Summarization and text generation

HSE
22.11.2021
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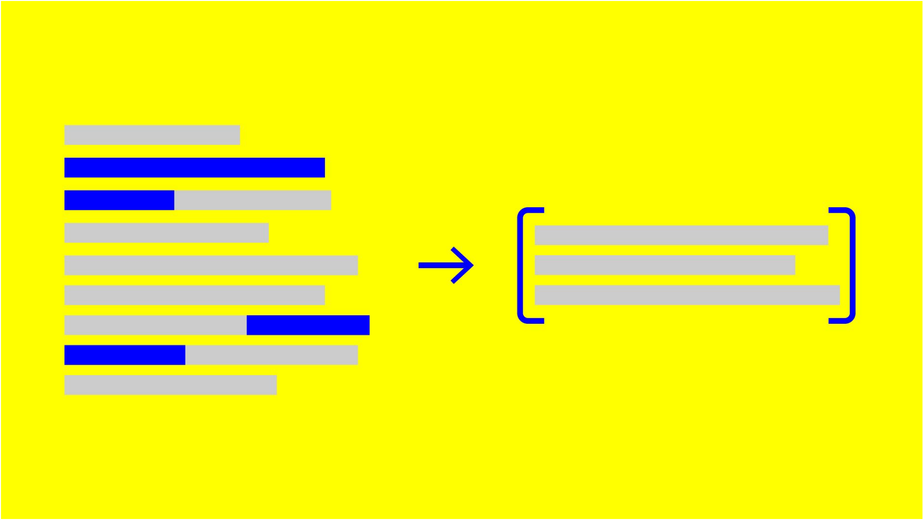
Today

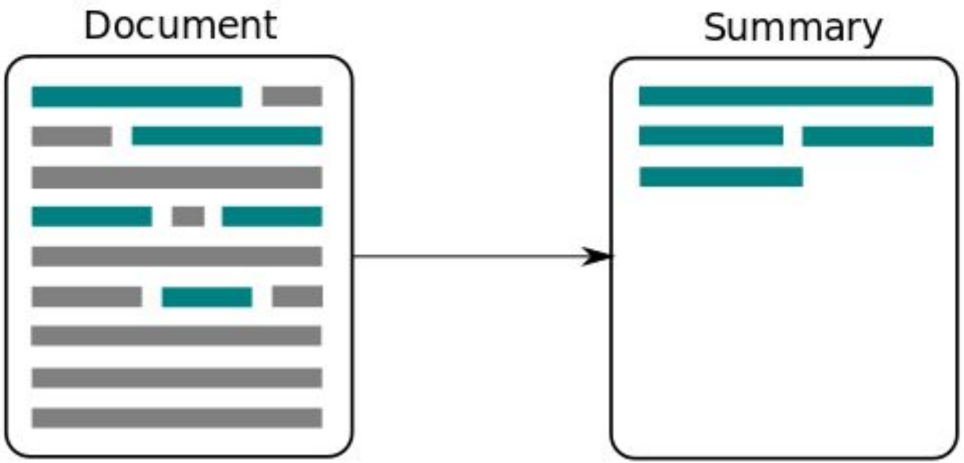
- Summarization
  - types
  - metrics
  - methods
- Paraphrasing
- Simplification



Summarization

Summarization is the task of condensing a piece of text to a shorter version, reducing the size of the initial text while at the same time preserving key informational elements and the meaning of content.

- data reduction
- important/key information
- the same meaning



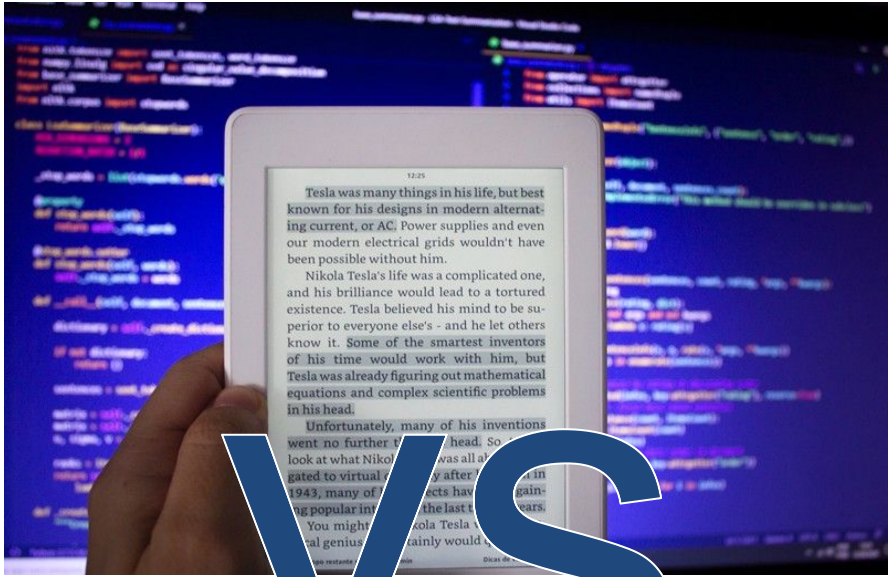
Summarization. Application

- News
- Books/series/referats summaries
- Documents sum
- Media monitoring
- Video scripting
- Emails overload
- Financial research
- E-learning and class assignments
- in chatbots
- etc.

