Accuracy in Neural Text Generation

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Selected topics in Machine Learning and Natural Language Processing

23. 7. 2021

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Outline

- NLG & Accuracy
  - mainly for data-to-text (~ conditioned on input)
  - motivation: what's new in neural vs. previous systems
- Making neural NLG systems (more) accurate
  1) overgenerate & rerank
  2) cleaning data
  3) additional classifier tasks
  4) explicit planning step
  5) neural editing only
- Detecting inaccuracy in NLG outputs
  1) sentence-level classification
  2) word-level error tagging
- stuff I was involved in, with links elsewhere

Accuracy in NLG

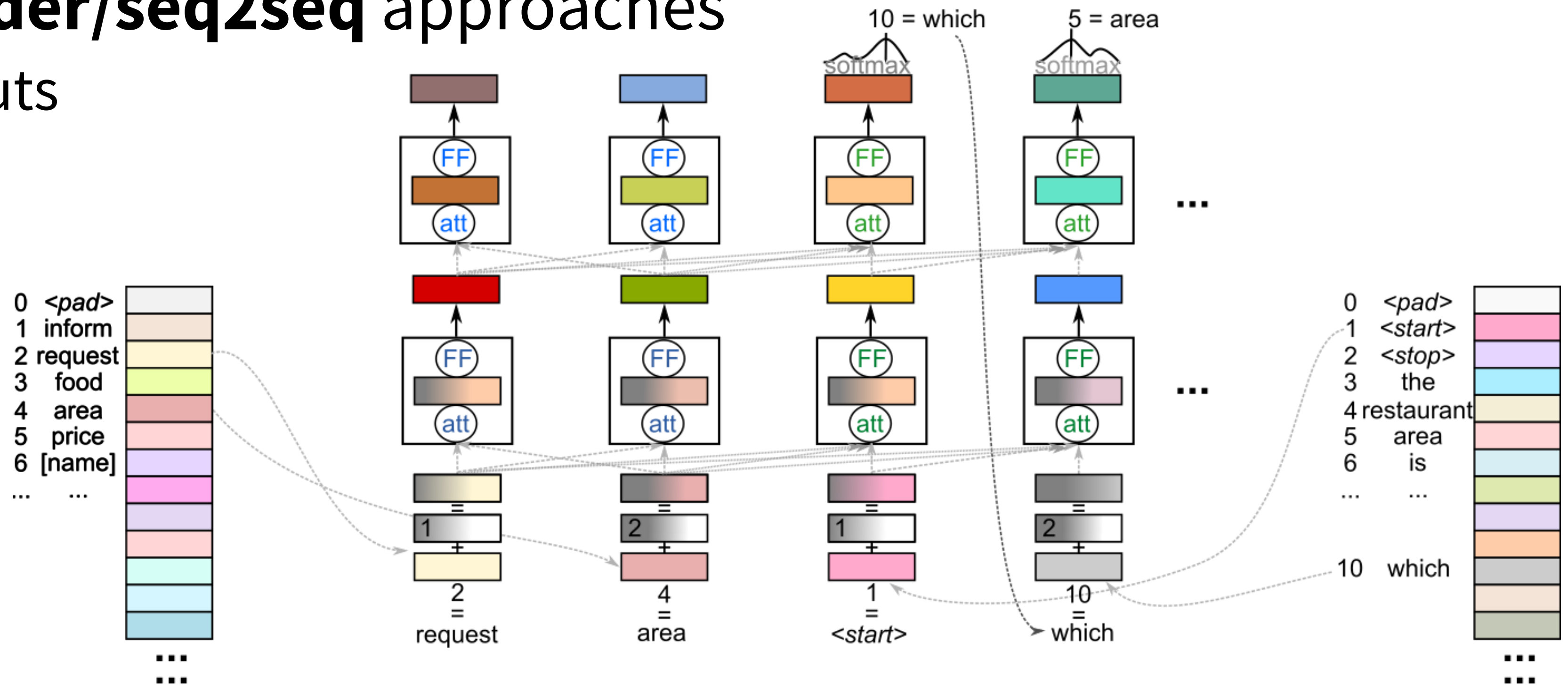
- **data-to-text NLG** = verbalizing structured outputs
  - RDF triples, dialogue acts etc. → text
- **accuracy** = input-output correspondence

