Artificial Researcher

Artificial Researcher

Can Generative AI aid or solve the Patent Summarization puzzle?

Invited speaker at 1st Workshop patent4Science

Outline

- Academic Overview
  - Text summarization algorithm
  - Patent text summarization
- What can Generative AI do with confident?
- How do we solve the puzzle to automatic generate patent summaries?
  - What is the information requirement of good patent summarization
  - How build a patent summarization algorithm that meet the need of the user and the different purpose

Text Summarization Algorithms

(~990 articles on summarization ACL)

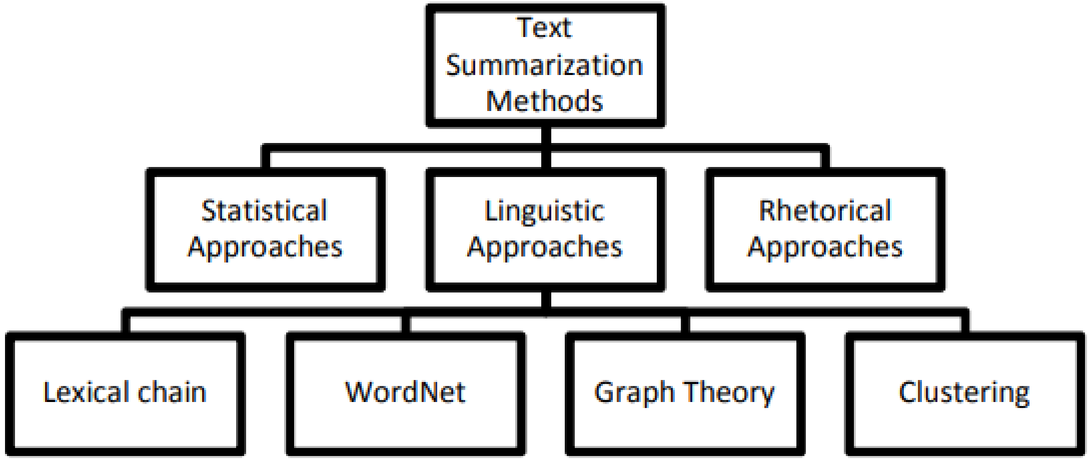


Figure 2. Text summarization methods

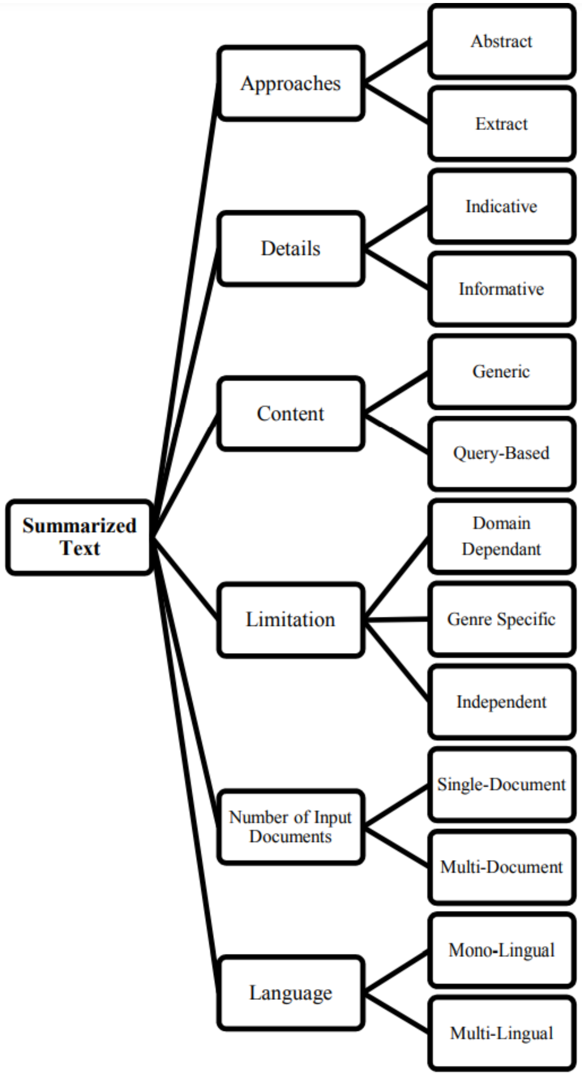


Figure 1. Type of summary

S. Gholamrezazadeh, M. A. Salehi and B. Gholamzadeh, "A Comprehensive Survey on Text Summarization Systems," *2009 2nd International Conference on Computer Science and its Applications*, Jeju, Korea (South), 2009, pp. 1-6, doi: 10.1109/CSA.2009.5404226. (Appendix)

Patent text Summarization

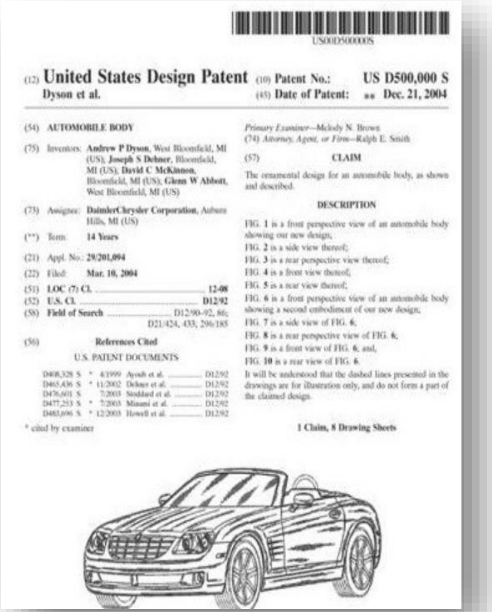
- There exists approximately 60 to 80 research articles related to patent summarization
- Used for query formulation
  - Evaluation the ability to retrieve relevant patent
- Used for to summarization
  - Evaluation abstract is defined as Gold Standard
- TRIZ
  - Manual or semi manual handcrafted data set

Query formulation

- Cetintas S. and Si Li. Effective query generation and post processing strategies for prior art patent search. J. AM. Soc Info. Tec., 2012.
  - Discovered that the segment to use as query formulation is the Brief summary segment of US patent.
    - Evaluation on TREC-Chem

- Andersson L, Lupu M, Palotti J., Hanbury A., Rauber A. (2016) When is the time Ripe for Natural Language Processing for Patent Passage Retrieval? In Proceedings of the 25th ACM International Conference on Conference on Information and Knowledge Management (CIKM 2016)
  - Evaluation on CLEF-IP Passage Patent retrieval

