Judgments and other Metrics

	METEOR	TER	Fluency	Grammar	Semantics	ESA_I
BLEU	0.74	-0.57	0.39	0.43	0.53	0.59
METEOR		-0.54	0.57	0.63	0.72	**0.87**
TER			-0.42	-0.45	-0.4	-0.42
Fluency				0.89	0.51	0.49
Grammar					0.57	0.57
Semantics						**0.66**

- Correlation with human judgement of Semantic Adequacy is strong for 2017 (Semantics), moderate for 2020 (Correctness, DataCoverage, Relevance)
- Correlation varies with human evaluation scheme
- Correlation with other automatic metrics is moderate

	Bl-nltk	Met	chrf	TER	BSC-P	-R	-F1	BL	Cor	Cov	Fl	REl	Str	**ESA**
AUTO														
BLEU	0.97	0.71	0.82	-0.67	0.69	0.66	0.71	0.49	0.42	0.3	0.34	0.33	0.31	0.41
BLEU NLTK		0.77	0.87	-0.74	0.74	0.72	0.77	0.54	0.45	0.34	0.39	0.36	0.36	0.39
METEOR			0.9	-0.62	0.67	0.82	0.78	0.67	0.49	0.49	0.4	0.42	0.36	**0.45**
chrF++				-0.69	0.74	0.82	0.82	0.6	0.51	0.46	0.41	0.43	0.37	**0.45**
TER					-0.76	-0.67	-0.75	-0.61	-0.41	-0.31	-0.42	-0.39	-0.4	-0.24
BERT-score P						0.83	0.95	0.73	0.6	0.41	0.52	0.56	0.5	0.39
BERT-score R							0.95	0.75	0.57	0.52	0.49	0.49	0.45	0.43
BERT-score F1								0.77	0.61	0.49	0.53	0.55	0.5	**0.44**
BLEURT									0.62	0.54	0.52	0.59	0.5	0.43
HUMAN														
Correctness										0.75	0.71	0.83	0.67	0.56
DataCoverage											0.62	0.76	0.57	**0.57**
Fluency												0.67	0.86	0.41
Relevance													0.65	0.53
TextStructure														0.36

Qualitative Analysis

WebNLG 2017: 7 texts with low ESA and high human semantics score

- 6 with missing mentions
- 1 degenerate text

WebNLG 2020: 4 texts with low ESA and high human semantics score

- all with missing mentions

  Human evaluation may be incorrect

Detecting Hallucinations

Model	>1	>1✓	Dist	↓ ESI$_C$[1]
RALI	0	0	0	0%
B-2017	1	1	1	0.1%
B-2020	1	1	1	0.1%
NUIG	4	3	3	0.2%
UPC	4	4	3	0.2%
DANGNT	5	5	5	0.3%
TGen	8	7	2	0.5%
cuni-ufal	9	7	6	0.5%
Amazon	9	9	3	0.5%
FBConvAI	17	11	6	1%
CycleGT	19	18	10	1%
OSU	20	19	3	1%
bt5	36	17	3	2%
Huawei	48	47	28	3%
NILC	117	99	66	7%
ORANGE	288	288	60	16%
UIT	1	0	1	0.1%
Tilburg SMT	4	0	4	0.2%
Tilburg NMT	11	4	7	0.6%
UPF	12	8	4	0.6%
Tilburg Pl	14	11	6	0.8%
Melbourne	114	112	24	6%
Adapt	241	234	151	13%
PKUWriter	286	283	135	15%
Baseline	754	144*	147	40%

Hallucinations: ***Mentions in the output text that have no corresponding RDF entity in the input graph*** (Entity linking only).

On 144 randomly chosen texts

1: Number of texts with at least one hallucination

1✓: Number of texts with at least one hallucination which are manually validated

Qualitative Analysis

Three main causes for omissions: short output, hallucinations, degenerate output

Short Text

(*Liselotte_Grschebina*, *nationality*, *Israel*)
(*Israel*, *areaTotal*, *20769100000.0*)
(*Israel*, *officialLanguage*, *Modern_Standard_Arabic*)
(*Liselotte_Grschebina*, *birthPlace*, *German_Empire*)
(*Liselotte_Grschebina*, *training*, *School_of_Applied_Arts_in_Stuttgart*)

Liselotte Grschebina is a German national who was born in the German Empire and has a total area of 20769100000. 0.

