Fast Text Generation with Text-Editing Models

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https://text-editing.github.io/

Slides

https://textedit.page.link/slides

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Presenting today

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Goals

1. Present an overview of the research on Text-Editing models
    a. Focus on general themes rather than individual models
2. Provide practical guidelines for *when* and *how* to apply Text-Editing models

Outline

1. **What are text-editing models?** [15 min; Eric]
2. **Model design** [35 min; Eric, Jonathan]
   - Main components of editing models; obtaining target edits
3. **Applications** [35 min; Eric, Yue]
   - GEC, Style Transfer, Utterance Rewriting, Simplification
4. **Controllable generation** [25 min; Yue]
   - Hallucinations, dataset generation, etc.
5. **Multilingual text editing** [15 min; Yue]
6. **Faster (Large) Language Models** [40min; Jonathan]
7. **Recommendations and future directions** [5 min; Eric]

10:30-11:00 Coffee break ☕

What Are Text-Editing Models?

Text-editing models **generate** natural language by applying **edit operations** to the **input text** to produce the **target text**

Motivation

- Most NLP tasks besides MT are **monolingual**
- Sources and targets often **overlap**
  - Generating the target from scratch is **wasteful**
  - Target can be reconstructed from the source via basic ops like KEEP, DELETE, **INSERT**

Turing	was	born	in	1912	.	Turing	died	in	1954	.
KEEP	KEEP	KEEP	KEEP	KEEP	DEL INS	PRON	KEEP	KEEP	KEEP	KEEP
Turing	was	born	in	1912	and	he	died	in	1954	.

Poll:

How many of you have used
a text-editing model?

Let’s review some NLG tasks

Application	**Example** Source (S) and target (T) text	**Use Text Editing?**
Machine translation	S: Turing studied at King's College, where he was awarded first-class honours in mathematics. T: Turing studierte am King's College, wo er erstklassige Auszeichnungen in Mathematik erhielt.	✕

Let’s review some NLG tasks

Application	**Example** Source (S) and target (T) text	**Use Text Editing?**
Machine translation	S: Turing studied at King's College, where he was awarded first-class honours in mathematics. T: Turing studierte am King's College, wo er erstklassige Auszeichnungen in Mathematik erhielt.	✗
Summarization	S: Court members Deborah Poritz and Peter Verniero didn’t participate in the Nelson case. T: Two court members didn’t participate in the case.	?

Let’s review some NLG tasks

Application	Example Source (S) and target (T) text	Use Text Editing?
Machine translation	S: Turing studied at King's College, where he was awarded first-class honours in mathematics. T: Turing studierte am King's College, wo er erstklassige Auszeichnungen in Mathematik erhielt.	✗
Summarization	S: Court members Deborah Poritz and Peter Verniero didn’t participate in the Nelson case. T: Two court members didn’t participate in the case.	?
Sentence fusion	S: Turing was born in 1912. Turing died in 1954. T: Turing was born in 1912 and he died in 1954.	✓

Let's review some NLG tasks

Application	Example Source (S) and target (T) text	Use Text Editing?
Machine translation	S: Turing studied at King's College, where he was awarded first-class honours in mathematics. T: Turing studierte am King's College, wo er erstklassige Auszeichnungen in Mathematik erhielt.	✗
Summarization	S: Court members Deborah Poritz and Peter Verniero didn't participate in the Nelson case. T: Two court members didn't participate in the case.	?
Sentence fusion	S: Turing was born in 1912. Turing died in 1954. T: Turing was born in 1912 and he died in 1954.	✓
Grammar correction	S: New Zealand have a cool weather. T: New Zealand has cool weather.	✓

Applications often studied in the Text-Editing literature

- Grammatical Error Correction (GEC)
- Text Simplification
- Sentence fusion
- Style transfer
- Sentence splitting & rephrasing & fusion
- Text normalization
- Text summarization
- Automatic post-editing for machine translation