Summarization. Types

Extractive Summary: the network calculates the most important sentences from the article and gets them together to provide the most meaningful information from the article.

Abstractive Summary: The network creates new sentences to encapsulate maximum gist of the article and generates that as output. The sentences in the summary may or may not be contained in the article.



VS

Summarization. Types

Document summarization (extreme)

Many documents or huge texts into very short form.

Sentence Compression

Sentence: Floyd Mayweather is open to fighting Amir Khan in the future, despite snubbing the Bolton-born boxer in favour of a May bout with Argentine Marcos Maidana, according to promoters Golden Boy

Compression: Floyd Mayweather is open to fighting Amir Khan in the future.

Summarization. Types

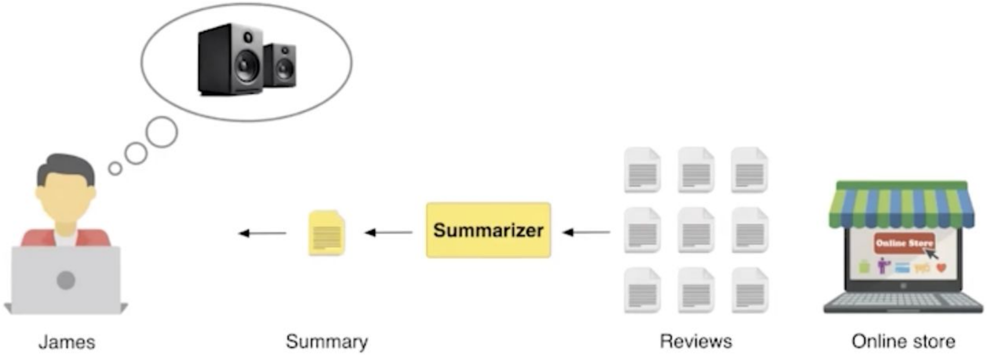
Opinions summarization - lots of opinions need to sum in one join opinion.

Opinion summary should be:

(1) centered on entities and aspects

and sentiments about them

(2) quantitative



Contrastive summarization (for some style) jointly generating summaries for two entities in order to highlight their differences.
(for example)

Summarization. Metrics

<u>ROUGE-N:</u> Overlap of N-grams

Recall: $$\frac{|\text{ngrams}(ref)\ \&\ \text{ngrams}(hyp)|}{|\text{ngrams}(ref)|}$$

Precision: $$\frac{|\text{ngrams}(ref)\ \&\ \text{ngrams}(hyp)|}{|\text{ngrams}(hyp)|}$$

F1: $$2\frac{P * R}{R + P}$$

<u>ROUGE-L</u>: Longest Common Subsequence (LCS) based statistics. Longest common subsequence problem takes into account sentence level structure similarity naturally and identifies longest co-occurring in sequence n-grams automatically.

Better for abstractive! FLUENCY

Summarization. Metrics

The Meteor automatic evaluation metric scores machine translation and other generation tasks hypotheses by aligning them to one or more references.

Alignments are based on exact, stem, synonym, and paraphrase matches between words and phrases.

Weighted F-score $F = \frac{PR}{\alpha P + (1-\alpha)R}$

Penalty function for incorrect word order $Penalty = \gamma(\frac{c}{m})^{\beta}, \quad \text{where} \quad 0 \leq \gamma \leq 1$

$$Score = Fmean * (1 - Penalty)$$

Summarization Metrics

https://github.com/Yale-LILY/SummEval#evaluation-toolkit

Read: https://direct.mit.edu/tacl/article/doi/10.1162/tacl_a_00373/100686/SummEval-Re-evaluating-Summarization-Evaluation

Metric	Paper	Code
ROUGE	ROUGE: A Package for Automatic Evaluation of Summaries	Link
ROUGE-we	Better Summarization Evaluation with Word Embeddings for ROUGE	Link
MoverScore	MoverScore: Text Generation Evaluating with Contextualized Embeddings and Earth Mover Distance	Link
BertScore	BertScore: Evaluating Text Generation with BERT	Link
Sentence Mover's Similarity	Sentence Mover's Similarity: Automatic Evaluation for Multi-Sentence Texts	Link
SummaQA	Answers Unite! Unsupervised Metrics for Reinforced Summarization Models	Link
BLANC	Fill in the BLANC: Human-free quality estimation of document summaries	Link
SUPERT	SUPERT: Towards New Frontiers in Unsupervised Evaluation Metrics for Multi-Document Summarization	Link
METEOR	METEOR: An Automatic Metric for MT Evaluation with Improved Correlation with Human Judgments	Link
S^3	Learning to Score System Summaries for Better Content Selection Evaluation	Link
Misc. statistics (extractiveness, novel n-grams, repetition, length)	Newsroom: A Dataset of 1.3 Million Summaries with Diverse Extractive Strategies	Link

Summarization. Datasets

English:

- CNN / Daily Mail (single document, many extractive)
- X-Sum (single doc, short summaries)
- Newsroom
- MultiNews (multi documents)
- DUC 2004 Task 1
- Webis-TLDR-17 Corpus
- Gigaword
- BIGPATENT https://www.aclweb.org/anthology/P19-1212

Summarization. Datasets

Russian

- https://huggingface.co/datasets/csebuetnlp/xlsum
- https://huggingface.co/datasets/mlsum MLSUM (CNN/Daily)
- https://huggingface.co/datasets/IlyaGusev/gazeta Gazeta. Russian News
  https://github.com/IlyaGusev/gazeta
- https://huggingface.co/datasets/wiki_lingua

Extractive datasets. Lifehack:

- utilize abstractive sum datasets
- select sentences that have max ROUGE scores

Summarization. Extractive methods

Ussually framed as tagging problem.