Automatic Query formulation
- From text segment to automatic Boolean query



Claims (1)

1. The ornamental design for an automobile body, as shown and described.

Example of automatic query generation

<QUERY>
(conured OR clutch OR connectability OR nmofs OR fclp OR dnsr OR slippage OR anda OR rotational OR acceleration OR backlash OR subordinate OR estimating OR ure OR brake OR torque OR stopped OR vehicle OR wheel OR command OR outputting O
wheels OR shaft OR prohibiting OR determining
estimated OR prescribed OR stopping OR elapse
OR output OR controller OR rotating OR accelera
AND
("vehicle driving force control apparatus" OR "dr
OR "clutch connection command" OR "rear whe
path" OR "output rotational speed" OR "input ro
"detected parameter" OR "generation load torq
"determination occurrence" OR "four-wheel driv
proceed" OR "wheel speed sensor" OR "output s
"backlash elimination" OR "drive mode switch" O
range" OR "transition time" OR "wheel speed" O
connection" OR "motor torque" OR "generator lo
"high rate" OR "electric motor" OR "throttle ope
force" OR "connected state" OR "previous equat
"prescribed rotational speed difference" OR "12-
"disconnected state" OR "electric clutch" OR "fo
</QUERY>

Automatic query expansion terms

brake pedal:
vehicle operating pedal,
conventional hydraulic brake system
pedal devices
position brake actuating member
brake actuating member
hydraulically-assisted rack pinion steering gear
brake operating member
conventional braking system
pair pedals

accelerator pedal
case pedal device
pedal device

Proof-of-concept

Artificial Researcher

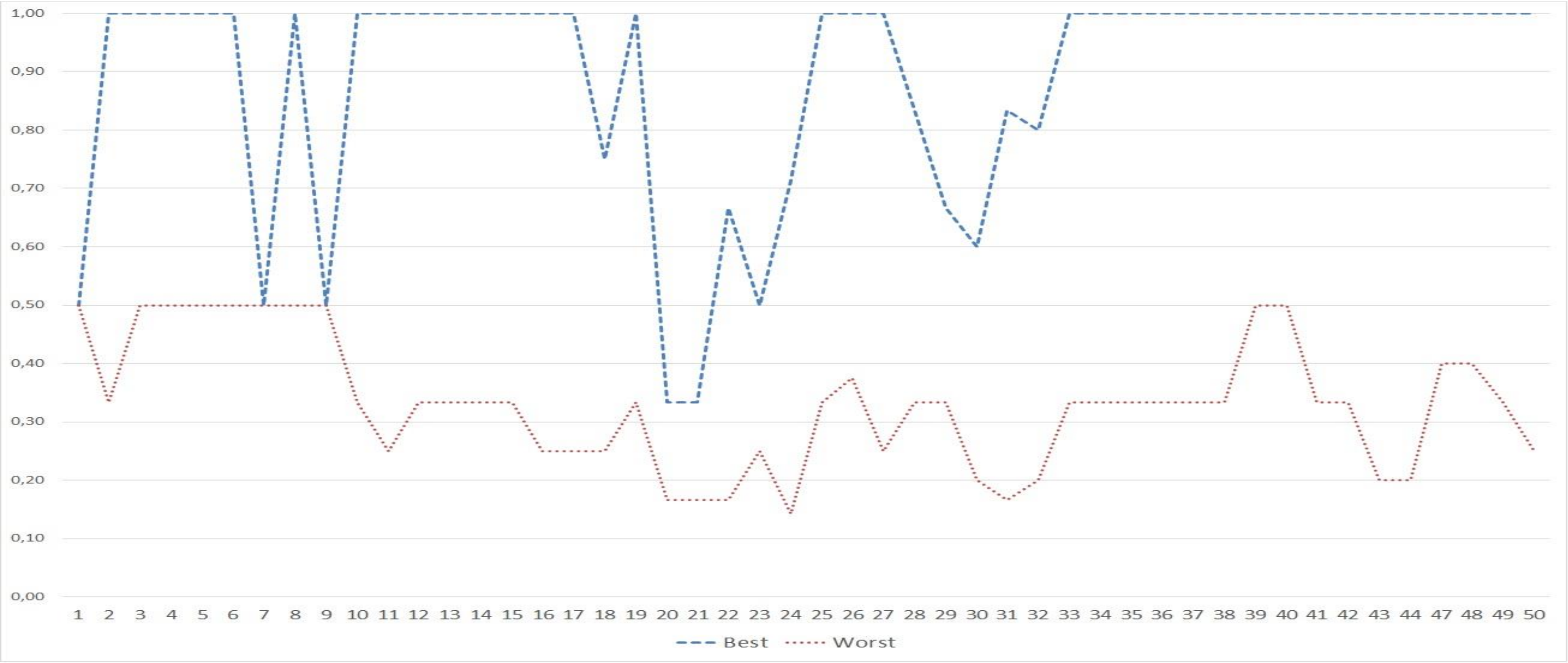
-Passage retrieval performance on CLEF-IP 2013 text collection.

Method	PRES@ 100	Recall@ 100	MAP@ 100	Prec(D)
(Albarede et. al. 2021)	0.461	0.603	0.173	0.231
(Andersson et. al., 2016)	0.444	0.560	0.187	**0.282**
(Andersson et. al., 2017)	**0.558**	**0.647**	**0.269**	0.207
(Luo J and Yang H. 2013)	0.433	0.540	0.191	0.213

Artificial Researcher Passage Retrieval Service™
Artificial Researcher Graph Search Service™

Albarede L., & Mulhem P., Goeuriot L., Le Pape-Gardeux C., Sylvain M., Trindad C. (2021). Passage retrieval in context: Experiments on Patents.
Andersson L, Lupu M, Palotti J., Hanbury A., Rauber A. (2016) When is the time Ripe for Natural Language Processing for Patent Passage Retrieval? In Proceedings of the 25th ACM International Conference on Conference on Information and Knowledge Management (CIKM 2016)
Andersson L, Rekabsaz N., Hanbury A. (2017) Automatic query expansion for patent passage retrieval using paradigmatic and syntagmatic information The first WiNLP Workshop co-located with the Annual Meeting of the Association for Computational Linguistics (ACL 2017), Vancouver
Luo J and Yang H. (2013). Query formulation for prior art search-Georgetown university at clef-ip 2013. In Proc. of CLEF.

