

The background is a dark, deep blue space filled with numerous glowing, translucent cubes. These cubes are arranged in a somewhat chaotic but structured pattern, with some appearing to be in motion or floating. Bright, starburst-like light rays emanate from several points, particularly from the cubes, creating a sense of depth and energy. The overall aesthetic is futuristic and technological.

Data Quality Metrics

(IN COLLABORATION WITH BMW GROUP)

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Supervisors: Dr Maka Karalashvili (ext.), Prof. Dr Matthias Schubert (int.)

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(Summarization&classification tasks,
Existing methods)

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(Storyline, insights, results)

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(Future work, conclusion)

MOTIVATION

When (or after) the car is produced, different defects occur. These defects are recorded and stored in the data source – the “Knowledge base” – that summarizes similar defects and assigns them to the prebuilt defect cluster. Each defect contains high amount of human written-text data, which makes analysis time-consuming and complicated

OUR GOAL

To build a model that will process the human created text data of different length, create a summary of it, classify it based on the „sense“ of the generated summary and evaluate the quality of it

Summarization

– a text that is produced from one or more texts, that contains a significant portion of the information in the original text(s).

If it was created with the computer, it is called **automatic summarization**.

Can be **abstractive** and **extractive**.



Classification

– categorizing open-ended text into two or more predefined classes based on some rules or similarities between these texts.

Can be performed based on of the three approaches:

- **Rule-based systems**
- **ML-based systems**
- **Hybrid systems**





Models, used only for summarization

(e.g. Sumy)



Models, used only for classification

(e.g. Naive Bayes, SVMs)

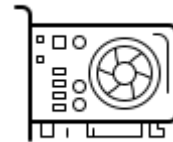


Models, used for both tasks

(e.g. Gensim, CNNs, RNNs,
BERT-based models,
GPT models, XLNet, T5)



**Data access and
security issues**



**Insufficient
resources issues**



Data access and security issues

(new open-source dataset should be found, that would match the original one)

Data



Amazon Product Review Dataset

Information



10 columns:

Structure

*ID, Product ID, User ID, Profile Name,
Helpfulness Numerator, Helpfulness
Denominator, Score, Time, Summary, Text*



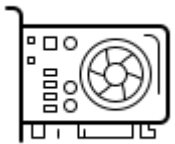
568.427 reviews

Content



2 columns kept: *Summary, Text*

Useful data



Lack of proper computational resources

(lightweight models should be found to complete the task)



OUR CHOICE: T5 model summarization

Encoder & Decoder blocks

(encoder block helps model to create better summary)

The output is a text string

(many other models have labels/spans as output
→ improper output for summarization task)

Robust and extensible

(weights are assigned more properly,
the model can be easily modified to other tasks)



OUR CHOICE: DistilBERT model classification

Small, fast, cheap

(40% less parameter than BERT → 60% faster)

Distilled & transfer-learning adapted

(mix of the distillation and transfer-learning
→ Above 90% accuracy on classification)

Open-source & flexible

(model available via HuggingFace,
retains 97% of BERT performance)

PROJECT TIMELINE



Oct, 2021

(Getting to know the supervisor, the project and the goal of it, searching for the data)



Nov, 2021

(Exploration of the dataset, metric extraction & processing ideas, building a data loader)



Dec, 2021

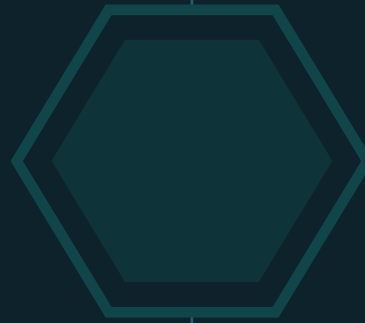
(Research on summarization techniques, exploring necessary packages)



Jan, 2022

(First-choice model research, baseline model building (RoBERTa), research on classification)

PROJECT TIMELINE



Feb, 2022

(RoBERTa issue handling, parameter fine-tuning, classification implementation)



Mar, 2022

(Classification model issue handling, testing and parameter fine-tuning)



Apr, 2022

(Second-choice model research and implementation (Google T5 model))



May, 2022

(New model issue handling, parameter fine-tuning, documentation preparation)



Implementation: Set Up

Computational System

Google Colab Pro
(up to 24GB RAM, K80, P100, T4 GPUs)

Environment

Python ver. 3.8.5 and above

Model & documentation



Note on summarization model change

RoBERTa

vs.