- Given document *D*.
- Select *K* summaring (most important) fragments
- Concatenate K fragments in summary

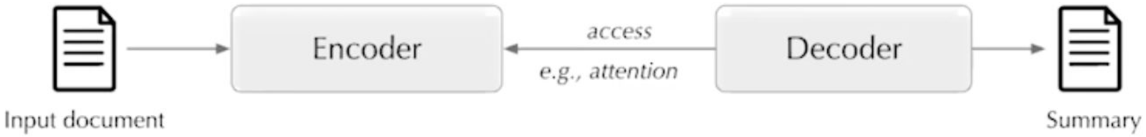
Methods:

$$PR(n_i) = \frac{1-d}{N} + d \sum_{n_j \in In(n_i)} \frac{PR(n_j)}{|Out(n_j)|}$$

- LSA (Latent semantic analysis)
- Luhn Summarization algorithm (tf-idf)
- TextRank, LexRank
- ...
- As binary classification assign tags 0 or 1 to important sentences.
  Neural encoder => sentence semantic representaion => sigmoid

Summarization. Abstractive methods

Abstract answer
=> Generation



Encoder-decoder architectures
BertSum, BART, T5

Or just decoders GPT-2, GPT-3

Pros:

- richer vocabulary
- abstract/rephrase
- conflict info/opinions

NEED DATA

Summarization. Methods

Pretrained models / Fine-tuning

BertSum (extractive)

BertSum assigns scores to each sentence that represents how much value that sentence adds to the overall document. So, [s1,s2,s3] is assigned [score1, score2, score3]. The sentences with the highest scores are then collected and rearranged to give the overall summary of the article.

- Based on a pre-trained encoder (Liu and Lapata, 2019)
- Use a pre-trained BERT encoder (Devlin et al., 2019)
- BertSum has a transformer encoder-decoder architecture
- The decoder is trained from scratch

Summarization. Pointer generation

Augment the standart attention module

Attention mechanism

COPY mechanism

(pointer network)