Qualitative Analysis

Three main causes for omissions: short output, hallucinations, degenerate output

Hallucination

(*Lady_Anne_Monson*, *birthPlace*, *Darlington*)
(*Lady_Anne_Monson*, *birthDate*, *1726-01-01*)
(*Lady_Anne_Monson*, *deathDate*, *1776-02-18*)
(*Lady_Anne_Monson*, *birthPlace*, *Kingdom_of_England*)
(*Lady_Anne_Monson*, *residence*, *India*)

Born in the Kingdom of England in 1726-01-01, and living in India, on the 18th of July, 1776, **the country** is the birth place of **Joh Davutoglu**.

Qualitative Analysis

Three main causes for omissions: short output, hallucinations, degenerate output

Degenerate Output

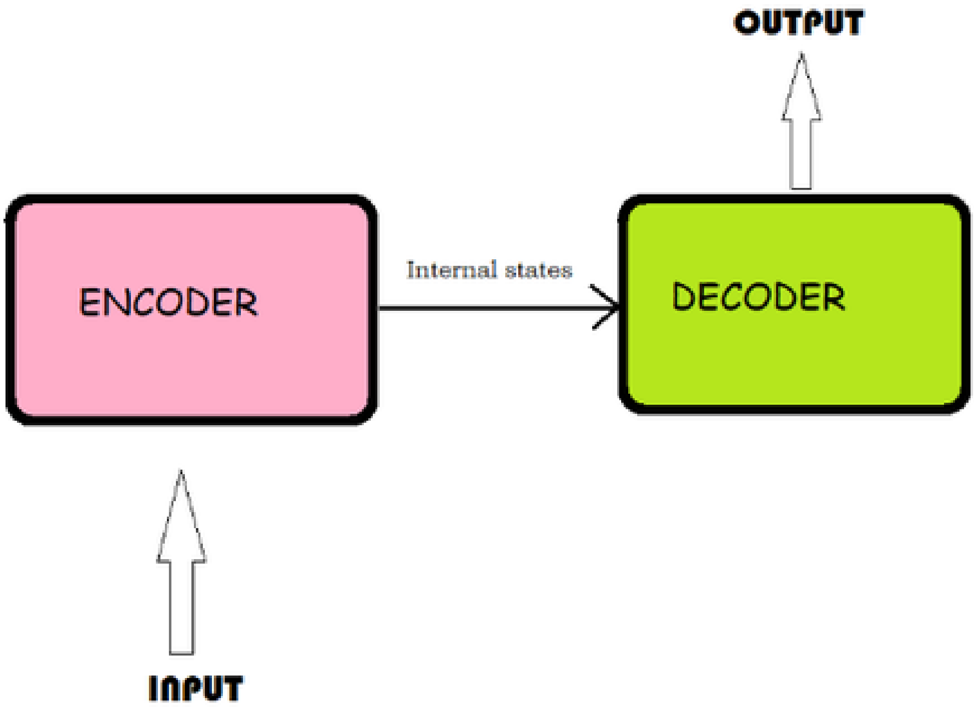
(*Lady_Anne_Monson*, *birthPlace*, *Darlington*)
(*Lady_Anne_Monson*, *birthDate*, *1726-01-01*)
(*Lady_Anne_Monson*, *deathDate*, *1776-02-18*)
(*Lady_Anne_Monson*, *birthPlace*, *Kingdom_of_England*)
(*Lady_Anne_Monson*, *residence*, *India*)

Born in the Kingdom of England, and died on 1776-02-18, on 1726-01-01, in the Kingdom of England, the prime minister of community of England is called, Germanic duties, and arrabbiata (born on the 18th of July, 1726-01-01).

Analysing Omissions

Where do omissions come from ?

Where do omissions come from ?



Probing the Encoder

Can we detect omissions in the encoder representations?

Two probing methods

- Parametric: classifier probe
- Non parametric method based on encoding similarity

Creating Omission Data

RDF-to-Text Model

- T5 and BART
- fine-tuned on the WebNLG training data, 47k (RDF graph, text) pairs where the RDF graphs are subgraphs of DBPedia and texts are crowd-sourced.