Not one algorithm is suitable for all technical fields



Patent Summarization (topicalization)

- Elin Gustafsson(2020) Automatic Text Summarization of Patent Documents, Master Thesis Lunds University
  - Evaluation - manually written summaries (code and data set not accessible for research)
- BIGPATANT
  - Sharma E., Li C, and Wang C. 2019. BIGPATENT: A Large-Scale Dataset for Abstractive and Coherent Summarization. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2204–2213, Florence, Italy. Association for Computational Linguistics.
  - Casola S, Lavelli A, (2022) Summarization, simplification, and generation: The case of patents, Expert Systems with Applications,

TRIZ

(Russian acronym corresponding to “Theory of Inventive Problem Solving”)

- DeWulf, S. "Patent data driven innovation logic." (2020). Imperial College London (UK)
- Guarino, G., Samet A., Nafi A. and Cavallucci D., "SummaTRIZ : Summarization Networks for Mining Patent Contradiction," *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, 2020, pp. 979-986, doi: 10.1109/ICMLA51294.2020.00159.
- Guarino G., Samet A, Cavallucci D, PaTRIZ: A framework for mining TRIZ contradictions in patents, Expert Systems with Applications, Volume 207, 2022
- Wang J, Zhang Z., Feng L, Lin K, Liu P, (2023) Development of technology opportunity analysis based on technology landscape by extending technology elements with BERT and TRIZ, Technological Forecasting and Social Change, Volume 191,
- Chikkamath R., Ramsinh Parmar V. Hewel C. PaSA: A Dataset for Patent Sentiment Analysis to Highlight Patent Paragraphs (ICAIL 2022, SINGAPORE MAY 05-06, 2022)

Artificial Researcher

What can Generative AI do with confident?

Generative AI models as chatGPT are as teenager – the behave as grown-ups but are still just in the beginning of their journey.

I compare it with asking teenager to clean the room.
After 1 0min the teenager is back claiming it's done, and you do inspection, and you find that everything is just swept under the bed.

You ask to re-do the cleaning-up and after 20 min the teenager is back with claim at least now it's done. You do a second inspection, and it turns out everything in the wardrobe this time around.

So, you end up monitoring the teenager /AI generative model and give clear instruction and in every step, you verify that the task has been conducted according to instruction.
But sometimes it does happen occasionally that sometimes you ask the teenager/Generative AI model a task and it does it perfect the first time around!


Data is the king maker

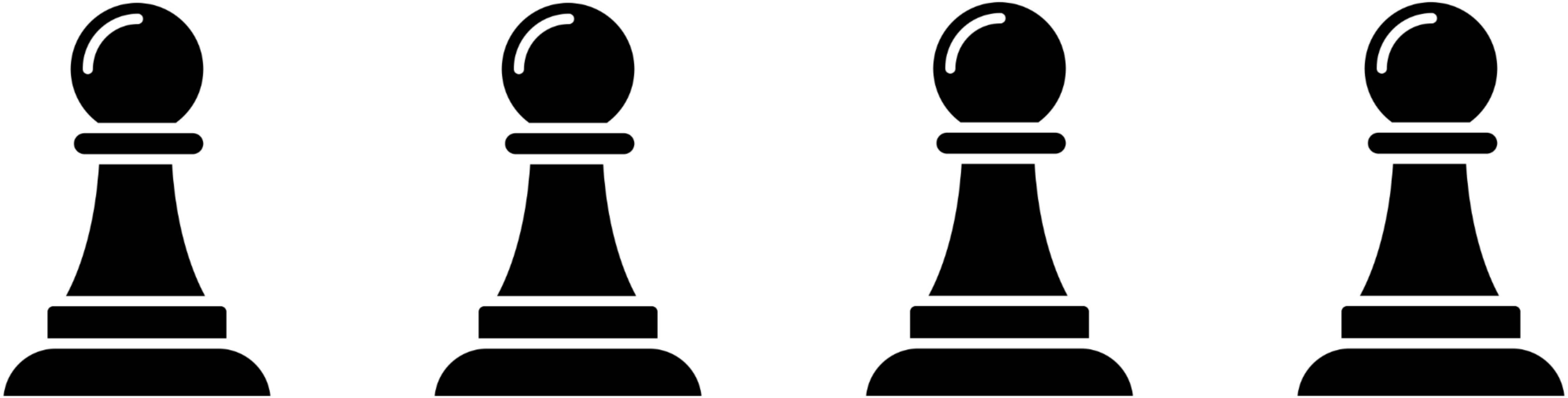
Artificial Researcher

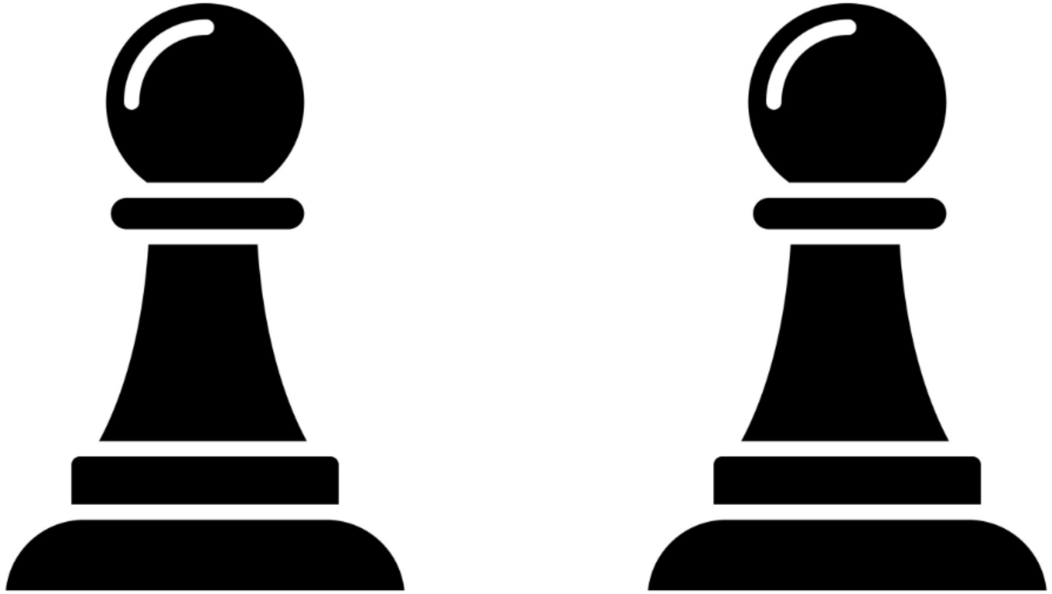
Data

- Large Language Models (LLM) are not knowledge-based by themselves; they are intermediaries.
  - For specific text domains, these models can provide additional knowledge and contextual information, as well as offer natural language inference. However, verification of correctness is always required.
- Therefore…
  - Use your own knowledge based
    - Collect, categories and curate your data
    - LLM models can assist in the curation step, but verifying correctness is a necessity.
  - Always ensure to allocate time for data curation and normalization.
    - In a successful text mining application, 60% of the time is dedicated to collecting, normalizing, and data annotation, while only 40% is allocated to software development.