Google T5

Pre-training

5 datasets containing
about 160GB of text

Multi-task un-&supervised
tasks on 16 datasets

Pre-training time

1 day (1024xV100 GPUs,
batch size 8k)

~12 hours (Titan RTX,
batch size 8k)

Base of the model

BERT (bi-directional
transformer model)

—

Parameter set

354M parameters
(RoBERTa-large)

11B parameters
(t5-11b)

Optimizer used

Adam
(learning rate = 0.0006)

AdamW & AdaFactor
(learning rate = 0.0003)

ROUGE Score
(official paper)

F-measure (ROUGE-L)
= 25.67

F-measure (ROUGE-L)
= 38.35

Tokenization

- a way of separating a piece of text into smaller units called tokens. Either words, characters or subwords can be **tokens**.

Tokenizer breaks natural language text into chunks of information that can be considered discrete elements.

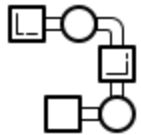
This immediately turns an unstructured string (text document) into a numerical data structure suitable for machine learning.



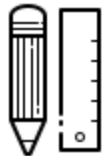
Implementation: T5 Tokenizer & Optimizer



robust & in-built



uses SentencePiece



based on Unigram

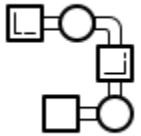


easy configurable



inherits main methods of 📖 PreTrainedTokenizerFast

Implementation: DistilBERT Tokenizer



uses WordPiece algorithm



reachable via 🧠 Transformers



easy configurable



inherits most properties of 🧠 BERT Tokenizer

Implementation: DistilBERT Classes

Initial text of the review

Generated summaries

Positive

Reviews showing that customer was satisfied with the purchased product

Positive

Negative

Reviews showing that customer was not satisfied with the purchased product

Negative



Performance: Metrics

Running time

shows the amount of time that was required to perform the training (only)

Validation and training losses

describe the performance of the model, indicating how well it is fitting the training and the new data correspondingly

ROUGE Score

compares automatically produced summary against reference (human-written) ones

Accuracy & Error

defines the number of correctly predicted data points out of all the data points

Performance: T5 summarization

10k sample

vs.

100k sample

Running time	approx 30 min	approx 3 hours
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Train loss	2.481	2.849
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Validation loss	3.532	3.859
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ROUGE Scores

Rouge-1	0.266	0.143
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recall	1.0	1.0
precision	0.421	0.250
f-measure		

Rouge-L	0.266	0.143
---------	-------	-------

recall	1.0	1.0
precision	0.421	0.250
f-measure		

Performance: Classification

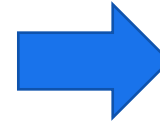
	10k sample	vs.	100k sample
Running time	approx 36 min		approx 3.5 hours
Train loss	0.137		0.094
Accuracy	0.953		0.963
Validation loss	0.274		0.194
Validation accuracy	0.901		0.935
Classification error	0.1		0.1

Summarization Example

Initial review text

didn't think artisana could improve coconut butter (pure delicious treat jar). however addition cacao butter think definitely took notch. love use slice toast morning provides wealth nutrients well filling

sure applications, right can't move past slightly melting slice warm toast!



Initial summary

Holy Yum!

Generated summary

Delicious!