(RDF,Text) Data

- 22,657 RDF input graphs
  - 16,657 RDF graphs from the WebNLG V3.0 dataset
  - 6k graphs from the KELM dataset (1k graphs for each graph size from 1 to 6 triples)
- permute input
- generate
- filter repeated output

71,644 (graph, text) pairs

Creating Omission Data

Labelling (RDF,Text) pairs with omissions

- Automatic annotation (R:0.74, P:0.75)
  - All 71K texts
- Manual annotation
  - 3 NLP MSc students
  - Kappa between each pair of annotators: 0.56 to 0.69
  - 12,886 texts
  - omissions and distortions

Data for probing experiments

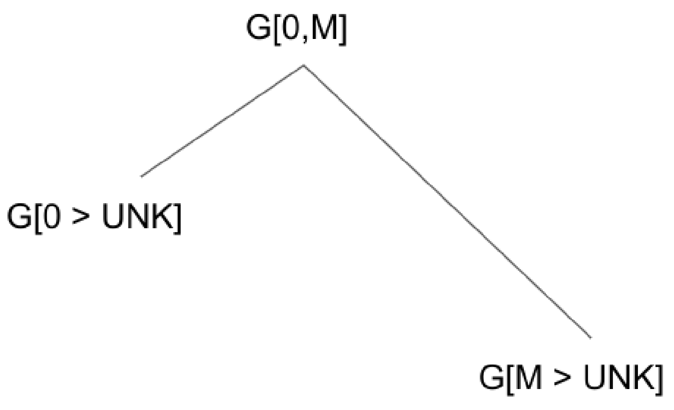
- Texts with at least one omission or distortion
- ***33,160 texts automatically labelled with omissions***
- ***6,249 texts manually labelled with omission, 6,518 with distortion***
- Train/dev/test: 70/15/15

Example Distortions

RDF Entity	Distortion
Olga_Bondareva	Olgaondarev
177539.0	1777539
Ciudad_Ayala	Ciudad Ayalatus
Lee Jae-hak	Lee Lee-hak
Doosan Bears	Donosan Bears
Lionsgate	Lionsburg
1997	1996
EGBF	EAWFB
Columbia_Records	The Columbus Records
1929-06-11	June 5th, 1929
St._Louis,_Missouri	St Louis, Mississippi
11.51147.0	11.5
-6	Delta 6

Parameter free probing

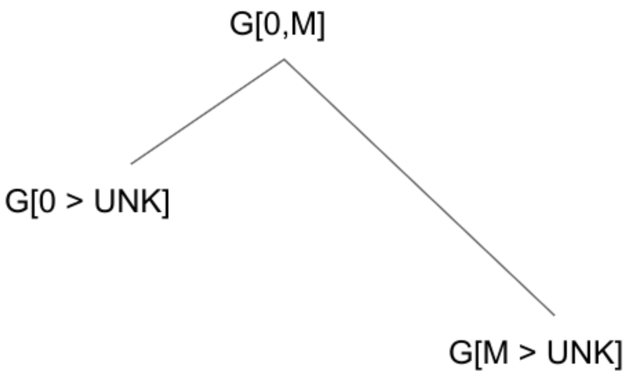
Intuition



- The encoder representations of RDF graphs which lead to omission have a weak signal for the omitted entity.
- Because it lacks specificity, the representation of an omitted entity is more similar to the representation of the unknown token UNK than the representation of an entity that is correctly verbalised in the output text.

Parameter free probing

We compare the similarity between the encoder representation of a graph leading to an omission with two alternative representations



Average similarity for mentions:

$$cos(g, g^{\setminus M}) = \frac{1}{K_g} \sum_{k=1}^{K_g} sim(g, g^{\setminus mk})$$

Ratio of graphs such that:

$$cos(g, g^{\setminus o}) > cos(g, g^{\setminus M})$$

Parameter free probing Results

	All	In Domain			OOD	
		W-T	W-D	W-S	W-U	K
O	0.68	0.64	0.72	0.61	*0.52*	0.77
O+D	0.54	0.66	0.70	0.46	0.38	*0.50*
D	0.44	0.70	0.68	0.47	0.45	0.47
Auto	0.66	0.83	0.85	0.56	0.44	0.65

Most results are statistically significant showing that encodings of graphs lieading to omissions are different from those that do not.