Designing is the Queen

- Control the flow of the data
  - Modelling the data
  - Amount of text
  - Annotation
    - Seed and Anti-seed
  - Feedback loops





Technology is just the pawns

- Utilize technologies that are suitable for the given task.
- Use the technologies that are applicable for the data
- <u>Most likely you will arrive at an ensemble solution</u>

Can LLM models assist in the curation step?

- Text augmentation
- Pre-Seed
  - Domain name entity
  - Text segment comparison

ChatGPT 3.5 is instructed to extract device concepts from text 1

- Text 1
  - A turbine is a rotary mechanical device that extracts energy from a fluid flow and converts it into useful work," the following device concepts can be extracted:
- Extraction & explanation from chatGPT 3.5
  - Turbine: The primary device being described.
  - Rotary Mechanical Device: Indicates that the turbine has a rotating mechanism.
  - Extracts Energy: Describes the function of the turbine, which is to take energy from a fluid flow.
  - Fluid Flow: The source of energy for the turbine.
  - Converts it into Useful Work: Indicates the purpose of the turbine, which is to convert the extracted energy into useful work.

Can LLM do text augmentation?

Original sentence: The use of a cation cross-linked polysaccharide coating for reducing the glycemic response of a carbohydrate-containing food.

Not all part of a sentence can be substituted in text augmentation, since it changes the theme and rheme need to be kept intact to not change to underlying semantic the sentence

Traditional method (NLP + Semantics Related Extraction)

- The process of applying a cation cross-connected pectin coating for diminishing the glycemic response of a carbohydrate-containing nourishment product.
- The utilize of an ion cross-connected pectin covering for diminishing the glycemic response of a carbohydrate-containing foodstuff.
- The application process of an ion cross-connected alginate film for lessening the glycemic response of a carbohydrate-containing nourishment product.

Using chatGPT 3.5 for paraphrasing

- Implementing a cation cross-linked polysaccharide coating to mitigate the glycemic response of carbohydrate-rich food.
- Utilizing a coating of cation cross-linked polysaccharide to minimize the glycemic impact of carbohydrate-containing food. (response and impact is not equivalent)
- Employing a cation cross-linked polysaccharide coating to decrease the glycemic response associated with a carbohydrate-based food.

Can LLM model do claim analyses comparison?

Artificial Researcher

US2021350229A1 TRAINING TEXT SUMMARIZATION NEURAL NETWORKS WITH AN EXTRACTED SEGMENTS PREDICTION OBJECTIVE

What is claimed is: 1 . A method comprising:

pre-training a text summarization neural network including learning values of a plurality of network parameters through self-supervised learning using unlabeled data comprising unlabeled first texts, the pre-training comprising:

obtaining an unlabeled first text comprising a plurality of segments;

selecting one or more of the plurality of segments;

processing, using the text summarization neural network and in accordance with current values of the plurality of network parameters, a masked first text that excludes the one or more selected segments to generate a prediction of the one or more selected segments; and

determining, based on a difference between the prediction and the one or more selected segments, an update to the current values of the plurality of network parameters; and

adapting the pre-trained text summarization neural network for a specific text summarization task including adjusting learned values of the plurality of network parameters using labeled data comprising second texts and respective summaries of the second texts.

US5918240A Automatic method of extracting summarization using feature probabilities

What is claimed is:

A processor implemented method of automatically extracting a subset of sentences from sentences of a natural language document presented in machine readable form to the processor, the document including a second multiplicity of sentences, the processor being coupled to a memory storing machine readable instructions for extracting sentences, the method comprising the steps of:

a) designating a sentence of the document as a selected sentence;

b) determining values for the selected sentence of each feature of a feature set, the feature set including a location feature and an upper case feature, the location feature having a first location value, a second location value, and a third location value, the first location value indicating that the selected sentence is included within a beginning portion of the document, the second location value indicating that the selected sentence is included within a middle portion of the document, and the third location value indicating that the selected sentence is included within an ending portion of the document, the upper case feature having a first upper case value and a second upper case value, the first upper case value indicating that selected sentence does not include any of a multiplicity of selected upper case phrases, the second upper case value indicating the selected sentence includes a one of the selected upper case phrases;

c) for each feature increasing a score for the selected sentence based upon the value of the feature for the selected sentence and upon a probability associated with the value of the feature;

d) if all sentences of the document have not been designated as the selected sentence, repeating steps a) through c); and

e) selecting the subset of sentences to be extracted based upon sentence scores.

chatGPT 3.5 instructed to do claim analyse comparison

Text 1 and Text 2 are different in terms of their content and the subject matter they describe:

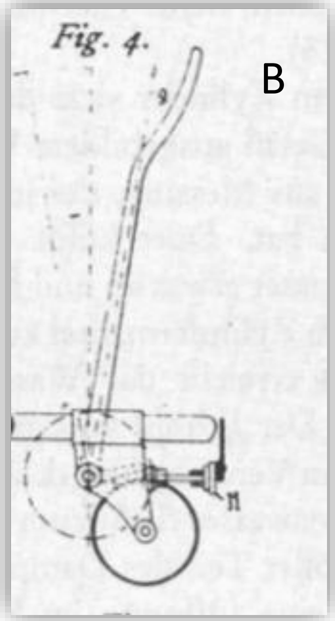
Subject Matter:

- Text 1 is describing a method related to pre-training a text summarization neural network and adapting it for a specific text summarization task.
- Text 2 is describing a method for automatically extracting a subset of sentences from a natural language document based on features and scores.