Blue Spice | eat_type | pub
Blue Spice | area | riverside
→ NLG → *You can bring your kids to Blue Spice in the riverside area.*

- accuracy error types
  - **hallucination** = output not grounded in input
  - **omission** = input not verbalized
- measurement: **semantic/slot error rate**
- different for other NLG tasks
  - summarization, NLG with content selection: omissions allowed
  - open-domain dialogue, creative text generation: just internal consistency

Neural NLG

- Neural **encoder-decoder/seq2seq** approaches
  - encode linearized inputs
  - decode word-by-word (autoregressively)



- Multiple architectures (but the same principle)
  - RNNs (LSTM, GRU) + attention
  - Transformer (=positional embeddings, feed forward & attention)
  - Pretrained Transformers (+ pretrained on lots of data for a self-supervised task)

Neural NLG vs. older methods

- End-to-end – 1 model does everything
  - previously: pipelines (or “end-to-end” templates, which aren’t trainable)
- No need for fine-grained alignments in data
  - previously: most trainable methods required that

`name [Loch Fyne], eatType[restaurant], food[Japanese], price[cheap], familyFriendly[yes]`

Loch Fyne is a kid-friendly restaurant serving cheap Japanese food.

- Very fluent outputs (especially with pretrained models)
  - previously: formulaic, sometimes incorrect outputs
- Needs more training data (~10k range)
  - previously: 100-1k range
- Opaque & has no guarantees on accuracy

(Kasner & Dušek, 2020)
https://www.aclweb.org/anthology/2020.webnlg-1.20/

E2E NLG Challenge (2017/18)

(Dušek et al., 2020)
http://arxiv.org/abs/1901.07931

- Known domain: restaurant data
- More data than prior approaches
  - 6k MRs, 50k texts
  - (prior: mostly 0-10k)
- Diverse & natural, but noisy
  - crowdsourced, partially based on images
- 17 challenge entries (12 neural)
- **Problems**:
  - **accuracy** – lots of omissions & hallucinations
    - only 100% accurate system: hand-written templates
  - **diversity** – repetitive vs. inaccurate

```
name [Loch Fyne], eatType[restaurant],
food[Japanese], price[cheap],kid-friendly[yes]
```