On average, the proportion of graphs for which $sim(g, g^{\setminus o}) > sim(g, g^{\setminus M})$ is

- 66% for the automatically annotated data
- 68% for the manually annotated data

The difference is less on OOD data as these have weaker signal than graphs seen during training.

Parametric probe

Binary Classifier

- Two-layer Multi-layer Perceptron
- Trained on ***(encoding(graph), encoding(entity), label)***
- Label = 1 if the entity is not omitted, 0 otherwise

Aka entailment relation between a graph representation and an entity

1 if $g \models e$, else 0

Manual-O+D	
F1	**0.82**
Manual-O	
F1	**0.69**
Manual-D	
F1	**0.79**

- The probe successfully classifies distortions and omissions
- Distortions are easier to detect
- Complementary to parameter-free probe

Upper Bound

Binary Classifier

- Trained to distinguish entities present in a graph from ***entities absent from that graph***
- Trained on 18k graphs and 198K entities
- Entity not present in the input graph viewed as an extreme case of omission
- Input: encoding(Graph), encoding(entity)
- Label: 1 if the entity is in graph, 0 otherwise

Manual-O+D	
F1	**0.82**
Manual-O	
F1	**0.69**
Manual-D	
F1	**0.79**
Upper-Bound	
F1	**0.97**

F1 on class 0 is high

- The probe can detect whether or not an entity is present from the embedding of an RDF graph.
- Absent entities are easier to spot than omitted or distorted entities

Control Task

Is the probe really evaluating the embeddings or does it memorise the training data?

Training set with random labels

Manual-O+D	
F1	**0.82**
C_{F1}	**0.00**
S_{F1}	0.82
Manual-O	
F1	**0.69**
C_{F1}	**0.00**
S_{F1}	0.69
Manual-D	
F1	**0.79**
C_{F1}	**0.00**
S_{F1}	0.79
Upper-Bound	
F1	**0.97**

Selectivity = drop in performance between the probe (trained on the original dataset) and the control probe (trained on the randomised dataset).

Selectivity is high, our probe is not memorising the data

Testing on Hard Examples

- Entities that are sometimes omitted, sometimes mentioned /or and sometimes distorted
- Permits testing whether probe classifies omissions/distortions/mentions or graph that contain specific entities

Training Data	Test Data	% Data	F1 (B.Acc)
Manual-O	M&O	13%	0.81 (0.74)
Manual-D	M&D	14%	0.84 (0.81)
Manual-O+D	M&O&D	9%	0.78 (0.82)
Manual-O+D	M&O	13%	0.82 (0.82)
Manual-O+D	M&D	14%	0.78 (0.81)

The probe also performs well on difficult examples.

Generalising to Other RDF-to-Text Models

	# T	# T(O)	# O
WebNLG			
Train	36,704	7,064 (19%)	7,824
Dev	4,658	882 (19%)	993
Test	6,173	2,286 (37%)	2,855
KELM	24,963	17,852 (72%)	29,596
ALL	72,498	28,084(39%)	41,268

	All	**In Domain**			**OOD**	
		W-T	W-D	W-S	W-U	K
NP.P	0.89	0.84	0.84	0.88	0.81	0.91
P.P						
F1	0.8	0.84	0.83	0.79	0.7	0.78
B.Acc	0.85	0.88	0.88	0.83	0.77	0.81

Probing T5

- T5 fine tuned on same data
- Automatic annotation of omissions

- Higher results than for BART

In both cases, the embeddings of graphs leading to omissions differ from those that do not.

Analysing Omissions

How much is omitted ?

- Generate texts
- Automatically annotate omissions
- Quantify

To what extent does the encoder play a role ?

- Fine tune the probes and test on the annotated data

Analysing Dialog Coherence and Cohesion

Knowledge-Based Dialog

Knowledge Graph

(*Elsa Morante, place of birth, Rome*)
(*Elsa Morante, cause of death, myocardial infarction*)
(*Elsa Morante, spouse, Alberto Moravia*)
(*Elsa Morante, manner of death, natural causes*)
(*natural causes, inv. opposite of, unnatural death*)
(*Rome, inv. airline hub, Norwegian Air Shuttle*)
(*Rome, inv. enclave within, Vatican City*)
(*Rome, official language, Italian*)
(*Alberto Moravia, inv. founded by, Nuovi Argomenti*)
(*Alberto Moravia, place of death, Rome*)