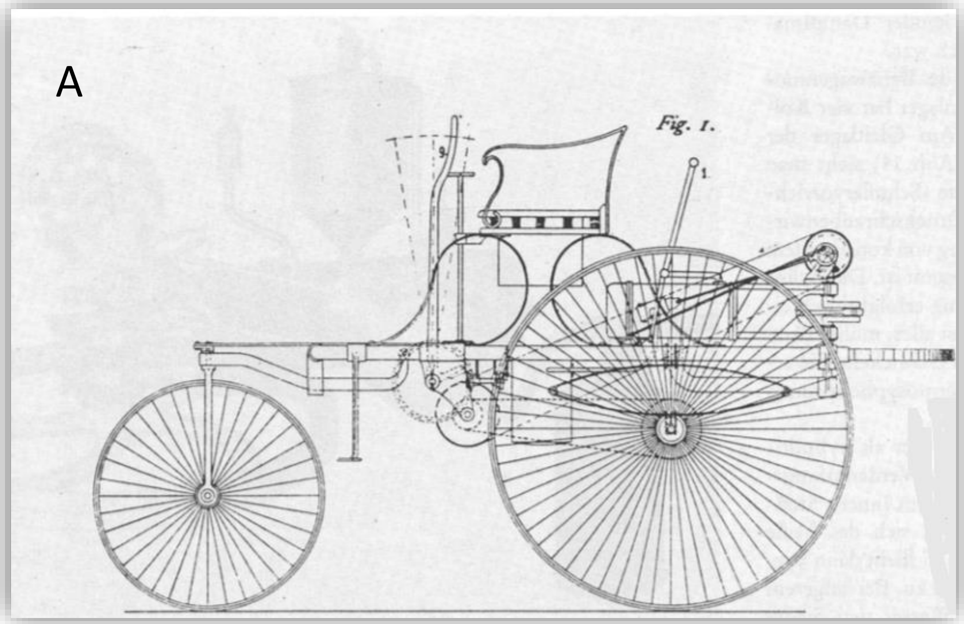
- Specificity:
  - Text 1 is more specific in terms of its context, focusing on the pre-training and adaptation of a text summarization neural network.
  - Text 2 is more general and seems to be about a method for sentence extraction from a natural language document using features and scores.
- Technical Details:
  - Text 1 includes technical details related to neural networks, parameter learning, and self-supervised learning.
  - Text 2 includes technical details about features, probabilities, and scoring for sentence extraction.
- Application:
  - Text 1 is more related to natural language processing and text summarization tasks.
  - Text 2 is more related to information retrieval or document processing tasks.
- General analyses
  - In summary, Text 1 is focused on neural network training and adaptation for text summarization, while Text 2 deals with the extraction of sentences from a document based on features and scores. They differ in their subject matter and technical details.

How do we solve the puzzle to automatic generate patent summaries?

What is the information requirement of good patent summarization
No 37435 Benz Patent – Motorwagen (1886)



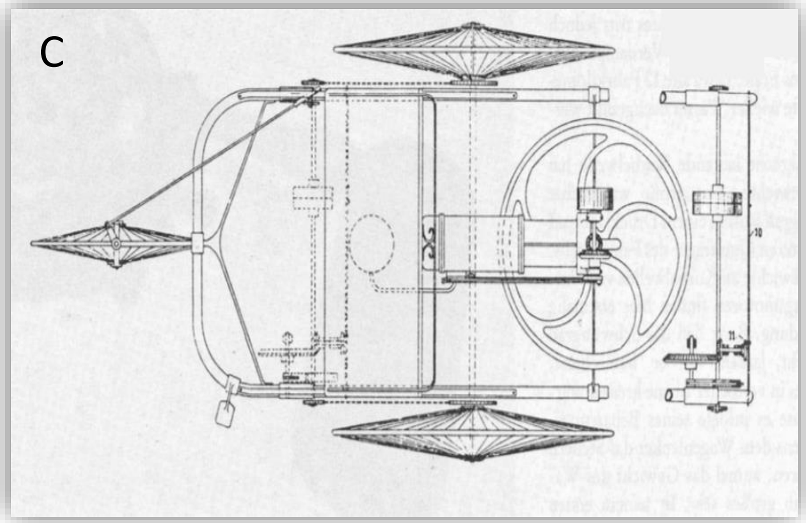
Steering mechanism



The transcport vehicle

Search for:

- Problem and Solution (A)
- Scope of the invention (A,B,C)
- Specific technical details (B,C)



Engine function

Artificial Researcher

Discourse Information

- Lexical cohesion (TEXTTILIG)
  - Andersson L, Mahdabi P, Hanbury A, Rauber A(2012) *Report on the CLEF-IP 2012 Experiments: Exploring Passage Retrieval with the PIPExtractor* In Proceeding of the of the Conference and Labs of the Evaluation Forum (CLEF2012)
- Connecting claim sentence to relevant text segment within the patent itself
  - Mase H., Matsubayashi T, Ogawa Y, Iwayama M, and Oshio T. Proposal of two-stage patent retrieval method considering the claim structure. 4(2):190–206, June 2005
- Sentence labelling
  - https://github.com/nlpTRIZ
  - Contradiction
  - https://github.com/Renuk9390/Patent_Sentiment_Analysis
    - Solution to problem
    - Advantageous effect invention
    - Technical problem

But most important are the **Technical Terms**

The majority of entities in technical English dictionaries consist of terms with more than one word.

J. S. Justeson and S. M. Katz, "Technical terminology: some linguistic properties and an algorithm for identification in text," Natural Language Engineering, vol. 1, pp. 9–27, 3 1995

The identification of technology terms within a collection of patents is a challenging information extraction task due to the nature of technology terms themselves, which may be ambiguous or generic and have multiple nuances of interpretation.

Anick P, Verhagen M, and Pustejovsky J. Identification of technology terms in patents. Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), Reykjavik, Iceland, may 2014. European Language Resources Association (ELRA).

Artificial Researcher

What is Technical Term in patent?