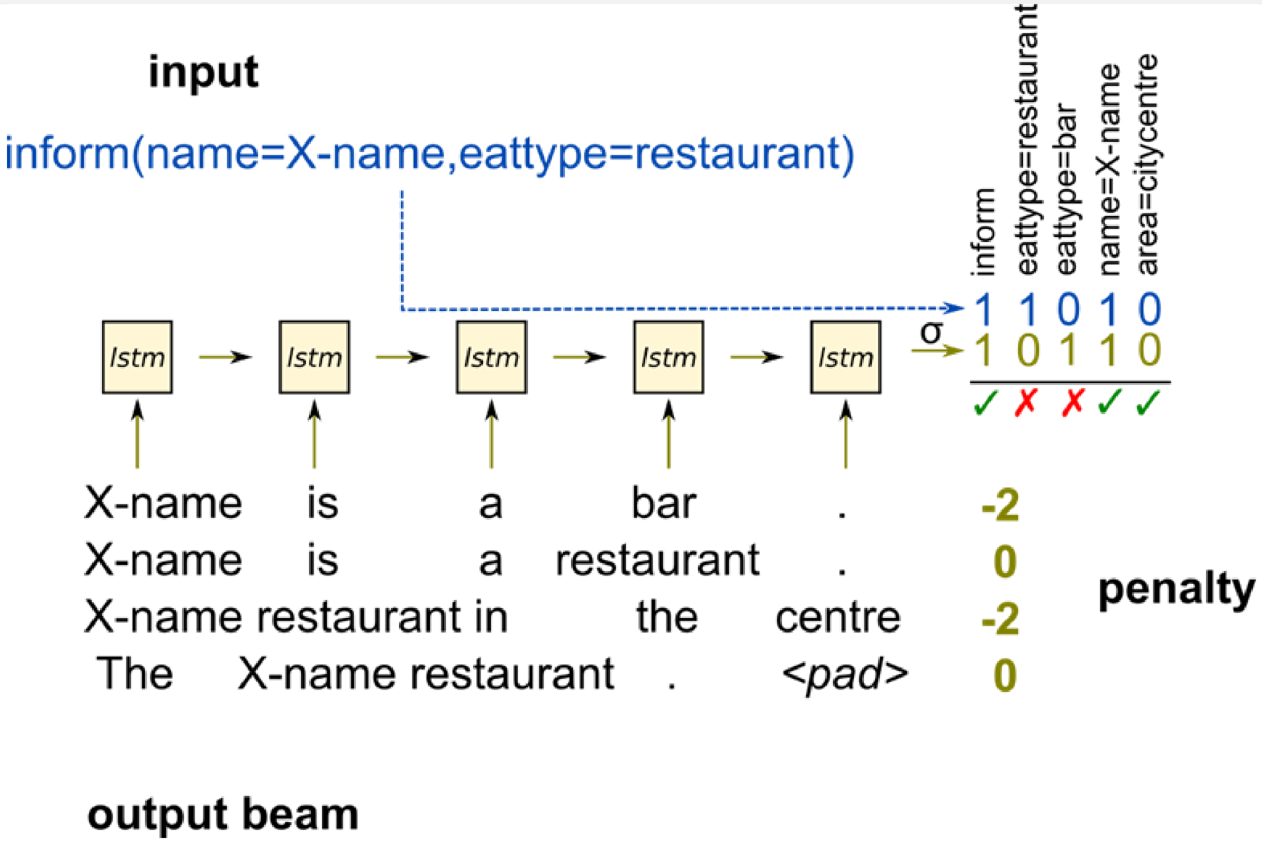
Loch Fyne is a kid-friendly restaurant serving cheap Japanese food.

Serving low cost Japanese style cuisine, Loch Fyne caters for everyone, including families with small children.

NLG1: Reranking

(Dušek & Jurčíček, 2016)
https://aclweb.org/anthology/P16-2008

- 2-step:
  1) Generate multiple outputs
     - beam search
  2) Rerank (penalize inaccuracies)
     - classify MRs
     - penalty for each difference w. r. t. input
- **TGen**
  - LSTM-based seq2seq with attention
  - LSTM-based MR classifier for ranking
- increases accuracy significantly
  - but still can't guarantee it completely
  - also, it's slow



system / E2E	BLEU	SER
Seq2seq	63.4	15.94%
TGen	66.4	4.27%

NLG2: Data cleaning

- NLG errors are often caused by **data errors**
  - ungrounded facts (← hallucination)
  - missing facts (← omission)
  - noise (e.g. source instead of target)
    - just 5% untranslated stuff kills an NMT system

(Khayrallah & Koehn, 2018)
https://www.aclweb.org/anthology/W18-2709

- Easy-to-get data are noisy
  - web scraping – lot of noise, typically not fit for purpose
  - crowdsourcing – workers forget/don't care
- E2E data: 11-17% slot error rate
  - approx. 40% references have ≥1 error

