2. Model Design

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2-1. Example model: LaserTagger (2019)

Malmi, Krause, Rothe, Mirylenka, Severyn. *Encode, Tag, Realize: High-Precision Text Editing*. EMNLP 2019 (pdf)

High-Overlap Example: Sentence Fusion

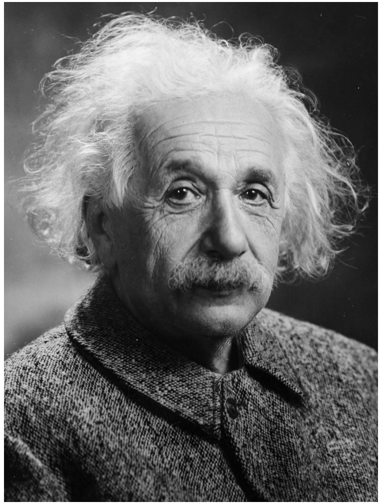
Given two or more answers, fuse them into a single coherent answer.

-- Example --

Query: [einstein birth and death]

Answers:

- Albert Einstein was born in 1879.
- Albert Einstein died in New Jersey.
- Albert Einstein died at the age of 76.



Fusion: Albert Einstein was born in 1879 and he died in New Jersey at the age of 76.

Sentence Fusion via Text Editing

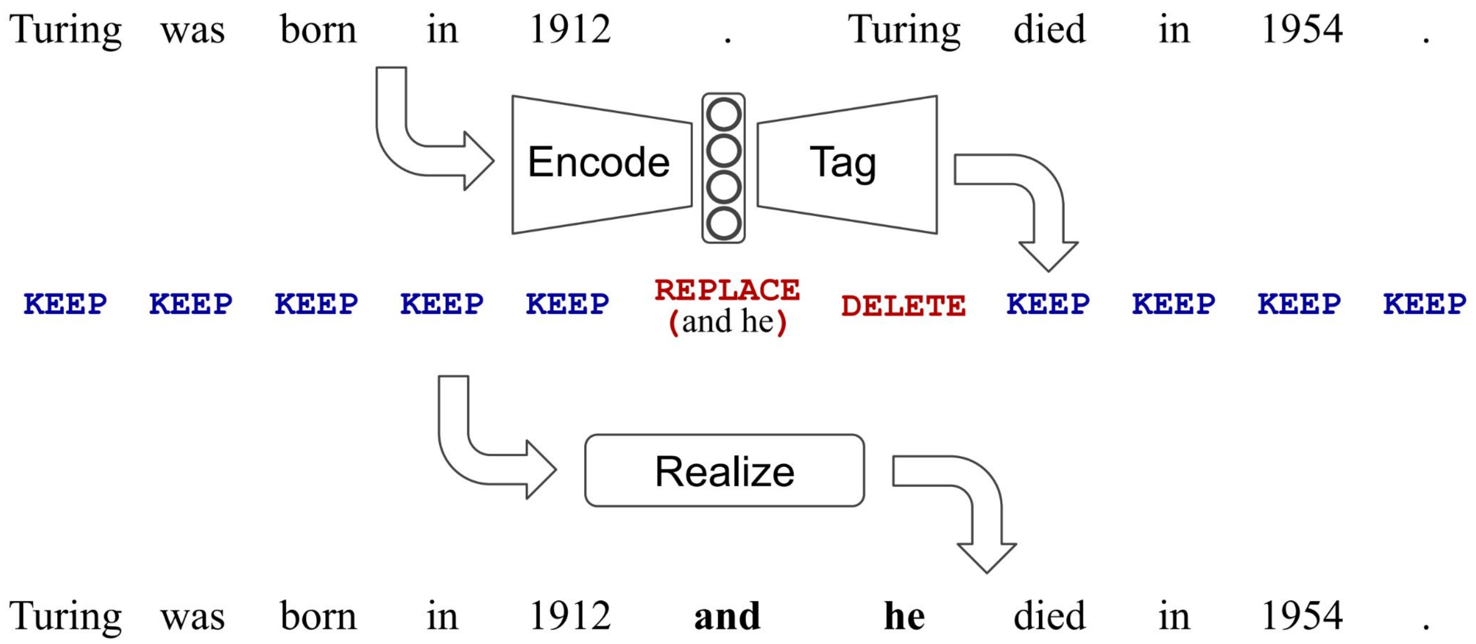
Observation: High overlap between the answers and the fusions.