Dialog Context

Where was Elsa Morante born?
Rome
What is Rome's administrative territory?
Vatican City
Who was Morante married to?
Alberto Moravia
Which communication medium was founded by Moravia?
Nuovi Argomenti
Where did Moravia take his last breath ?
Rome

Generation

Was Morante's death an accident or a suicide?
Natural causes

Challenges

Dialog coherence

- Relevant turn (Content Selection)
- No répétition

Factuality

- Factually correct question (KB Fact)

Dialog Cohesion

- Appropriate anaphors

An Interpretable Model

Knowledge Graph
(*Elsa Morante, place of birth, Rome*)
(*Elsa Morante, cause of death, myocardial infarction*)
(*Elsa Morante, spouse, Alberto Moravia*)
(*Elsa Morante, manner of death, natural causes*)
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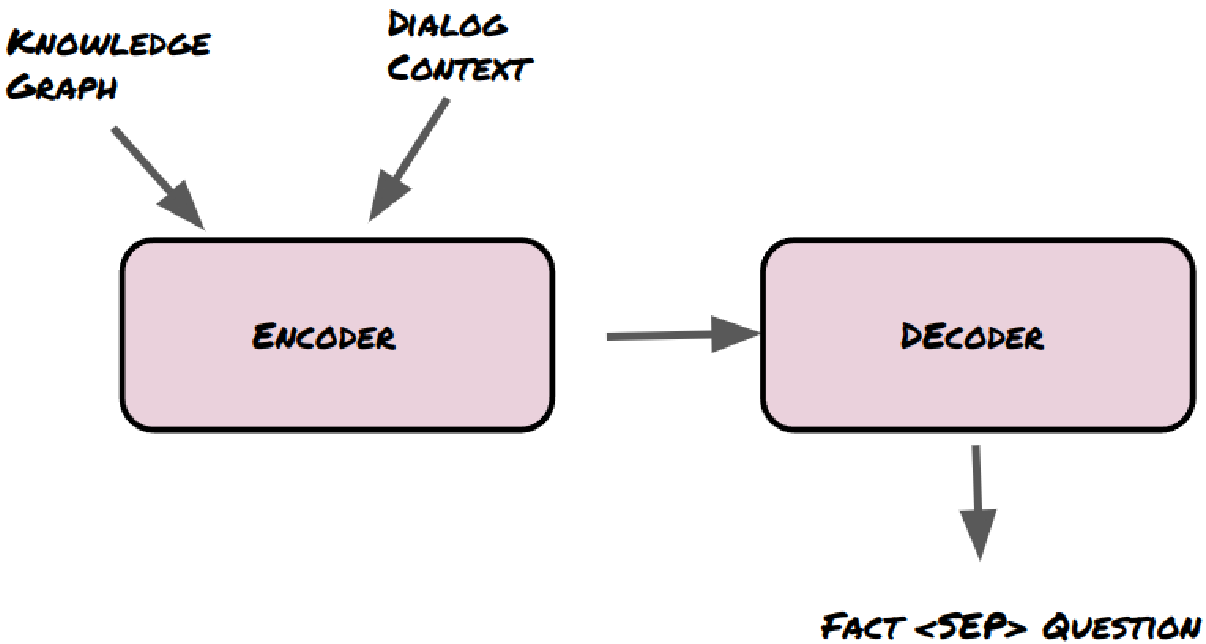
Dialog Context
Where was Elsa Morante born?
Rome
What is Rome's administrative territory?
Vatican City
Who was Morante married to?
Alberto Moravia
Which communication medium was founded by Moravia?
Nuovi Argomenti
Where did Moravia take his last breath ?
Rome

Generation
(*Elsa Morante, cause of death, myocardial infarction*)
Was Morante's death an accident or a suicide?

Knowledge-Guided Response Generation

T5 trained on KGConv dataset



Analysing Generation

Factuality

- Is the ***predicted fact*** true (is it in the KB)?
- Does the question match the predicted fact
- If both are true the question is factual

Dialog Coherence

- Is the predicted fact different from those already predicted ? (New information)
- Is it relevant ? (Content Selection)

Dialog Cohesion

- Are pronouns correct and unambiguous ?
- Does the genre of the pronoun match that of the corresponding entity in the predicted triple ?
- Does the pronoun denote the last entity with matching genre ?