(Dušek et al., 2019)
https://www.aclweb.org/anthology/W19-8652/

- Rotowire: 40% ungrounded

(Wang, 2019)
https://www.aclweb.org/anthology/W19-8639/

NLG2: Data cleaning

(Dušek et al., 2019) https://www.aclweb.org/anthology/W19-8652/

- E2E data: SER evaluation script
  - based on regular expressions
  - can be used for data cleaning
- Keep text, adjust MR
  - works up to a point (SER 4.2%, 19% error refs)
  - keep test set, remove overlaps from train
- Retraining Seq2Seq&TGen on cleaned E2E
  - less training examples
  - still 94-97% SER reduction
  - confirmed by manual analysis
- Extensions:
  (Nie et al., 2019) https://www.aclweb.org/anthology/P19-1256
  - cleaning by a trained classifier (two-step)
  - generating more data (& checking)

(Kedzie & McKeown, 2019) https://www.aclweb.org/anthology/W19-8672/

Original MR and an accurate reference

MR name[Cotto], eatType[coffee shop], food[English], priceRange[less than £20], customer_rating[low], area[riverside], near[The Portland Arms]

Reference At the riverside near The Portland Arms, Cotto is a coffee shop that serves English food at less than £20 and has low customer rating.

Example corrections

Reference: Cotto is a coffee shop that serves English food in the city centre. They are located near the Portland Arms and are low rated.
Correction: removed price range; changed area
Reference: Cotto is a cheap coffee shop with one-star located near The Portland Arms.
Correction: removed area

A faulty correction

Reference: Located near The Portland Arms in riverside, the Cotto coffee shop serves English food with *a price range of $20* and a low customer rating.
Correction: incorrectly(!) removed price range
– our script's slot patterns are not perfect

system	data	BLEU	SER	
Seq2seq	original	63.4	15.94%	-94%
	cleaned	65.8	0.97%	
TGen	original	66.4	4.27%	-97%
	cleaned	66.2	0.12%	

NLG3: Additional Classification Tasks

(Peng et al., 2020) https://arxiv.org/abs/2005.05298
(Kulhánek et al., 2021) https://arxiv.org/abs/2102.05126

- Generate & classify at the same time
  - additional classification layer
  - on top of decoder – last layer logits, last step
- Aim: robustness – detect problems
  - ½ training data are artificially corrupted
    - corrupted state (does not fit context)
      - whole (SOLOIST)
      - per domain (AuGPT)
    - corrupted system response
- improves dialogue success
  - MultiWOZ (corpus-based & simulation)