Text-editing models: key characteristics

Key assumption

- High **overlap** between the input and the output

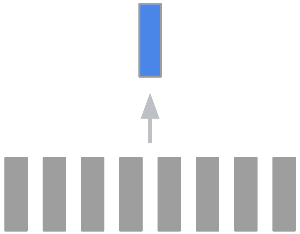
Generation

- **Delegates** part of the generation to the encoder

Key benefits

- **Faster inference** and on-par quality with seq2seq

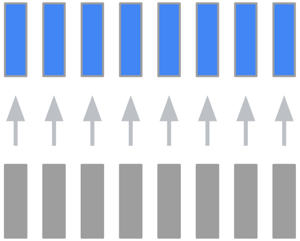
NLP tasks map



Classification

Task
- Single label
- binary, multi-class

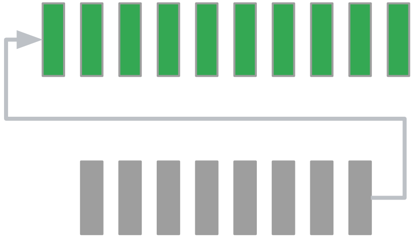
Model
- Encoder



Sequence labeling

Task
- Per token label
- Small softmax

Model
- Encoder

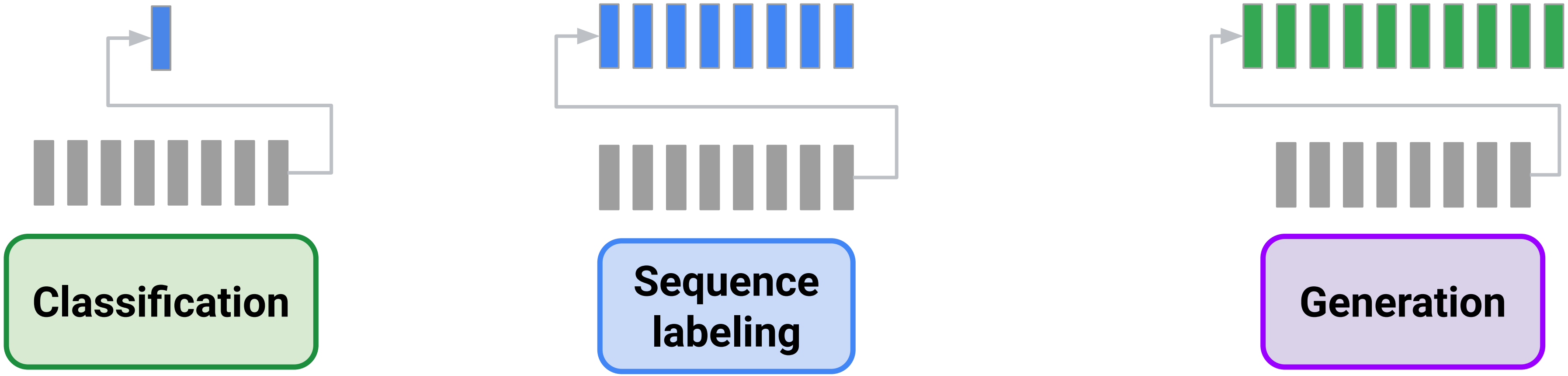


Generation

Task
- New sequence
- Large softmax

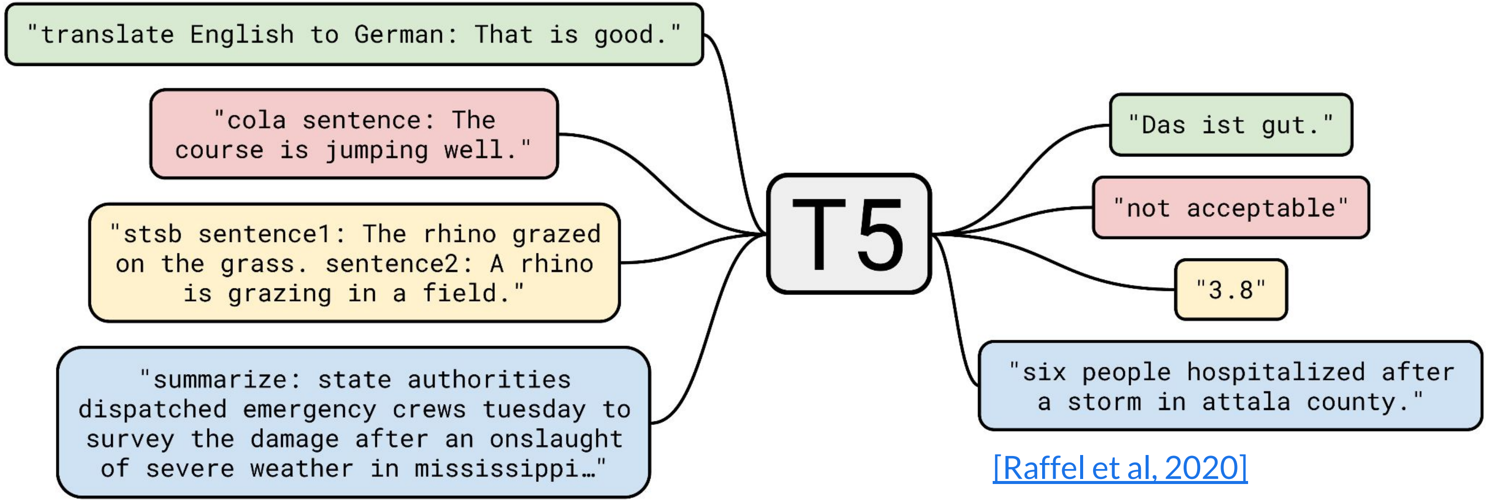
Model
- Encoder + decoder

Trend #1: Generation is all you need



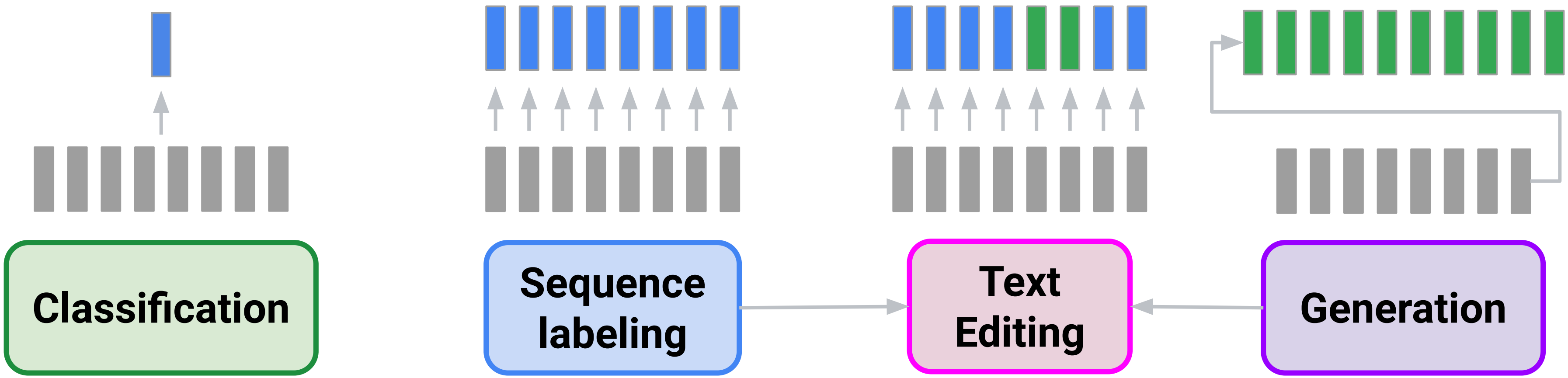
- seq2seq can also generate classification labels and do sequence labeling

LLMs like T5 also excel across various NLP tasks



[Raffel et al, 2020]

Where does Text Editing fit?