Decoder hidden states

$$P_{\text{vocab}} = \text{softmax}(V'(V[s_t, h_t^*] + b) + b')$$

Context vector

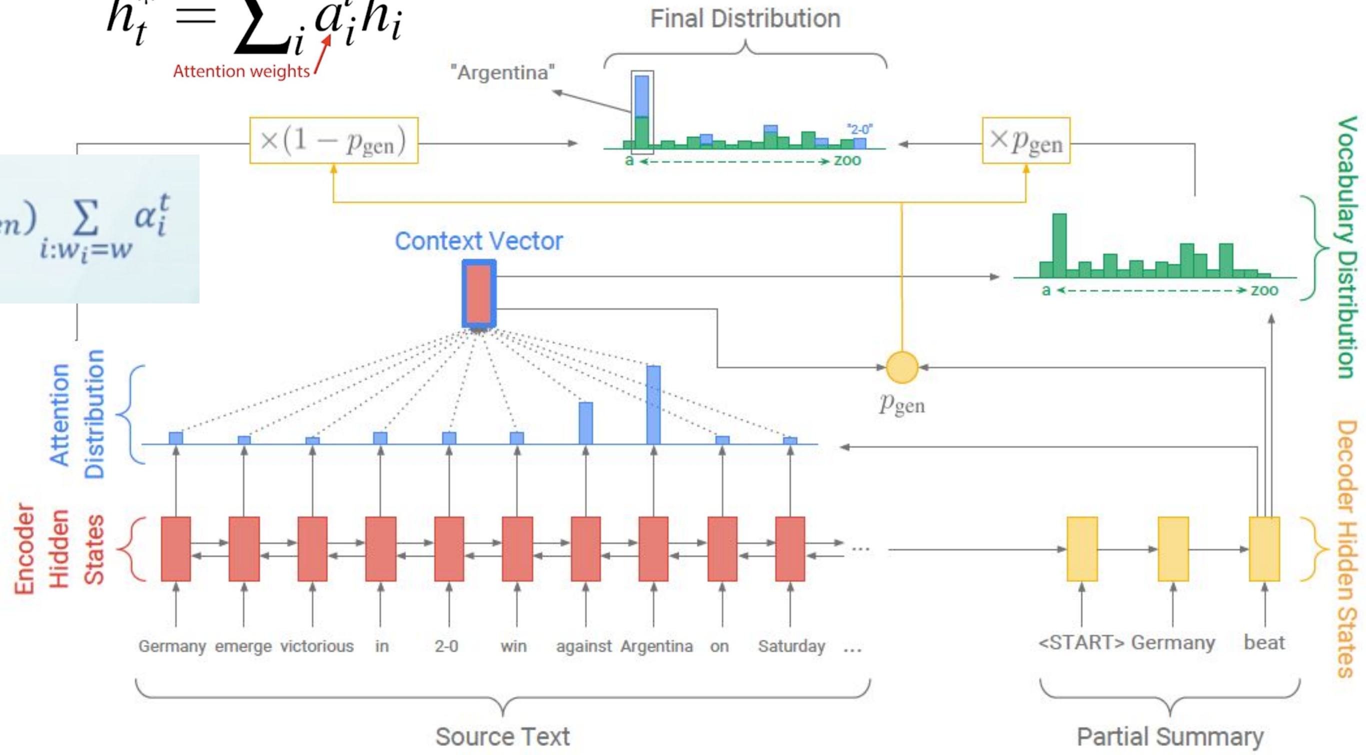
Encoder hidden states

$$h_t^* = \sum_i a_i^t h_i$$

Attention weights

$$P(w) = P_{gen} P_{vocab} + (1 - P_{gen}) \sum_{i:w_i = w} a_i^t$$

solve OOV problems

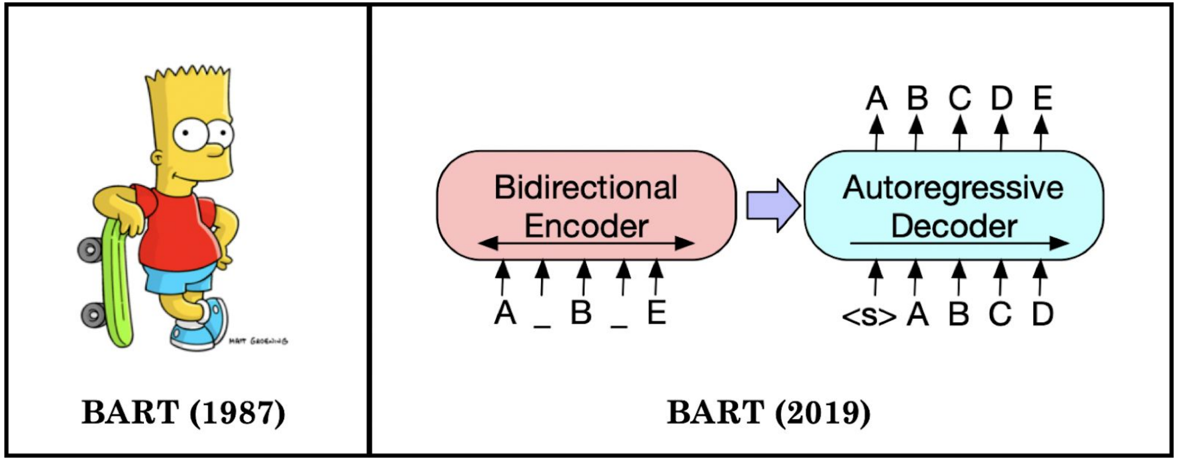


Summarization. BART

Encoder + decoder

MBART (multilingual variant, Russian included)

Unsupervised denoising objective



	CNN/DailyMail			XSum		
	R1	R2	RL	R1	R2	RL
Lead-3	40.42	17.62	36.67	16.30	1.60	11.95
PTGEN see:2017	36.44	15.66	33.42	29.70	9.21	23.24
PTGEN+COV see:2017	39.53	17.28	36.38	28.10	8.02	21.72
UniLM	43.33	20.21	40.51	-	-	-
BERTSUMABS (bertsum)	41.72	19.39	38.76	38.76	16.33	31.15
BERTSUMEXTABS (bertsum)	42.13	19.60	39.18	38.81	16.50	31.27
BART	**44.16**	**21.28**	**40.90**	**45.14**	**22.27**	**37.25**

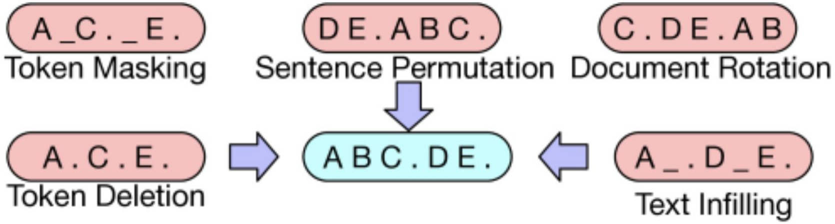


Figure 2: Transformations for noising the input that we experiment with. These transformations can be co

Pegasus by Google

Training objective:
Gap Sentence Generation (GSG) + MLM

Complete sentences are removed from a document (i.e. they are ‘masked’), and the **model is trained to predict these masked sentences**.

Choosing the most important sentences from the document for masking works best. This is done by finding sentences that are the most similar to the complete document.

https://arxiv.org/abs/1912.08777
https://ai.googleblog.com/2020/06/pegasus-state-of-art-model-for.html