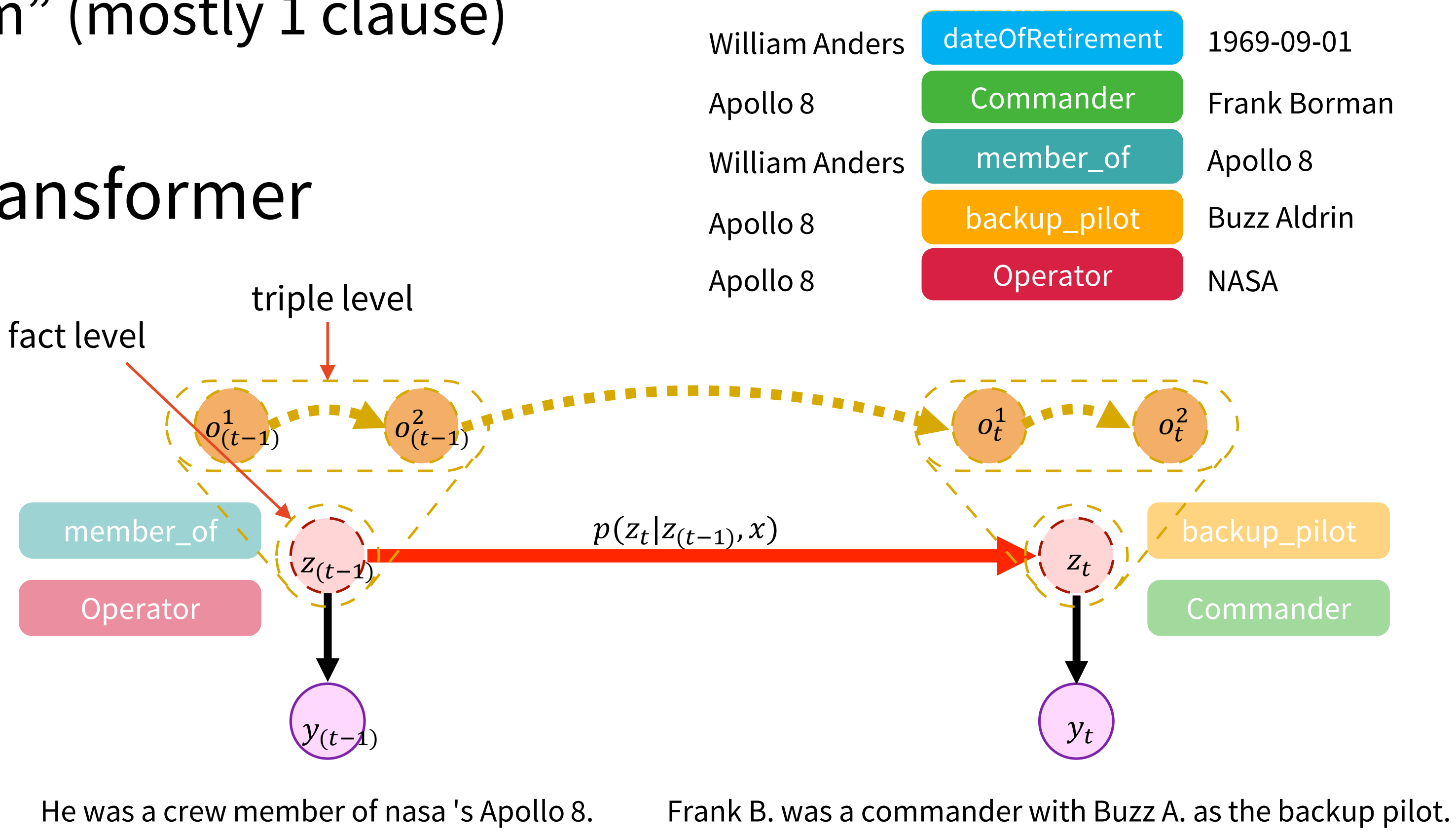
system	inform	success	BLEU
baseline	81.9	64.5	16.3
SOLOIST	81.4	65.8	17.0
AuGPT	83.5	67.3	17.2

	consistent?
i want a cheap italian restaurant { price range = cheap , food = Italian } ok which area ?	✓
i want a cheap italian restaurant { area = north , food = Indian } ok which area ?	✗
i want a cheap Italian restaurant { price range = cheap , food = Italian } what price range ?	✗

NLG4: Planning

(Xu et al., 2021)
https://arxiv.org/abs/2106.05580

- Add an explicit planning step (ordering & aggregation)
- Split texts into **facts** by SRL
  - ~1 event "who did what to whom" (mostly 1 clause)
  - ~1 or more input triples
- Hierarchical HMM planner + Transformer
  1) order triples
  2) aggregate into facts
  3) generate each fact
     - condition on triples for current fact only
- trained: backward algorithm
  - end-to-end with generation
  - no explicit annotation needed