Fusion requires mainly:

- Deleting repeated phrases
- Adding short glue phrases

Solution: Predict edit operations instead of generating from scratch.

LaserTagger



Malmi, Krause, Rothe, Mirylenka, Severyn. *Encode, Tag, Realize: High-Precision Text Editing*. EMNLP 2019 ([pdf](pdf))

LaserTagger: Key Ingredients

- **Convert** training target texts into **target tag** sequences.
  - Tag = Base tag {KEEP, DELETE} + added phrase
  - Additionally: SWAP tag to reverse sentence order
- **Phrase vocabulary:** Set of phrases the model can add.
  - Counters hallucination
  - Optimized to cover as many training examples as possible
- **Tagging Model:** BERT (+ 1-layer Transformer decoder)

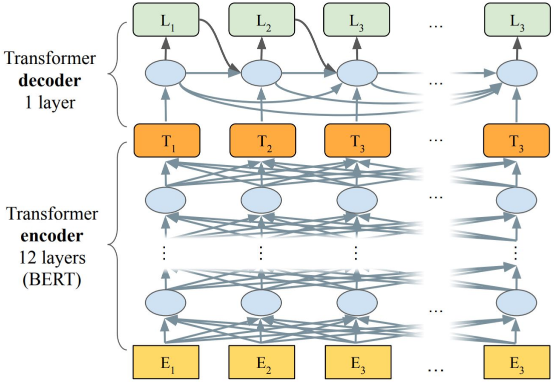


Figure 3: The architecture of LASERTAGGER$_{AR}$.

Source: Malmi et al. 2019 (pdf).

LaserTagger's Limitations

1. Realized text is sometimes unnatural since we only pretrain the encoder.
2. Limited phrase vocabulary can be too restrictive.
3. Reordering words is difficult.

2-2. Model landscape

Anatomy of a text-editing model

Encoder

- What edit operations to use?
- Tagging architecture?
- Auto-regressive vs. feed-forward?

Pointer

- How to reorder words?

Decoder

- How to insert words / phrases?

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2-3. Edit-operation types

Basic Edit-Operation Types

1. KEEP: Keeps the current token
2. DELETE: Deletes the current token
3. REPLACE: Replaces the current token
    a. REPLACE_X: Replace with a **specific token/phrase X** (e.g. LaserTagger, GECToR)
    b. REPLACE: Replace with a placeholder and use a **separate insertion component** to fill the blank (e.g. EditNTS, Felix, LEWIS)
4. APPEND / PREPEND: Inserts new token(s) next to the current token

REPLACE_X, APPEND_X, PREPEND_X

- Separate edit operation for each insertion x ∈ X where X is a predefined set of possible insertions
  - REPLACE_the, REPLACE_a, etc.
- Pros
  - Counters hallucinations (more on this later)
- Cons
  - X can become very large when having to do multi-word insertions
  - Hard to leverage pre-trained LMs to determine a good insertion

DfWiki	WikiSplit	AS	GEC
,	.␣⟨::::⟩	,	,
and	,	.	.
however␣,	.␣⟨::::⟩␣he	the	the
,␣but	.␣⟨::::⟩␣it	a	a
he	the	&	to
because	and	and	in
,␣although	was	is	of
but	is	in	on
,␣and	"	"	at
although	.␣⟨::::⟩␣she	's	for
his	.␣⟨::::⟩␣it␣is	with	have
,␣while	a	for	is
it	.␣⟨::::⟩␣they	of	was
,␣which	.␣⟨::::⟩␣however	n't	and
she	he	an	that

Table 1: The 15 most frequently added phrases in the datasets studied in this work, in order of decreasing frequency. ⟨::::⟩ marks a sentence boundary. "AS"/"GEC" is short for Abstractive Summarization/Grammatical Error Correction.

Source: LaserTagger paper (Malmi et al. 2019).

Other Edit-Operation Types

- SWAP: Swap the order of this and the previous sentence

Source:	Dylan	won	Nobel	prize	.	Dylan	is	an	American	musician	.
Tags:	DELETE	KEEP	KEEP	KEEP	SWAP	KEEP	*comma*DELETE	KEEP	KEEP	KEEP	*comma*DELETE
Realization:	Dylan , an American musician , won Nobel prize .										