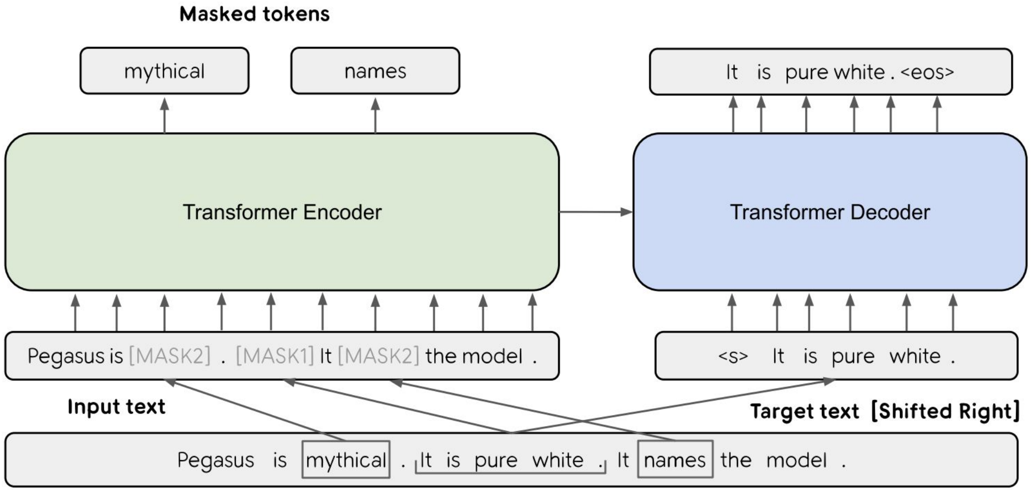
Pegasus by Google

Three strategies to select gap sentences (without replacement):

1) Random
2) Lead
3) Principal (selecting top-m scored sentences based on their importance, -measured by the ROUGE-1 score between the sentence and the rest of the document).

Both GSG and MLM are applied simultaneously to this example as pre-training objectives. Originally there are three sentences. One sentence is masked with [MASK1] and used as target generation text (GSG). The other two sentences remain in the input, but some words are randomly masked by [MASK2] (MLM).

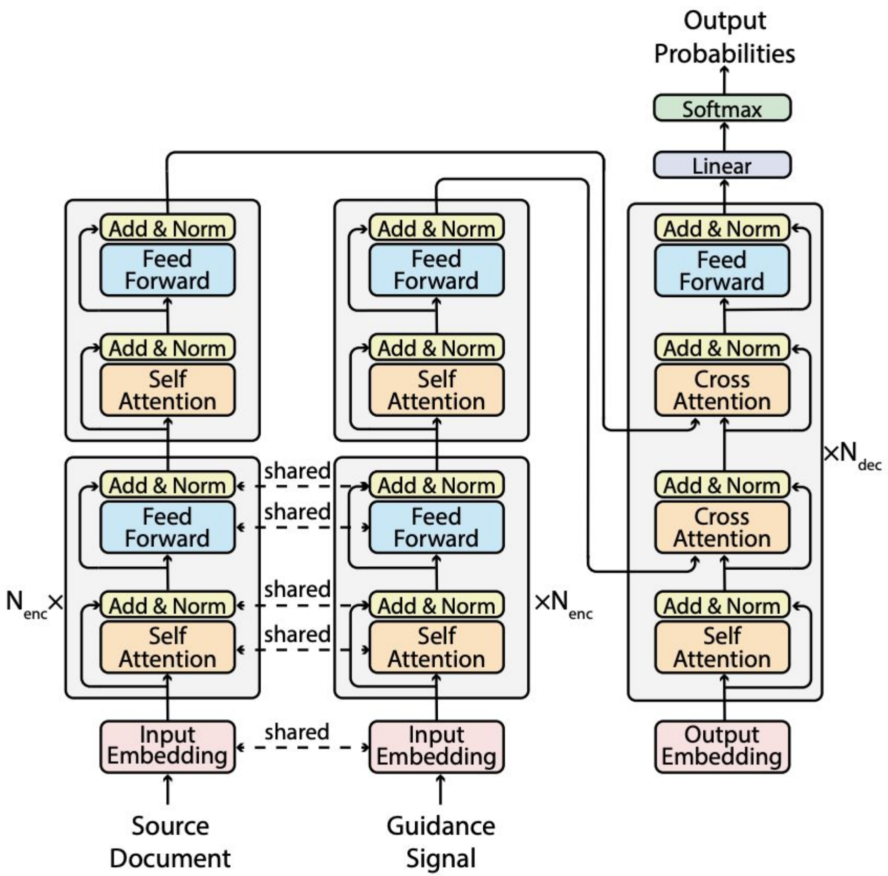
Pegasus by Google



https://arxiv.org/abs/1912.08777 https://ai.googleblog.com/2020/06/pegasus-state-of-art-model-for.html