NLG4: Planning

(Xu et al., 2021)
https://arxiv.org/abs/2106.05580

- Stays fluent + is more accurate
  - less “compressed” outputs than Transformer
- Allows explicit control
  - order & aggregation of triples is visible
    - interpretable, allows direct evaluation
  - you can set it manually
    - or set a parameter to control aggregation
- Needs some hacks to make it tractable
  - max. 3 triples per fact, partial hard alignment
- Still not a complete control
  - Transformer may hallucinate

system / E2E	BLEU	SER
TGen	66.4	4.27
Transformer	68.2	5.16
AggGen	64.1	2.16

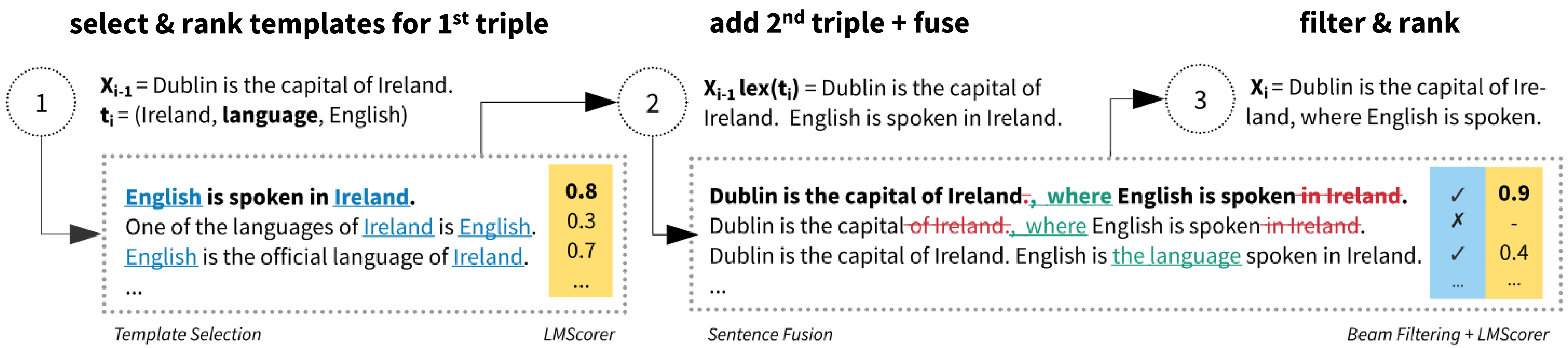
order & agg.	K-τ_{max}	K-τ_{avg}
Human	0.84	0.25
AggGen	0.64	0.21

see also: (Wiseman et al., 2018) http://aclweb.org/anthology/D18-1356
(Moryossef et al., 2019) https://www.aclweb.org/anthology/N19-1236/

NLG5: Iterative Editing

(Kasner & Dušek, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.9

- Concatenate templates & fuse them into sentences by a neural model
  - Template-based generation is accurate
  - Neural model only fuses sentences together
    - Less power = less opportunity to screw up
  - Inaccuracies filtered out & fallback to templates – ensures 0 entity errors
  - Ranking by fluency (neural model)



NLG5: Iterative Editing

(Kasner & Dušek, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.9

- Templates: 1 triple only (extracted from training data + handcrafted + backoff)

Arrabiata sauce | country | Italy

default → *The <subject> is found in <object>.* → *The Arrabiata sauce is found in Italy.*

backoff → *The <predicate> of <subject> is <object>.* → *The country of Arrabiata sauce is Italy.*

- Neural model: LaserTagger – BERT encoder & Transformer decoder
  - vocabulary limited (100 tokens): KEEP, DELETE, ADD word, ADD more words
- Fluency: vanilla GPT-2 geom. mean token cond. probability
- Semantic filter: entity match (regex/exact)
- Accurate but fluency suffers
  - fallback steps (no fusion): 28% E2E & 54% WebNLG
  - no reordering possible

	WebNLG		Clean E2E	
system	BLEU	METEOR	BLEU	METEOR
templates	27.7	37.9	20.7	33.4
fusion	35.3	38.6	25.2	33.8
T5 (~SotA)	57.1	44.0	42.1	38.5

(Kale & Rastogi, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.14
https://www.aclweb.org/anthology/2020.emnlp-main.527

Evaluating NLG Accuracy

- n-gram metrics (BLEU, METEOR)
  - derived from MT, no good for accuracy
  - dubious even as measures for overall quality