The KGConv Dialogs

Knowledge Graph
(*Afghanistan, lowest point, Amu Darya*)
(*Sitara Achakzai, birthplace, Afghanistan*)
(*Sitara Achakzai, field of work, feminism*)
(*Sitara Achakzai, death manner, murder*)
(*Afghanistan, capital, Kabul*)
...
Dialog
T (*Sitara Achakzai, field of work, feminism*)
Q What was Sitara Achakzai's field of work?
A feminism

T (*Sitara Achakzai, death manner, murder*)
Q What was the cause of death of Achakzai?
A homicide

T (*Sitara Achakzai, birthplace, Afghanistan*)
Q Where was she born ?
A Afghanistan

T (*Afghanistan, capital, Kabul*)
Q What is the capital of Afghanistan?
A Kabul

T (*Afghanistan, lowest point, Amu Darya*)
Q What is the lowest point of Afghanistan?
A Amu Darya

- 70,956 English Dialogs, 143K Wikidata triples
- Each dialog D is associated with a Knowledge-Graph K_D
- A dialog is a sequence of question/response pairs
- Each question/response pair is grounded in a Wikidata fact

Content Selection / Relevance

K_D extended with three types of distractors

- Out-of-Scope triples (entity)
    - triples whose subject is of the same Wikidata category as the dialog root entity .
- Out-of-Scope triples (property)
    - triples whose property appears in K_D.
- Noise triples
    - Triples that are not in KGConv (and most of time not in Wikidata) but whose subject, property and object are in KGConv

Dialog Context

4 types

- Natural Language only (NL)
- Triples only (KL)
- Natural Language Questions only (Q)
- NL + Triples (Hybrid)

Analysing Coherence

Context Type		$D_{QA_{nl}}$	(%)	$D_{Q_{nl}}$	(%)	D_{kl}	(%)	$D_{QA_{nl+kl}}$	(%)
# test examples		313583		321270		315815		313865	
# distinct generated triples		16519		18146		17875		16597	
Correct triples		303723	97	286439	89	301970	96	304794	0,97
	Exact match with target	123684	39	109031	34	123605	39	131453	42
	Other triple from input RDF	180039	57	177408	55	178365	56	173341	55
Incorrect triples		9860	3	34831	11	13845	4	9071	3
	Repetitions	1788	1	23149	7	1308	0	1705	1
	Out-of-scope (entity) triples	305	0	640	0	340	0	398	0
	Out-of-scope (property) triples	5327	2	6987	2	6437	2	5448	2
	Noise triples		0	0	0	0	0	0	0
	Ill-formed triples	460	0	2033	1	1663	1	710	0
	Triples not in KGConv	5514	2	7403	2	7761	2	4977	2

The model selects relevant facts

- Few OOS and Noise triples (0-2%)

Analysing Coherence

Context Type	$D_{QA_{nl}}$	(%)	$D_{Q_{nl}}$	(%)	D_{kl}	(%)	$D_{QA_{nl}+kl}$	(%)
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Noise triples		0	0	0	0	0	0	0
Ill-formed triples	460	0	2033	1	1663	1	710	0
Triples not in KGConv	5514	2	7403	2	7761	2	4977	2

Content Selection

The model selects relevant facts

- Few OOS and Noise triples (0-2%)

Some fake facts

- Triples not in KGConv (2%)

Analysing Coherence

Context Type		$D_{QA_{nl}}$	(%)	$D_{Q_{nl}}$	(%)	D_{kl}	(%)	$D_{QA_{nl}+kl}$	(%)
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	Other triple from input RDF	180039	57	177408	55	178365	56	173341	55
Incorrect triples		9860	3	34831	11	13845	4	9071	3
	Repetitions	1788	1	23149	7	1308	0	1705	1
	Out-of-scope (entity) triples	305	0	640	0	340	0	398	0
	Out-of-scope (property) triples	5327	2	6987	2	6437	2	5448	2
	Noise triples		0	0	0	0	0	0	0
	Ill-formed triples	460	0	2033	1	1663	1	710	0
	Triples not in KGConv	5514	2	7403	2	7761	2	4977	2

High relevance

- Few incorrect triples for most models (3%)
- Answers matter: Q generates more incorrect triples (11%), often repeating previous turns