- PRONOMINALIZE: Replace this entity with a pronoun (look up gender from a knowledge base)
- NOUN_NUMBER_SINGULAR: Convert noun to singular form
    a. Other grammar-related edit operations discussed in the Applications section

2-4. Tagging architecture + auto-regressiveness

Types of Models

Two major types of models used for tagging

Autoregressive (AR)

- Condition on previous predictions
- Seq2Seq
- Slow*

Non-Autoregressive (NAR)

- Predict simultaneously
- Feedforward NN
- More prone to errors
- Fast*

Case study: LaserTagger

LaserTagger supports **AR** and **NAR** version allowing for a direct comparisons

- Across **4** tasks AR outperforms NAR
  - Up to **7%** difference but as little as **1%**
- At a **40x** increase in latency (on GPU)
  - **13ms to 535ms**
- Trade off between **speed** and **performance**

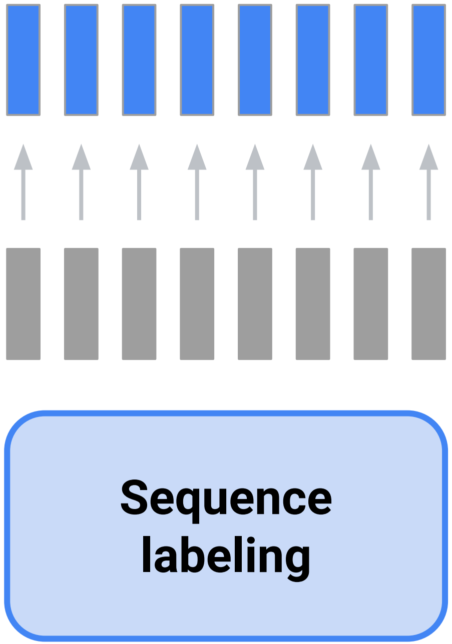
Non-AutoRegressive

Sequence labeling task

1. Encode source
2. For each token **predict a label**
    a. Maximize gold tag probability in training

$$P(y|x) = \prod_{i}^{|y|} P(y_i|x)$$

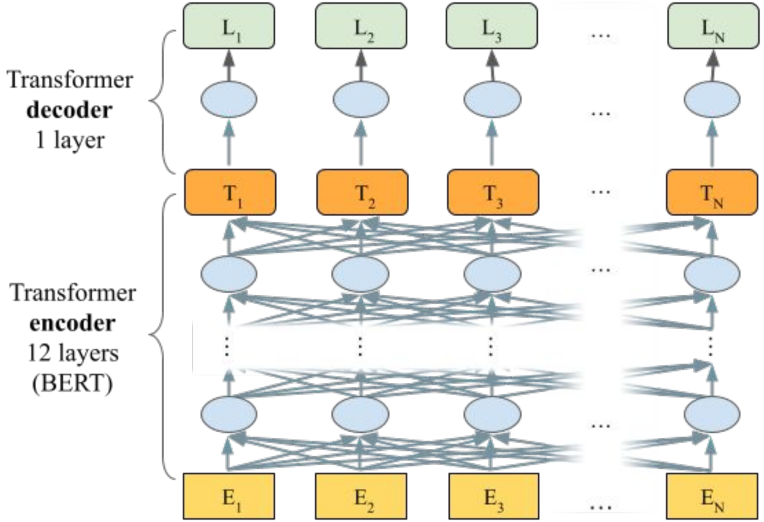
    b. Argmax in prediction



Non-AutoRegressive

1. **Encode source sentence**
   a. **Pre-trained** NAR models
   b. **BERT**: Felix, LaserTagger, GECToR
   c. **XLNet** : GECToR
2. **Predict the tags**
   a. Single layer Feedforward
   b. Output size: **2 - 1000** tags
   c. Each hidden state gets a single tag

Difficult to generate arbitrary outputs



Source: Malmi et al. 2019 (pdf).