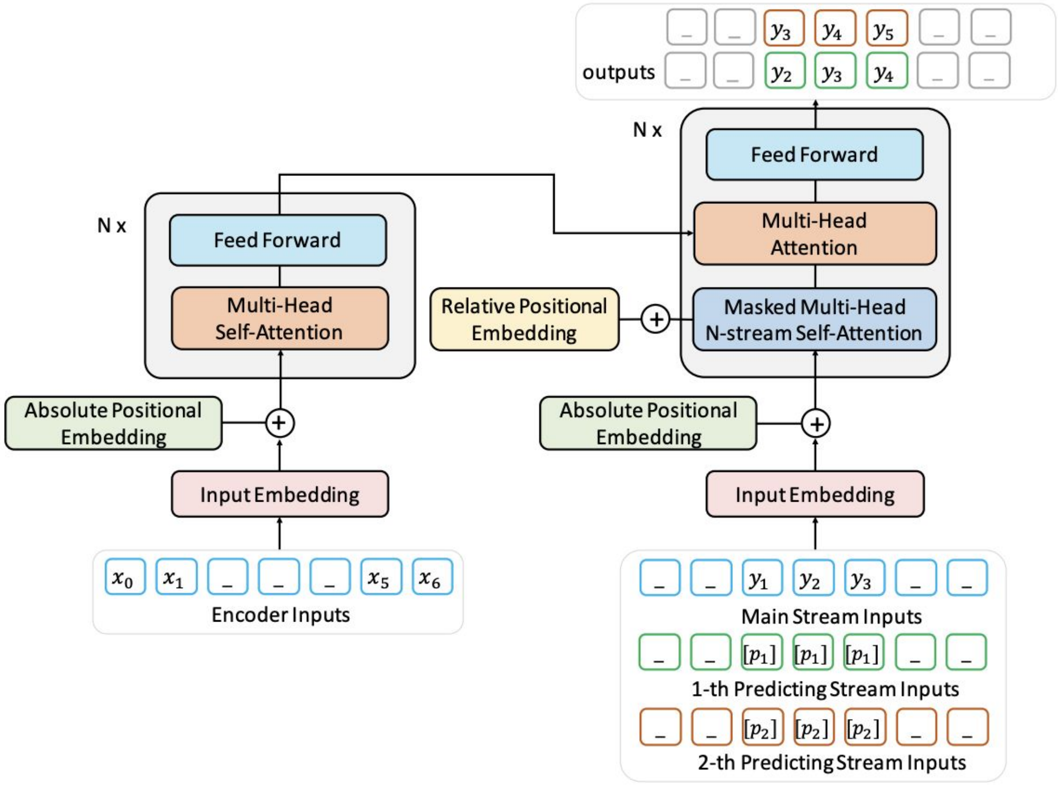
Abstractive methods. More

GSum - general and extensible guided summarization framework that can effectively take external various types of guidance signals.
https://arxiv.org/pdf/2010.08014v1.pdf



http://nlpprogress.com/english/summarization.html

Abstractive methods. More



ProphetNet is an encoder-decoder model and can predict n-future tokens for “ngram” language modeling instead of just the next token.

https://arxiv.org/pdf/2001.04063v3.pdf

http://nlpprogress.com/english/summarization.html

Abstractive methods. More

of course T5

mT5

see and use in huggingface

IlyaGusev/mbart_ru_sum_gazeta
Summarization • Updated 5 hours ago • ↓ 273k • ♡ 4

csebuetnlp/mT5_multilingual_XLSum
Summarization • Updated Oct 3 • ↓ 10.5k • ♡ 7

dmitry-vorobiev/rubert_ria_headlines
Summarization • Updated Sep 22 • ↓ 441

IlyaGusev/rubert_telegram_headlines
Summarization • Updated Mar 16 • ↓ 143

cointegrated/rut5-base-absum
Summarization • Updated 9 days ago • ↓ 53

IlyaGusev/rut5_base_sum_gazeta
Summarization • Updated yesterday

Abstract methods. Evaluation

Cnn/Daily

Model	ROUGE-1	ROUGE-2	ROUGE-L
GSum (Dou et al., 2020)	45.94	22.32	42.48
ProphetNet (Yan, Qi, Gong, Liu et al., 2020)	44.20	21.17	41.30
PEGASUS (Zhang et al., 2019)	44.17	21.47	41.11
BART (Lewis et al., 2019)	44.16	21.28	40.90