Analysing Coherence

Context Type		$D_{QA_{nl}}$	(%)	$D_{Q_{nl}}$	(%)	D_{kl}	(%)	$D_{QA_{nl+kl}}$	(%)
# test examples		313583		321270		315815		313865	
# distinct generated triples		16519		18146		17875		16597	
Correct triples		303723	97	286439	89	301970	96	304794	0,97
	Exact match with target	123684	39	109031	34	123605	39	131453	42
	Other triple from input RDF	180039	57	177408	55	178365	56	173341	55
Incorrect triples		9860	3	34831	11	13845	4	9071	3
	Repetitions	1788	1	23149	7	1308	0	1705	1
	Out-of-scope (entity) triples	305	0	640	0	340	0	398	0
	Out-of-scope (property) triples	5327	2	6987	2	6437	2	5448	2
	Noise triples		0	0	0	0	0	0	0
	Ill-formed triples	460	0	2033	1	1663	1	710	0
	Triples not in KGConv	5514	2	7403	2	7761	2	4977	2

High relevance

- Few incorrect triples for most models (3%)
- Answers matter: Q generates more incorrect triples (11%), often repeating previous turns

High Semantic Adequacy

- GLEU(Question,triple): 0.73 - 0.76

Most questions are relevant and factual

Analysing Cohesion

Gender

- each RDF entity is associated its "sex or gender" value from Wikidata
- A pronoun in a generated question has the correct gender if its gender is the same as the gender of its referent, i.e. the subject entity of the triple the question is conditioned on.

Ambiguity

- A pronoun with genre g is ambiguous if the last entity of genre g mentioned in the dialog context is not the referent of that pronoun.

Dialog Context
T: (*NGC 2539*, *discoverer or inventor*, *William Herschel*)
Q: Who found NGC 2423?
A: William Herschel

T: (*NGC 2539*, *constellation*, *Puppis*)
Q: What is the name of the constellation which NGC 2423 belongs?
A: Puppis

T: (*William Herschel*, *student of*, *Nevil Maskelyne*))
Q: What was the name of Herschel's teacher?
A: Nevil Maskelyne

Generation
(*William Herschel*, *place of burial*, *Westminster Abbey*)
Where was **he** buried?

he $\rightarrow$ William Herschel

Analysing Cohesion

Context Type	$D_{QA_{nl}}$	$D_{Q_{nl}}$	D_{kl}	$D_{QA_{nl+kl}}$
questions with a pronoun	9%	8%	13%	8%
"he"	53%	47%	54%	52%
"it"	32%	35%	34%	35%
"him"	7%	10%	8%	7%
"she"	8%	7%	3%	6%
"her"	<1%	1%	4%	<1%
pronouns with gender mistakes	5%	5%	3%	4%
"he"	29%	44%	68%	52 %%
"she"	62 %	39%	18%	34%
"him"	4 %	9 %	9 %	8%
"her"	3%	5 %	2 %	2%
"it"	2%	3%	3 %	4 %
ambiguous pronouns	30%	36%	34%	29%
"it"	64%	67%	76%	66%
"he"	18%	19%	15%	21%
"she"	14%	9%	4%	9%
"him"	3%	4%	4%	3%
"her"	1%	1%	1%	1%
pronominalized distinct triples	22%	19%	24%	19%

- Good proportion of questions containing pronouns (between 8 and 13% of the test examples)
- The KL context induces a much higher rate of pronouns
- Strong bias for masculine pronouns

Analysing Cohesion

Context Type	$D_{QA_{nl}}$	$D_{Q_{nl}}$	D_{kl}	$D_{QA_{nl}+kl}$
questions with a pronoun	9%	8%	13%	8%
"he"	53%	47%	54%	52%
"it"	32%	35%	34%	35%
"him"	7%	10%	8%	7%
"she"	8%	7%	3%	6%
"her"	<1%	1%	4%	<1%
pronouns with gender mistakes	5%	5%	3%	4%
"he"	29%	44%	68%	52 %%
"she"	62 %	39%	18%	34%
"him"	4 %	9 %	9 %	8%
"her"	3%	5 %	2 %	2%
"it"	2%	3%	3 %	4 %
ambiguous pronouns	30%	36%	34%	29%
"it"	64%	67%	76%	66%
"he"	18%	19%	15%	21%
"she"	14%	9%	4%	9%
"him"	3%	4%	4%	3%
"her"	1%	1%	1%	1%
pronominalized distinct triples	22%	19%	24%	19%

- Good diversity of the triples giving rise to pronominal questions (about 2% of the dataset triples).