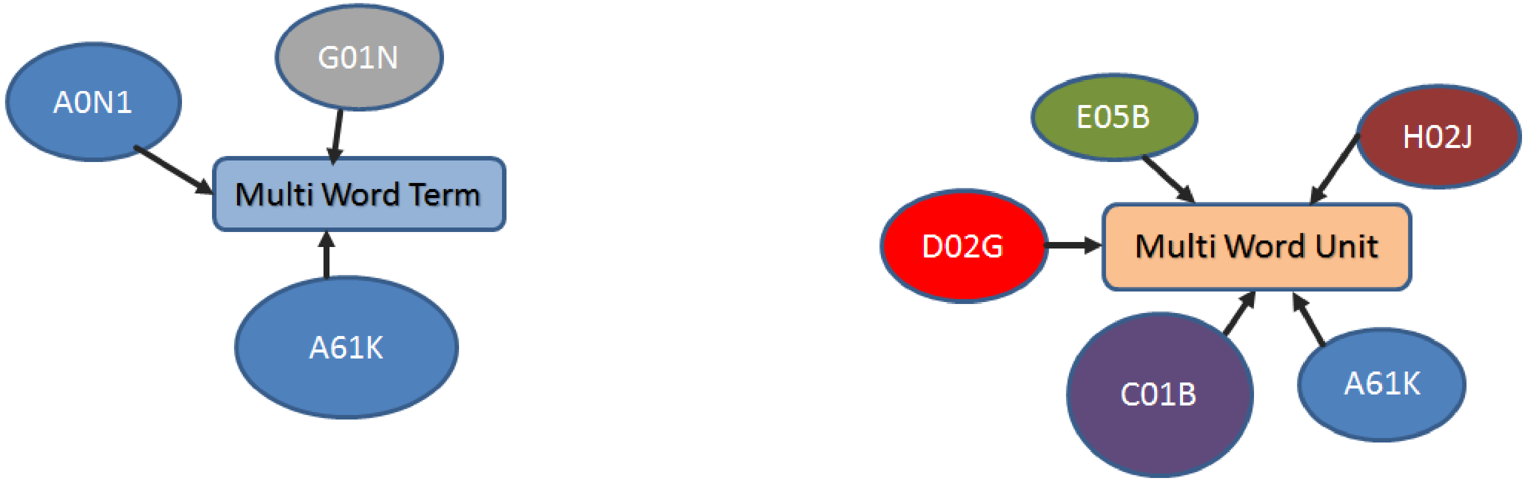
Depends on who you are asking and what context!

Candidate Term	Word2Vec	C-Value	Pointwise Mutual information	Human
Remote communication	Yes	No	No	No
Communication link	No	Yes	Yes	Yes
Resin particle	No	Yes	No	Yes
washed washing	No/Yes (0.642)	Yes	No	No
Bar code	No	Yes	No	Yes
Wet strength	Not	Yes	No	Yes

Learning Termhoodness using Classification distribution information

Our assumption

Phrases having a homogenous distribution of IPC codes will reflect the termhoodness compared to phrases with heterogeneous distribution



IPC-distributional-values

Using **Random Forest Regression** model obtained F1 score of 0.845 in accuracy on larger sample of 4,400 canditates

Using BERT – Technical Term Prediction

- Task: detect domain term spans in sentences

Domain Term

A	network	synchronization	method	allows
O	I	I	I	O

- Using pre-trained SciBERT Model
  - With additional training data for Technical Term detection
  - Randomly picked 22 patents with different International Patent Classification codes
  - Sentences 10,337, Technical Term dictionary of size 5,099

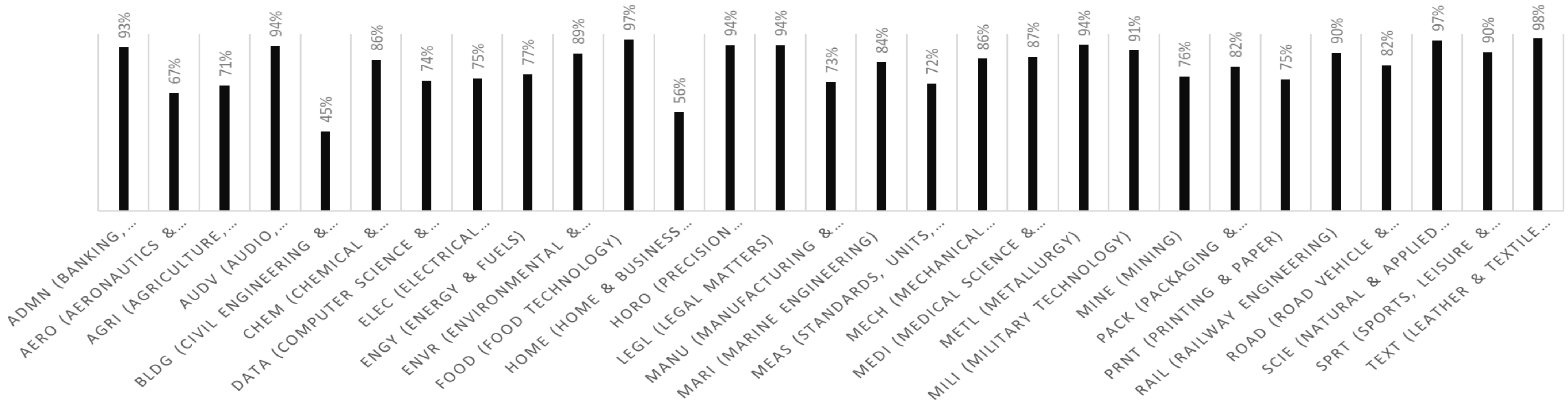
Fink T., Andersson L., Hanbury A. (2021) Detecting Multi Word Terms in patents the same way as entities / World Patent Information, 67 102078; 1 - 6

Technical term identification

- Evaluation using WIPO PEARL Terminology DB

Artificial Researcher

RECALL AND PRECISION ASSESSMENT	
WIPO CONCEPT RECALL	81%
ALL DOMAIN TERM RECALL	96%
ALL DOMAIN TERM PRECISION	85%



© Artificial Researcher,2022

Artificial Researcher

Why not combine the two?

Using semantically enriched data can retrieve up to 60% more related concepts than traditional pre-trained contextual models (a.k.a. Neural Network-based methods, BERT-family).

Artificial Researcher's text mining technology

Technical terms
Related concept

brake pedal:
- vehicle operating pedal,
- conventional hydraulic brake system
- pedal devices
- position brake actuating member
- brake actuating member
- hydraulically-assisted rack pinion steering gear
- brake operating member
- conventional braking system
- pair pedals

accelerator pedal
- case pedal device
- pedal device

Extraction using pre-trained contextual models only

brake pedal	PatBERT	SciBERT
conventional hydraulic brake system	0.69	0.89
hydraulically-assisted rack pinion steering gear	0.49	0.80
conventional braking system	0.66	0.84

Next step integrate the Domain Name Entity labels

Artificial Researcher

Task-oriented BERT

Medical industry: population (patient group) and therapy

- The promise of extracorporeal liver replacement therapy and non-invasive ventilation were other areas of interest.
  - Therapy: extracorporeal liver replacement therapy
- Based on the first 35 patients admitted to the hospital with COVID-19, we evaluated the various symptoms with which patients presented
  - Population: patients admitted to the hospital with COVID-19

Artificial Researcher

Training data: Prediction Intervention (I-INT)

- Task: Intervention (e.g., therapy and comparison) term spans in sentences

Therapy (I-INT)

Sentence:	of	extracorporeal	liver	replacement	therapy	and
IO Labels:	O	I-INT	I-INT	I-INT	I-INT	O

The promise of extracorporeal liver replacement therapy and non-invasive ventilation were other areas of interest.