FUTURE

1. Model adaptation to the BMW data
2. Further summarization model fine-tuning to make the model more precise
3. Expanding the classification of the data (based on the information, that the summaries contain)

CONCLUSIONS

I

Why task is important

(Analysing the human-written defects is not easy and time consuming)

II

What models exist

(*Summarization*: BERT (&variations), GPT, T5, CNN, RNN;
Classification: Naive Bayes, SVM, summarization ones)

III

What models were chosen

(*Summarization*: Google T5 model;
Classification: DistilBERT)

IV

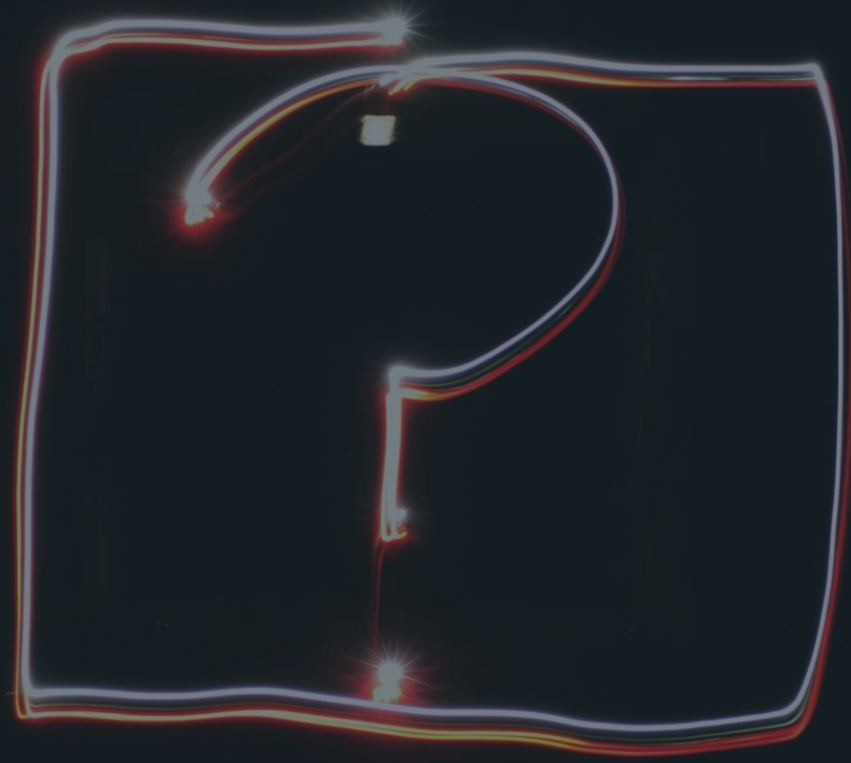
Performance analysis

(*Summarization*: all of the n-grams in the generated summaries are present in the reference text;
Classification: overall accuracy > 90%, error = 0.1)

V

What else can be done













(*Summarization*: fine-tuning to increase the quality;
Classification: expanding the number of classes)



THANK YOU













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Data:

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Imagery:

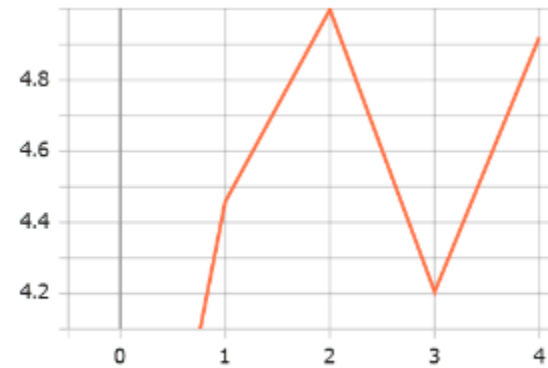
-  unsplash.com
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Graphics:

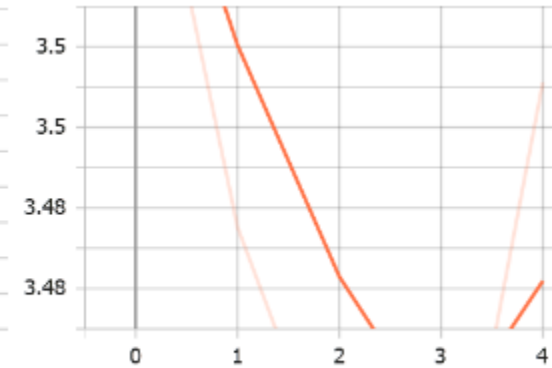
-  icons8.com

Performance analysis: T5 Graphs

10k sample

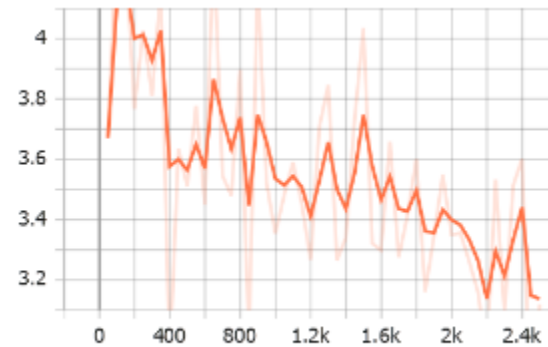


(a) Train loss calculated epoch-wise

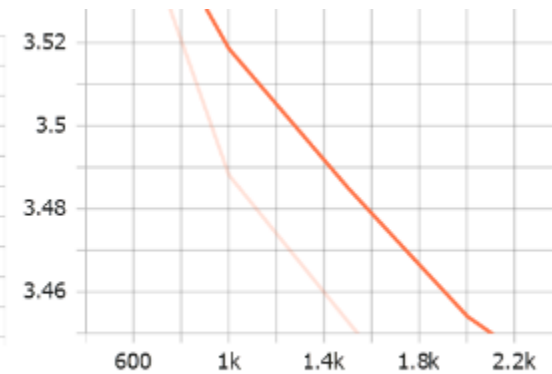


(b) Validation loss calculated epoch-wise

100k sample



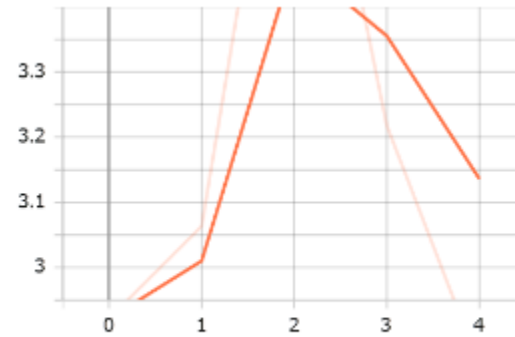
(a) Train loss calculated batch-wise



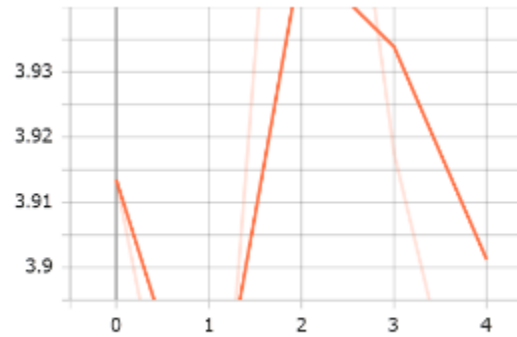
(b) Validation loss calculated batch-wise

Performance analysis: T5 Graphs

10k sample

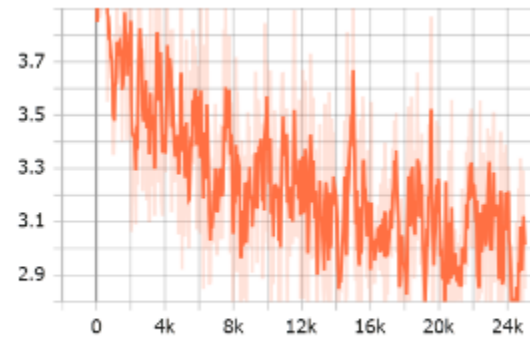


(a) *Train loss calculated epoch-wise*

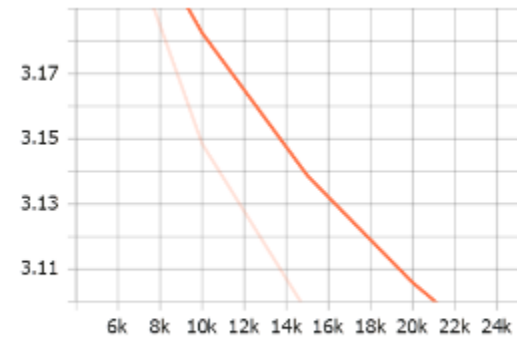


(b) *Validation loss calculated epoch-wise*

100k sample



(a) *Train loss calculated batch-wise*



(b) *Validation loss calculated batch-wise*