Non-AutoRegressive Agreement

NAR runs the risk of the edits not agreeing with each other

```
Source:          "We have an apples"
```

```
NAR Prediction: "We have some apple"
```

```
AR Prediction:   "We have an apple"
                 "We have some apples"
```

NAR don't condition on past edits

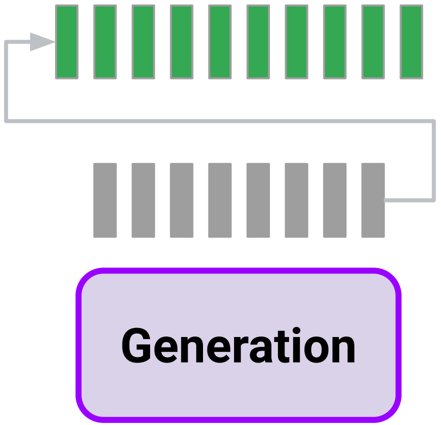
Agreement issues:

- Direction
- Grammar
- Subwords

NAR don't apply layers multiple times

Auto-Regressive

- Encode source
- Decode edit-by-edit
  - Condition on **previously decoded edit**
- RNN/Transformer
  - **Pre-trained AR**
  - **T5**: EdiT5
  - **BART**: LEWIS



$$P(y|x) = \prod_{i}^{|y|} P(y_i|y_{<i}, x)$$

Iterative Refinement

- Apply the model to its **own output**
  - Each iteration increases performance but adds latency
- Commonly used for GEC
- Can be used with any type of model
  - GECToR, PIE, Seq2Edits

Iteration #	P	R	$F_{0.5}$	# corr.
Iteration 1	72.3	38.6	61.5	787
Iteration 2	73.7	41.1	63.6	934
Iteration 3	74.0	41.5	64.0	956
Iteration 4	73.9	41.5	64.0	958

Table 4: Cumulative number of corrections and corresponding scores on CoNLL-2014 (test) w.r.t. number of iterations for our best single model.

GECToR – Grammatical Error Correction: Tag, Not Rewrite (Omelianchuk et al., BEA 2020)

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Reordering

Most text-editing apply their models left-to-right

Reordering allows us to model

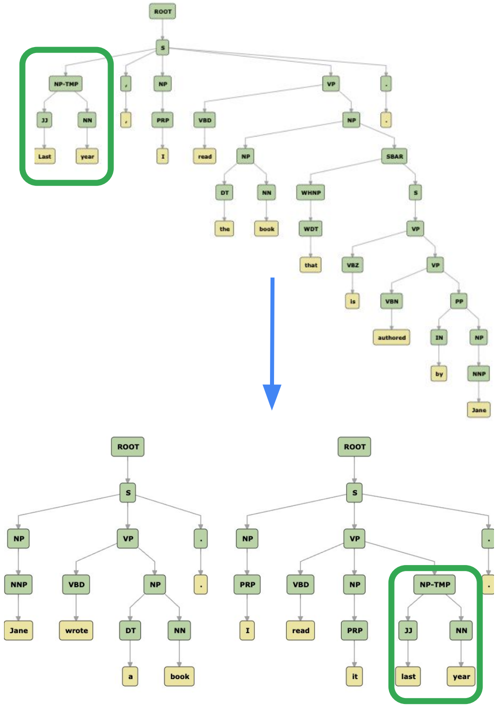
- Large syntactic changes
- Local changes

Without the need to **delete then insert**

Last year, I read the book that is authored by Jane.

[Original sentence]

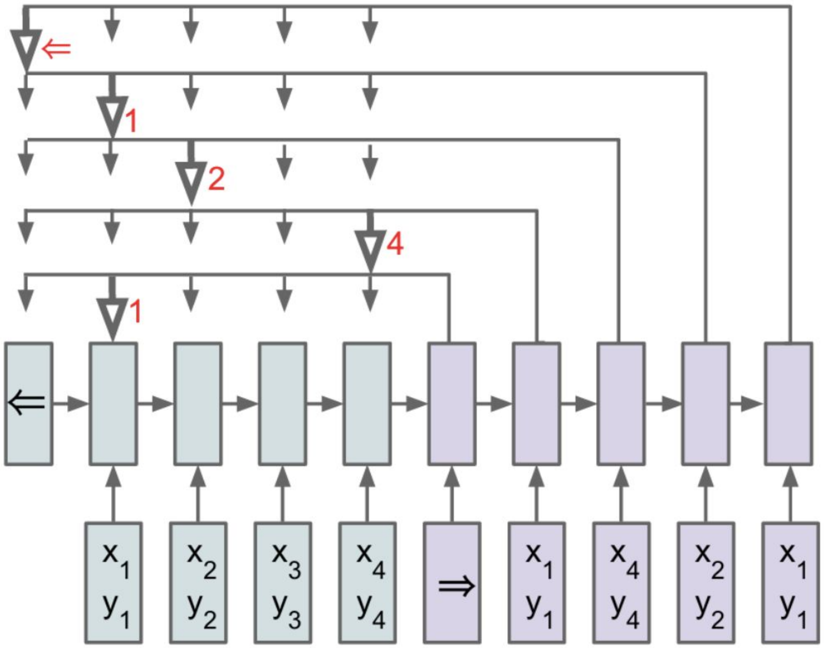
Jane wrote a book.
I read it **last year**.