(Reiter, 2018) https://ehudreiter.com/2018/11/12/hallucination-in-neural-nlg/

(Liu et al., 2016) https://aclanthology.org/D16-1230/
(Novikova et al., 2017) http://aclweb.org/anthology/D17-1238

- Neural metrics (BERTScore, BLEURT) mix accuracy & fluency
  - slightly better than n-gram, but still not ideal

(Zhang et al., 2020) http://arxiv.org/abs/1904.09675
(Sellam et al., 2020) https://aclanthology.org/2020.acl-main.704/

- SER evaluation uses regex or exact match
  - tedious to make / inaccurate
  - does not translate to other datasets
- Proper evaluation means full NLU
  - pretrained models are quite good at NLU-like tasks → use them?

Eval1: Natural Language Inference Classification

(Dušek & Kasner, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.19

- NLI task – relation of premise (= starting point) & hypothesis (= relating text)
  - **E**ntailment = all hypothesis facts are included in premise
  - **N**eutral = not all hypothesis facts included, but no directly opposing facts
  - **C**ontradiction = premise is opposed by hypothesis

P: *Blue Spice is a pub in the riverside area.*

H$_1$: *Blue Spice is located in the riverside.* ⟶ **E**

H$_2$: *You can bring your kids to Blue Spice .* ⟶ **N**

H$_3$: *Blue Spice is a coffee shop.* ⟶ **C**

- We'll use a vanilla model trained for NLI
- Check entailment in both directions
  - data entails text = no hallucination + text entails data = no omission
- Use templates to represent data (as in iterative editing)
  - needed, unlike summarization / open-domain dialogue

(Maynez et al., 2020)
https://www.aclweb.org/anthology/2020.acl-main.173
(Welleck et al., 2019)
https://www.aclweb.org/anthology/P19-1363

Eval1: NLI Classification

(Dušek & Kasner, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.19

1) **Check for omissions**
   - premise = whole generated text
   - hypothesis = each single fact, loop
     → also checks which fact is omitted

2) **Check for hallucination**
   - premise = concatenated facts
   - hypothesis = whole generated text
     - can't easily split into simpler checks

- output:
  - 4-way – *OK, omission, hallucination, o+h*
  - 2-way – *OK, not_OK*
  - OK confidence (min. **E** confidence)
  - list of omitted facts

Blue Spice | eat_type | pub
Blue Spice | area | riverside

NLG

You can bring your kids to Blue Spice in the riverside area.

P: *You can bring your kids to Blue Spice in the riverside area.*

$\mathbf{H_1}$: Blue Spice is a pub. C: 0.01 N: **0.97** E: 0.02
→ *omission*

$\mathbf{H_2}$: Blue Spice is located in the riverside. C: 0.00 N: 0.01 E: **0.99**
→ *OK*

P: *Blue Spice is a pub. Blue Spice is located in the riverside.*

H: *You can bring your kids to Blue Spice in the riverside area.*

C: 0.00 N: **0.99** E: 0.01
→ *hallucination*

---

omission+hallucination

OK: 0.01 omitted: Blue Spice | eat_type | pub

Eval1: NLI Classification

(Dušek & Kasner, 2020)
https://www.aclweb.org/anthology/2020.inlg-1.19

- NLI model: **RoBERTa-large-MNLI**, used as-is (no finetuning)
- WebNLG & E2E data
  - comparison vs. human ratings (WebNLG) & SER script (E2E)
  - both datasets: default & backoff-only versions of templates

system	WebNLG 2-way	E2E 4-way	E2E 2-way
Default templates	77.5%	91.1%	93.3%
Backoff template	76.8%	84.6%	87.4%