Identification of fragrance concepts in text

A task-oriented BERT model can extract following entities form text

- Perfumes **smell** **creamy** due to large doses of **vanillic**, **musky** and **milky** notes. **Coty Vanilla Fields** is a **familiar creamy vanilla fragrance**. An **opposite** of that is a **dry and sharp sensation**, **similar** to the one produced by **amber** in the base of **Paco Rabanne Black XS**.

Smell – different word and phrases related to fragrance concept related to fragrance referring to type

Fragrance description
A phrase or word describing type of fragrance

Quantity
Dosage and measures

Substance entity
Word or phrases defined as substance used for producing fragrance

familiar creamy vanilla fragrance
(linguistic: hypernym)

Adjective (descriptive & degree)
Describing a type of relations, here adjective

Proper name – a name of perfume or brand

Why not join all three?

Text classification & semantic relation extraction & domain NE labelling

Artificial Researcher

Input


```
{
    "api_key":"4d39678c5cbd428db3312a66d3dae13f",
    "text":"vinyl ethers methyl ketone such as vinyl hexyl ketone and
    "classification": [
        "Class 1",
        "Class 2"
    ],
    "request_similarity": [
        "SciBERT"
    ],
    "source_dataset": "some dataset",
    "source_file": "some file",
    "text_id": "in some file"
}
```


Output


```
{
  "results": [
    {
      "CLASSIFICATION": [
        [
          "Class 1",
          "Class 2"
        ]
      ],
      "DETECTOR": "LSP_PATTERN_DETECTOR",
      "GENERAL": "vinyl_ether_methyl_ketone",
      "LANGUAGE": "en",
      "SEARCH_HELPER": [
        "hexyl",
        "vinyl",
        "methyl",
        "ether",
        "ketone"
      ],
      "SIMILARITY": {
        "SciBERT": 0.9545886
      },
      "SOURCE_DATASET": "some dataset",
      "SOURCE_FILE": "some file",
      "SOURCE_TEXT": "vinyl ethers methyl ketone such as vinyl hexyl ketone and methyl isopropenyl ketone ; N - vinyl .",
      "SPECIFIC": "vinyl_hexyl_ketone",
      "TERM_HELPER": {
        "term0": "hexyl",
        "term1": "vinyl",
        "term2": "methyl",
        "term3": "ether",
        "term4": "ketone"
      },
      "TEXT_LOCATION": "in some file",
      "VERSION": 14
    },
```


Automatic classification according to taxonomies such as IPC/CPC, MeSH, PLoS, WIPO Scientific Subject fields

So, to the question can we use LLM for patent summarization?

The current LLM

- For text argumentation
- As part of the verification of sentence categorization and NE labelling
- To make the extracted text more fluently

The initial patent summarization experiment was conducted at PatentSemTech 2023

- We assumed that participants of PatentSemTech were all knowledgeable in the field of text mining, so we put automatic patent summarization with an LLM (ChatGPT 3.5) to the test.
- We selected five patents within the field of text mining
  - For each of them, we have created four summarizations, one of which is manually curated by domain experts.
  - We asked the participants to indicate their level of knowledge:
    - I have worked on related topics and have a good general understanding of the area of technology
    - I read few patents on this topic but not my main area of expertise
    - I read very few patents on this topic, and it is outside of my area of expertise
  - We asked the participants to rank the summarizations from poor to excellent quality.

Artificial Researcher

Text summarization, US20060206806A1

https://forms.office.com/e/aEyR2tampW

Title: Text summarization

Abstract

A method for summarizing text (**20**), comprising evaluating (**24**) selected words of the text according to predetermined criteria to provide word score values for each of the selected words. Thew method then provides for calculating (**25**) for each of the selected words a word weighted score that is dependent on the word score values and a number of occurrences of each of the selected words. Thereafter a step (**26**) of scoring sentences of the text to determine a sentence weighted score for the sentences is conducted. The sentence weighted score depends on sentence type and a combined word weighted score for words in the sentence. The method then provides for selecting (**27**) sentences to provide a summary of the text, the selecting being dependent on the sentence weighted score of the sentences.

Link: https://patents.google.com/patent/US20060206806

Artificial Researcher

Preliminary results for two patents

Human versus LLM (chatGPT 3.5)

US20060206806A1	Human	Algorithms
Poor	0	9
Fair	0	8
Good	4	3
Excellent	3	4

US10831345B2	Human	Algorithms
Poor	2	0
Fair	3	11
Good	2	7
Excellent	0	3

The estimated time for assessment by participants	
Shorter	11
15 to 25 minutes	4
25 to 35 minutes	0
longer	0

Questions!