AutoRegressive Reordering

Implemented using pointer network

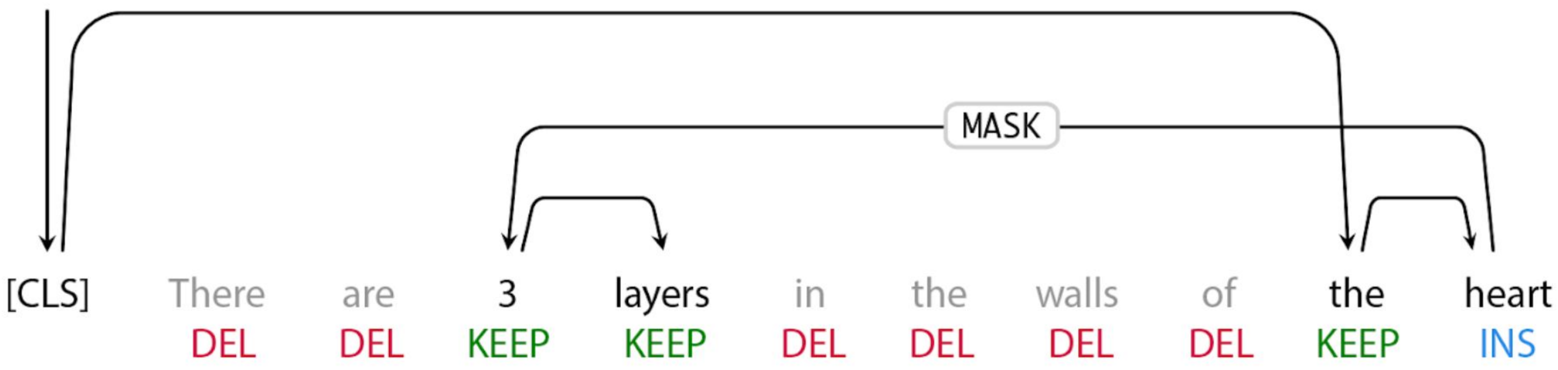
- When decoding use a **cross-attention**
- The source token with the highest attention is copied to the target
- Can copy the same source token multiple times



Source: Pointer networks paper (Vinyals et al., 2015).

Non-AutoRegressive Reordering

- **Self-attention** pointer network which are **daisy chained**
  - Attention between encoder hidden states
  - Felix & EdiT5
- Can only copy each source token once



Source: Felix paper (Mallinson et al. 2020).

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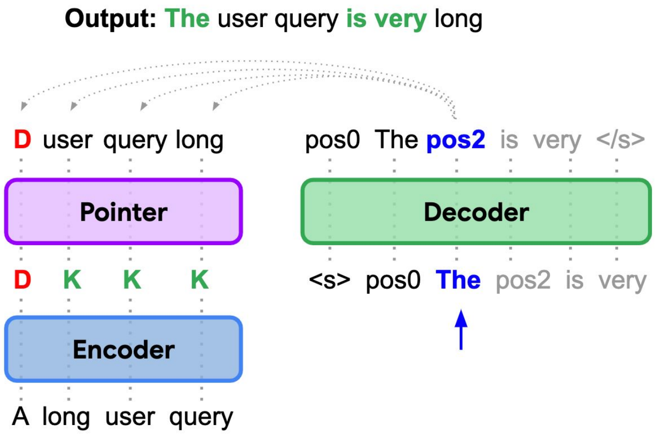
Separate Insertion Component