Task
- Single label (binary, multi-class)

Model
- Encoder + softmax

Latency
- Fast (feed-forward)

Task
- Per token label
- Small softmax

Model
- Encoder + softmax

Latency
- Fast (feed-forward)

Task
- Tagging + Insertion
- small/large softmax

Model
- Encoder + decoder

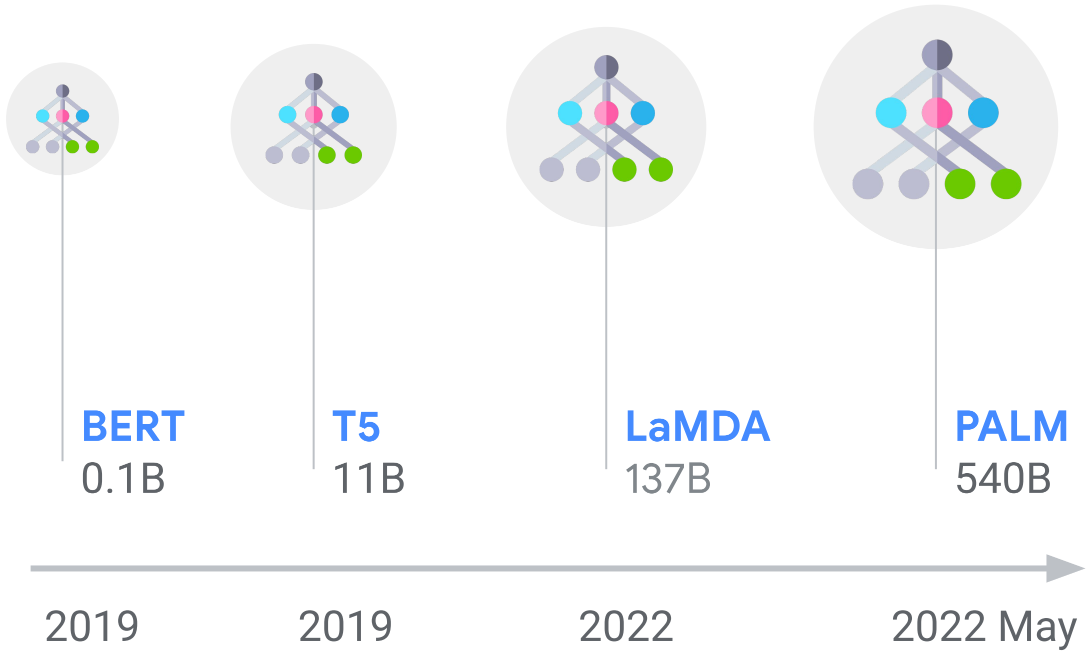
Latency
- Fast

Task
- New sequence
- Large softmax

Model
- Encoder + decoder

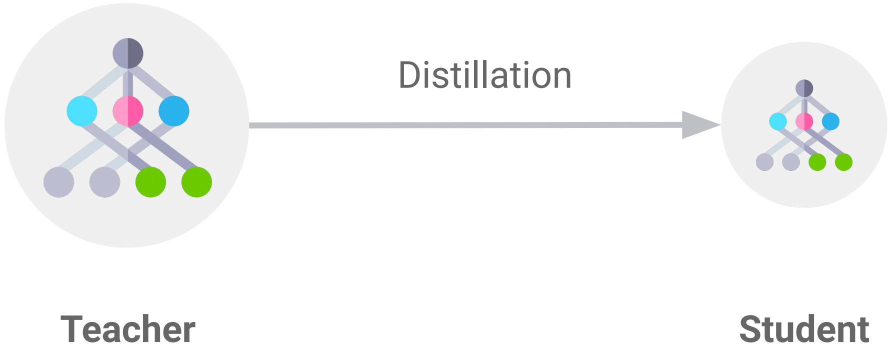
Latency
- Slow (autoregressive)

Trend #2: Scale is all you need



- Larger pretraining data
- More model params
- Slow & expensive **inference**

How to productionize?



- Trade-off between model size, accuracy and latency
- Student networks are often **autoregressive**

Text-Editing models leverage inductive bias (high overlap) to:

1. Make **inference** faster without compromising the quality
2. Simplify the task (smaller output space) to make models more **data efficient**

Text Editing Advantages

Data efficient	Text Editing models need less training data.
Latency	Can be >10x faster inference.
Faithfulness	Constraining decoders in seq2seq is an active area of research
Control	We can control the word a model can add / remove. Can incorporate external knowledge (e.g., pronoun).

Questions?