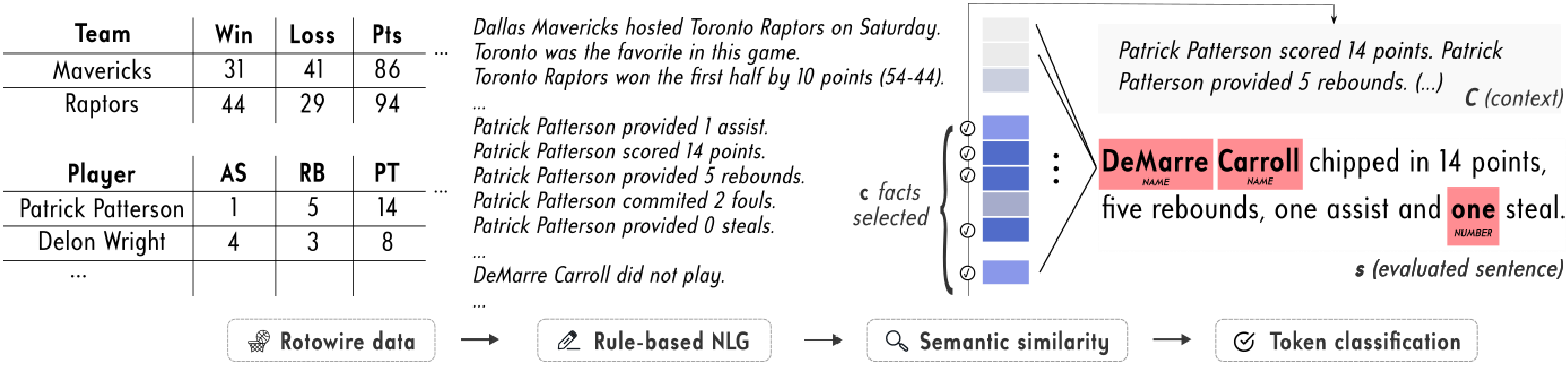
- manual analysis: ca. ½ “errors” are in fact correct
  - annotation noise / SER script errors
  - mined templates noise for WebNLG
  - edge cases (*high restaurant*)
  - irrelevant stuff that SER script doesn’t catch (*with full service*)

Eval2: Token-level Error Detection

(Kasner et al., 2021)
INLG Accuracy Evaluation shared task

- Not just OK/not checks, also identify individual errors
  - good for longer texts – Rotowire basketball summaries
- 3-stage:
  1) **convert input** table into texts (templates / rules) ← whole summary
  2) **select** relevant **context** using SBERT embedding similarity
  3) **tag errors** given context using RoBERTa with token-level classification head

  for each sentence



Eval2: Token-level Error Detection

(Kasner et al., 2021)
INLG Accuracy Evaluation shared task

- Training data:
  - 60 annotated NLG output summaries
  - Synthetic errors introduced into Rotowire training set (3.8k summaries)
    - only random replacement of names & numbers
- Best setup:
  - rule-based generator (more compact contexts)
  - using synthetic data, with 25% errors
  - contexts of 40 sentences (~what fits into RoBERTa)
- Evaluation: 30 annotated summaries
  - best out of 3 systems
  - still lagging behind human evaluation
  - the task is much more difficult than just OK/not OK

team	Recall	Prec
Laval (human eval)	84.1%	87.9%
Charles + UPF	69.1%	75.6%
NIJL	52.3%	49.4%
Eurocom	8.0%	31.1%

Summary

- Neural models produce very fluent outputs
  - especially true of pretrained Transformer LMs
  - due to data & model reasons, not guaranteed to be accurate
- There are ways to make them more accurate
  - reranking / data cleaning / multi-tasking / editing templates
  - always constraining the neural component
  - there are always downsides
    - lower speed, worse fluency, more annotation needed
- Finding errors in NLG is as hard as NLU
  - pretrained LMs are good at some NLU tasks, such as NLI → can be applied
  - works quite on well sentence-level, token level is hard
- Other interesting areas: data augmentation, few-shot, open domain

Thanks

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