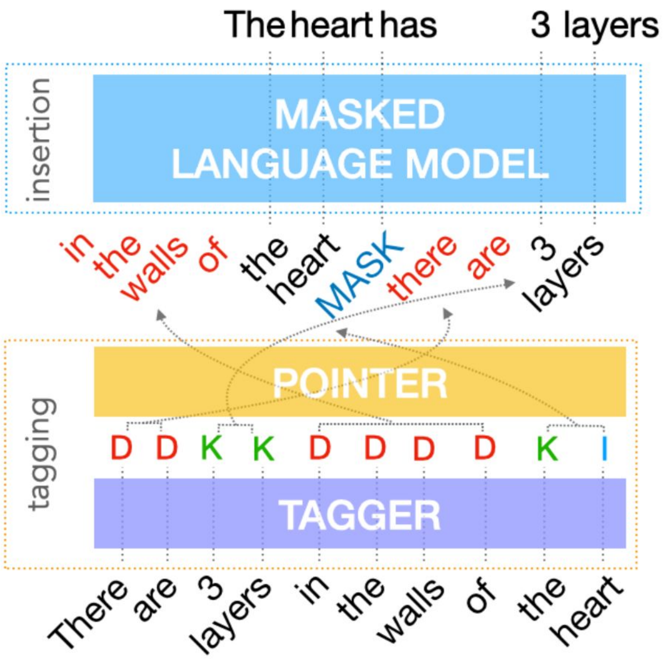
- Tagger predicts **where** to insert;
  a separate component **what** to insert
- Different insertion architectures
  - RNN (EditNTS)
  - BERT MLM (Felix, Masker)
  - Transformer decoder (Seq2Edits, EdiT5, LEWIS)



Source: EdiT5 paper (Mallinson et al. 2022).

Felix

- Idea 1: **Separate** insertion from tagging
  - Leverage pretrained BERT
- Idea 2: Predict word order using a **pointer network**



Source: Felix paper (Mallinson et al. 2020).

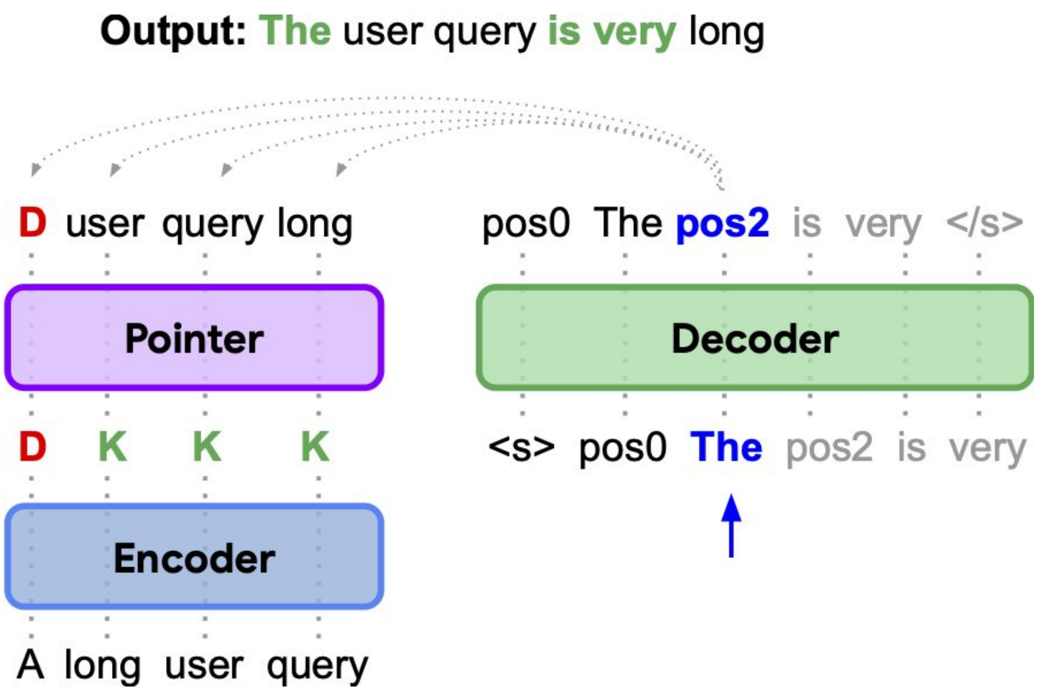
Insertion

- The output of the tagging model is the reordered input text with deleted words and MASK tokens
- The insertion model predict the content of MASK tokens
- Very similar to the **pretraining objective of BERT**

Source:	The	hearts	consist	of			layers
Tags:	DEL	KEEP	KEEP	KEEP$^{\text{INS_2}}$			KEEP
Insertion input:	[R] The [/R]	hearts	consist	of	MASK	MASK	layers
Prediction:		hearts	consist	of	many	different	layers

Source: Felix paper (Mallinson et al. 2020).