Analysing Cohesion

Context Type	$D_{QA_{nl}}$	$D_{Q_{nl}}$	D_{kl}	$D_{QA_{nl}+kl}$
questions with a pronoun	9%	8%	13%	8%
"he"	53%	47%	54%	52%
"it"	32%	35%	34%	35%
"him"	7%	10%	8%	7%
"she"	8%	7%	3%	6%
"her"	<1%	1%	4%	<1%
pronouns with gender mistakes	5%	5%	3%	4%
"he"	29%	44%	68%	52 %%
"she"	62 %	39%	18%	34%
"him"	4 %	9 %	9 %	8%
"her"	3%	5 %	2 %	2%
"it"	2%	3%	3 %	4 %
ambiguous pronouns	30%	36%	34%	29%
"it"	64%	67%	76%	66%
"he"	18%	19%	15%	21%
"she"	14%	9%	4%	9%
"him"	3%	4%	4%	3%
"her"	1%	1%	1%	1%
pronominalized distinct triples	22%	19%	24%	19%

- Antecedent/Pronoun Genre agreement is high (95%-96%)

Analysing Cohesion

Context Type	$D_{QA_{nl}}$	$D_{Q_{nl}}$	D_{kl}	$D_{QA_{nl}+kl}$
questions with a pronoun	9%	8%	13%	8%
"he"	53%	47%	54%	52%
"it"	32%	35%	34%	35%
"him"	7%	10%	8%	7%
"she"	8%	7%	3%	6%
"her"	<1%	1%	4%	<1%
pronouns with gender mistakes	5%	5%	3%	4%
"he"	29%	44%	68%	52 %%
"she"	62 %	39%	18%	34%
"him"	4 %	9 %	9 %	8%
"her"	3%	5 %	2 %	2%
"it"	2%	3%	3 %	4 %
ambiguous pronouns	30%	36%	34%	29%
"it"	64%	67%	76%	66%
"he"	18%	19%	15%	21%
"she"	14%	9%	4%	9%
"him"	3%	4%	4%	3%
"her"	1%	1%	1%	1%
pronominalized distinct triples	22%	19%	24%	19%

- The proportion of ambiguous pronouns is quite high, ranging between 29% and 36%

Ablating the Knowledge Graph

Context Type	$D_{QA_{nl}}$	$D_{Q_{nl}}$	D_{kl}	$D_{QA_{nl}+kl}$
# Test examples	323k	302k	323k	323k
Incorrect triple	92%	92%	91%	91%
Repetition	2%	1%	2%	1%
Triple not in KGCONV	84%	81%	83%	82%
Subject not in KGCONV	13%	28%	17%	15%
Property not in KGCONV	14%	33%	17%	16%
Object not in KGCONV	13%	29%	17%	15%

Conditioning question generation not only on the dialog context but also on a knowledge graph helps generating factually correct dialogs

- 91%-92% of generated triples are incorrect
- Almost all of them (81-84%) are hallucinated triples not belonging to the set of KGConv triples, a large set of 132K Wikidata triples.

Ablating the Dialog Context

	#	%
# test examples	323765	
Correct triples	166716	51
Exact match with target	36474	11
Other triple from input RDF	130242	40
Incorrect triples	157049	49
Repetitions	149363	46
Out-of-scope (entity) triples	327	0
Out-of-scope (property) triples	8713	3
Noise triples generated	0	0
Ill-formed triples	182	0
Triples with a property not in KGConv	6989	2

Unsurprisingly, ablating the dialog context

- drastically reduces the proportion of correct triples (51%) and
- increases the ratio of repetitions (46%).

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Conclusion

Like hallucinations, omissions impact seamntic adequacy

- More work is need to identify, quantify and explain omissions in other generation tasks and for other languages

Grounding Dialog Models in Knowledge helps getting a detailed picture of their coherence, factuality and cohesion

- Can the approach be extended to more complex questions, to other languages andto open domain dialogs ?

Questions ?