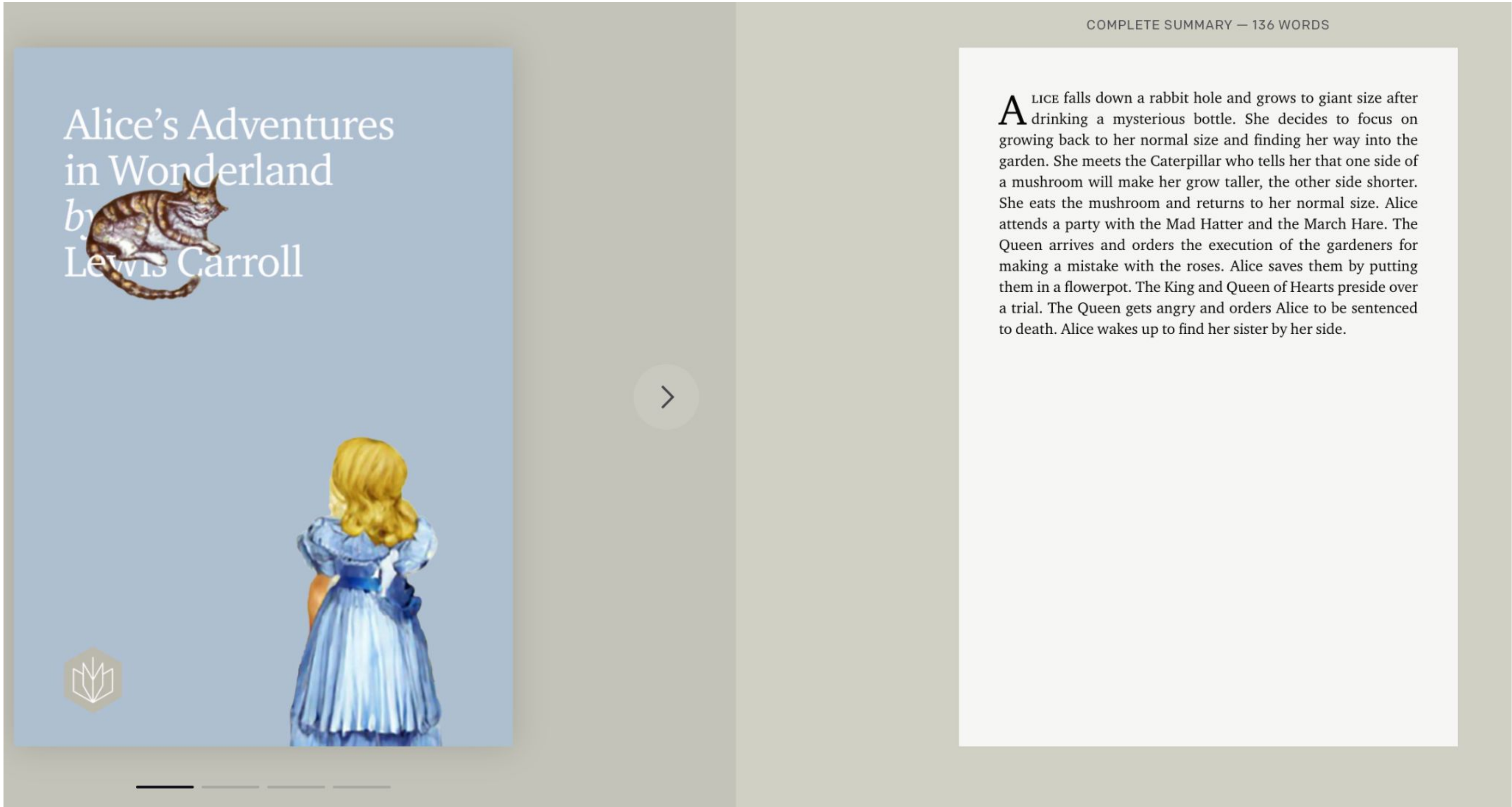
Xsum

Model	ROUGE-1	ROUGE-2	ROUGE-L
PEGASUS (Zhang et al., 2019)	47.21	24.56	39.25
BART (Lewis et al., 2019)	45.14	22.27	37.25

http://nlpprogress.com/english/summarization.html

Document summarization

https://openai.com/blog/summarizing-books/



Document summarization

Модель тренируется не один раз на заготовленном датасете по суммаризации, а итеративно улучшается с фидбеком от специальных тренированных людей. Фидбэк бывает двух видов: 1) человек пишет более правильное саммари 2) человек выбирает одно из двух саммари написанных моделью. В случае 1 понятно как улучшить модель — просто зафайнтюнить на дополнительных данных. Случай 2 — reinforcement learning.

Подход: Допустим у вас есть текст размера 10K токенов, а модель может читать только 2К. Разделим текст на 5 чанков по 2К и для каждого из них сгенерируем саммари допустим размера 500 токенов. Потом сконкатим их и получим текст длины 2.5K токенов. Всё ещё слишком длинно — разделим его на два куска и пусть каждый из них сгенерит саммари по 500 токенов. Сконкатим эти результаты, получим текст 1000 токенов. Теперь можно получить из него финальное саммари.

Подход очень простой и решает кучу проблем. Во-первых такую разметку просто делать. Вы не заставляете людей суммаризировать целые книги, а лишь просите из суммаризировать чанки по 2K токенов. Людям проще такое делать, машинам проще такое учить, плюс с одной книги получаете кучу разметки. В качестве инициализации для модели используют GPT-3.

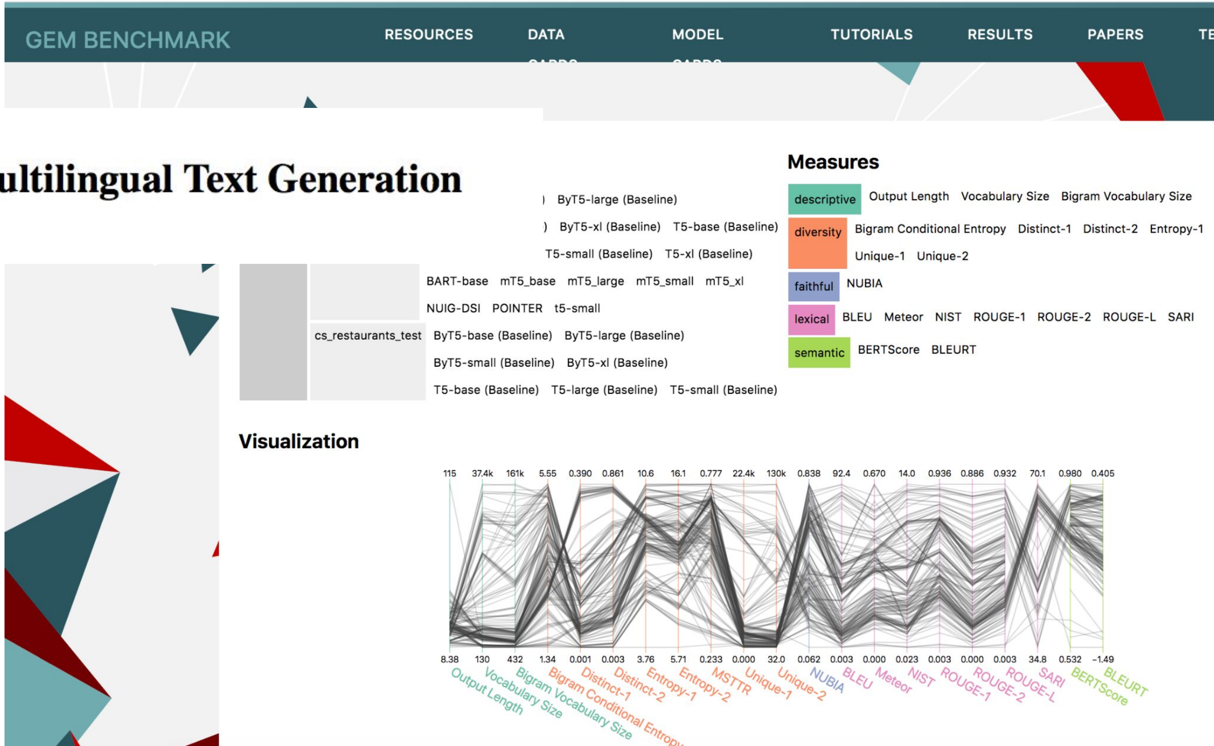
По результатам:

- Некоторые саммари близки по качеству к человекам, но их около 5% 🍒. В среднем скор человека ~6/7, а лучшей модели ~3.5/7
- Размер модели важен и 175млрд параметров дают огромный буст по сравнению с 6млрд.
- RL + NLP => его использование улучшает скор с 2.5 до 3.5

Text generation benchmarks

Texygen: A Benchmarking Platform for Text Generation Models

MTG: A Benchmarking Suite for Multilingual Text Generation



GEM
https://gem-benchmark.com/

Paraphrasing

Paraphrasing is expressing the meaning of an input sequence in alternative ways while maintaining grammatical, syntactical correctness.

1) Paraphrase identification - detecting if a pair of text inputs has the same meaning; classification task.

2) Paraphrase generation - producing paraphrases allows for the creation of more varied and fluent text; generation task

Build a model that reads a sequence of words and generates a different sequence with the same meaning

Paraphrasing

Why paraphrasing?

- style transfer:
  - translation from rude to polite
  - translation from professional to simple language
- data augmentation: increasing the number of examples for training ML-models
- increasing the stability of ML-models: training models on a wide variety of examples, in different styles, with different sentiment, but the same meaning / intent of the user

Paraphrasing

Paraphraser datasets:

- Paraphraser plus http://paraphraser.ru/
- Mix data: https://github.com/RussianNLP/russian_paraphrasers/tree/master/dataset
- Tapaco rus part: https://huggingface.co/datasets/tapaco.

Tools for paraphrasing

- https://github.com/RussianNLP/russian_paraphrasers

Simplification

Text Simplification (sentence simplification) is the task of <u>reducing</u> the complexity of the vocabulary and sentence structure of text while <u>retaining its original meaning</u>, with the goal of improving readability and understanding.

Sentence complexity criteria include:

- the presence of complex grammatical structures
- participial and adverbial expressions, subordinate sentences,
- the presence of rare, and ambiguous words,
- etc

Original Sentence	Simplified Sentence
Owls are the order Strigiformes, comprising 200 bird of prey species.	An owl is a bird. There are about 200 kinds of owls.
Owls hunt mostly small mammals, insects, and other birds though some species specialize in hunting fish.	Owls' prey may be birds, large insects (such as crickets), small reptiles (such as lizards) or small mammals (such as mice, rats, and rabbits).

Simplification

Datasets:

- based on Wikipedia - **WikiLarge, WikiSmall**
  Simple English Wikipedia is an online encyclopedia aimed at English learners. Its articles are expected to contain fewer words and simpler grammar structures than those in their
  Main English Wikipedia counterpart. Much of the popularity of using Wikipedia for research in Simplification comes from publicly available sentence alignments between “equivalent” articles in Main and Simple English Wikipedia.
- **Turk Corpus**
- **ASSET**
- **Newsela**

Simplification

<u>Metrics:</u>

SARI (Xu et al., 2016) is a *lexical simplicity* metric that measures “how good” are the words added, deleted and kept by a simplification model. The metric compares the model’s output to *multiple simplification references* and the original sentence.

$$SARI = \frac{1}{3}F_{добавление} + \frac{1}{3}F_{удаление} + \frac{1}{3}F_{сохранение}$$

$$ope \in \{добавление, удаление, сохранение\}$$

$$F_{ope}(n) = \frac{2 \times p_{ope}(n) \times r_{ope}(n)}{p_{ope}(n) + r_{ope}(n)}$$

$$F_{ope} = \frac{1}{k} \sum_{n=1,k} F_{ope}(n)$$

Simplification

Model	BLEU	SARI
MUSS (Martin et al., 2020)	78.17	42.53
ACCESS (Martin et al., 2019)	72.53	41.87
DMASS + DCSS (Zhao et al., 2018)		40.45

Generation aproaches - bart, gpts

RuGPT XL:

Origin:
Аспирин — это лечение первой линии для лихорадки и симптомов суставной боли при остром ревматизме.
Generated: Аспирин обычно используется для лечения лихорадки, боли в суставах и мышечных судорог.

Origin: Боевые действия проходили на фоне разыгравшейся в тылу масштабной эпидемии чумы, унёсшей большое количество жизней.
Generated: В ходе боевых действий эпидемия чумы унесла много жизней.