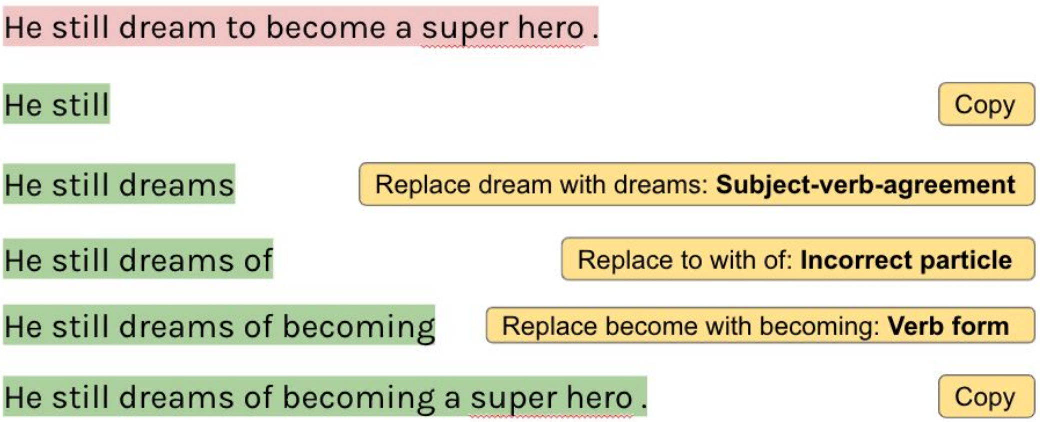
EdiT5



- **Idea 1:** Join insertion and tagging
  - Leverage **pretrained T5 models**
- **Idea 2:** Use autoregressive decoding on the small number of inserted tokens
- Decoder first predicts the location of the new text then decodes new tokens

Source: EdiT5 paper (Mallinson et al. 2022).

Seq2Edits: A model that can rewrite and explain



- Contains 3 sub-models for predicting tags, span-end positions and replacement tokens
- The model is able to provide explanations for each edit operation
- By avoiding unnecessary copying of input spans, it is up to 5 times faster than a regular seq2seq model

Source: Seq2Edits paper (Stahlberg and Kumar, 2020).

Overview of Text-Editing Models

Method	Non-autoregressive	Pre-trained decoder	Reordering	Unsupervised	Language-agnostic	Application(s)
EdiT5 (Mallinson et al., 2022)	(✓)	✓	✓		✓	*multiple*
EditNTS (Dong et al., 2019)					✓	Simplification
Felix (Mallinson et al., 2020)	✓	✓	✓		✓	*multiple*
GECToR (Omelianchuk et al., 2020)	✓	(✓)				GEC
LaserTagger (Malmi et al., 2019)	✓				✓	*multiple*
LevT (Gu et al., 2019)	(✓)	✓			✓	*multiple*
LEWIS (Reid and Zhong, 2021)		✓		✓	✓	Style Transfer
Masker (Malmi et al., 2020)	✓	✓		✓	✓	*multiple*
PIE (Awasthi et al., 2019)	✓	✓				GEC
Seq2Edits (Stahlberg and Kumar, 2020)					(✓)	*multiple*
SL (Alva-Manchego et al., 2017)	✓		✓		✓	Simplification

2-5. Converting target texts to target edits

Edit types

There are multiple different ways that one sentence can be edited into another:

- Edit operation types (insert, delete, replace, append, prepend, reorder…)
- Token-level vs. span-level edits
- Tagged vs. untagged edits
- Alignment algorithm

Example

Source: i like films when i was younger i watched on **TV**

Target: i like films i watched on **television** when i was younger

- We could delete everything and then use *insert* everything
- is TV a delete and insert after on? or singe a replace
- Do we want to reorder or delete everything after i like films?
- What should the i align to?

Questions?