Artificial Researcher IT GmbH is a Spin-off from TU Wien since 2019

More information visit https://artificialresearcher.com

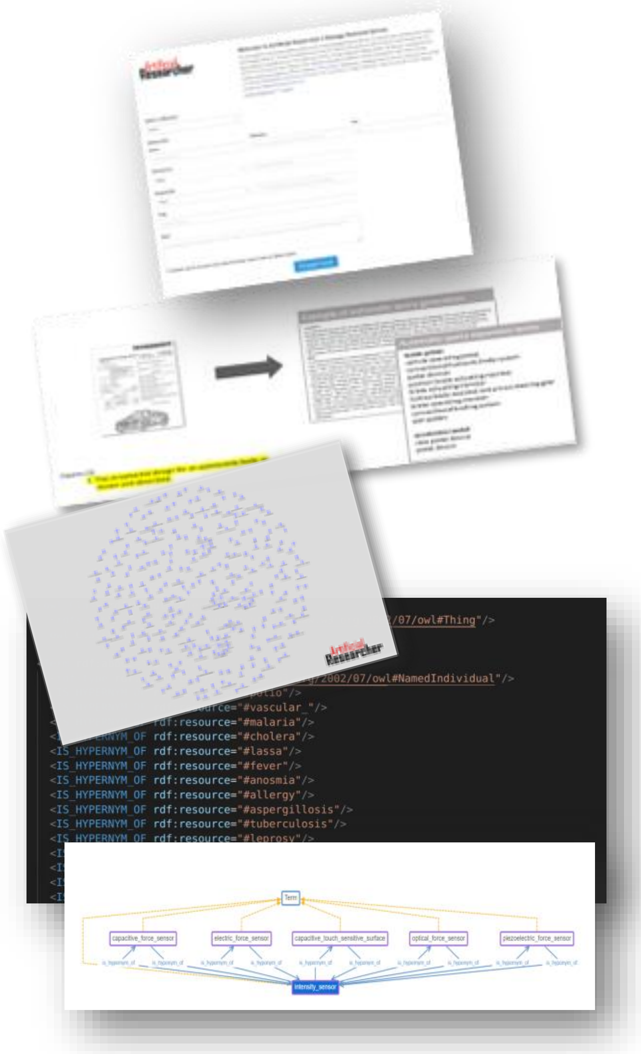
Appendix

© Artificial Researcher 2023

Artificial Researcher - Services & Products

Test access: API key **b10225791d2a478c9ff3d8cd106ad65a**

- **Artificial Researcher Passage Retrieval Service**
  - Access: rest API, Desktop App Script (Python)
    - https://swagger.artificialresearcher.com/ (developer)
    - https://passageretrieval.artificialresearcher.com/ (demo)
  - SaaS or on-premises software (Docker)
- **Artificial Researcher Ontology Service**
  - Access: rest API, Desktop App Script (Python)
    - https://swagger.artificialresearcher.com/?urls.primaryName=onto-api (developer)
    - Data format OWL or JSON
  - SaaS or on-premises software (Docker)
    - Ontology generator – only SaaS
- **Artificial Researcher NLP-toolkit Services**
  - Access: rest API
    - https://swagger.artificialresearcher.com/?urls.primaryName=unified-nlp-server (developer)
  - SaaS or on-premises software (Docker)
- **Artificial Researcher Graph Search Service**
  - UX: https://graph-demo.artificialresearcher.com/ (demo)



© Artificial Researcher,2022

The experiment

- For each patent, you will be presented with three summarizations created by algorithms, and one summary curated by a domain expert. The summarizations range between 250 to 700 words.

  Instruction:
- Read the abstract and take a brief look at the patent using the provided link.
  - Please aim to spend no more than 15 minutes on reviewing the patent application itself.
- Grade the four different summarizations in terms of quality, ranging from poor to excellent.
  - You have the option to rate all of them as poor if none of them offer a representative summary of the invention.

© Artificial Researcher 2023

Artificial Researcher

Text summarization, US20060206806A1

https://forms.office.com/e/aEyR2tampW

Title: Text summarization

Abstract

A method for summarizing text (**20**), comprising evaluating (**24**) selected words of the text according to predetermined criteria to provide word score values for each of the selected words. Thew method then provides for calculating (**25**) for each of the selected words a word weighted score that is dependent on the word score values and a number of occurrences of each of the selected words. Thereafter a step (**26**) of scoring sentences of the text to determine a sentence weighted score for the sentences is conducted. The sentence weighted score depends on sentence type and a combined word weighted score for words in the sentence. The method then provides for selecting (**27**) sentences to provide a summary of the text, the selecting being dependent on the sentence weighted score of the sentences.

Link: https://patents.google.com/patent/US20060206806

© Artificial Researcher 2023

Unsupervised ontology-based graph extraction from texts, US10169454B2

https://forms.office.com/e/NjZuNSUHrk

Title:Unsupervised ontology-based graph extraction from texts

Abstract

A method for extracting a relations graph uses an ontology graph in which nodes represent entity classes or concepts and edges represent properties of the classes. A property is associated with a constraint which defines a range of values that can be taken without incurring a cost. Input text in which entity and concept mentions are identified is received. An optimal set of alignments between a subgraph of the ontology graph and the identified mentions is identified by optimizing a function of constraint costs incurred by the alignments and a distance measure computed over the set of alignments. The relations graph is generated, based on the optimal set of alignments. The relations graph represents a linked set of relations instantiating a subgraph of the ontology. The relations graph can include relations involving implicit mentions corresponding to subgraph nodes that are not aligned to any of the concept or entity mentions.

Link: https://patents.google.com/patent/US10169454B2

© Artificial Researcher 2023

Artificial Researcher

Establishing user specified interaction modes in a question answering dialogue, US10831345B2

https://forms.office.com/e/VTZ3LY02Lm

Title: Establishing user specified int
eraction modes in a question ans
wering dialogue

Abstract

An approach is provided for automatically generating user-specific interaction modes for processing question and answers at the information handling system by receiving a question from a user, extracting user context parameters identifying a usage scenario for the user, identifying first input and output presentation modes for the user based on the extracted user context parameters, monitoring user interaction with the system in relation to the question, and adjusting the first input and output presentation modes based on the extracted user context parameters and detected user interaction with the system.

Link: https://patents.google.com/patent/US10831345B2

© Artificial Researcher 2023

User-centric soft keyboard predictive technologies US10156981B2

https://forms.office.com/e/pjDwaCu85f

Abstract

An apparatus and method are disclosed for providing feedback and guidance to touch screen device users to improve text entry user experience and performance by generating input history data including character probabilities, word probabilities, and touch models. According to one embodiment, a method comprises receiving first input data, automatically learning user tendencies based on the first input data to generate input history data, receiving second input data, and generating auto-corrections or suggestion candidates for one or more words of the second input data based on the input history data. The user can then select one of the suggestion candidates to replace a selected word with the selected suggestion candidate.

Link: https://patents.google.com/patent/US10156981B2

© Artificial Researcher 2023

Title: Regularized latent semantic indexing for topic modeling, US8533195B2

Artificial Researcher

https://forms.office.com/e/6DEBXDUPGz

Title: Regularized latent semantic indexing for topic modeling

Abstract

Electronic documents are retrieved from a database and/or from a network of servers. The documents are topic modeled in accordance with a Regularized Latent Semantic Indexing approach. The Regularized Latent Semantic Indexing approach may allow an equation involving an approximation of a term-document matrix to be solved in parallel by multiple calculating units. The equation may include terms that are regularized via either l1 norm and/or via l2 norm. The Regularized Latent Semantic Indexing approach may be applied to a set, or a fixed number, of documents such that the set of documents is topic modeled. Alternatively, the Regularized Latent Semantic Indexing approach may be applied to a variable number of documents such that, over time, the variable of number of documents is topic modeled.

Link: https://patents.google.com/patent/US8533195B2

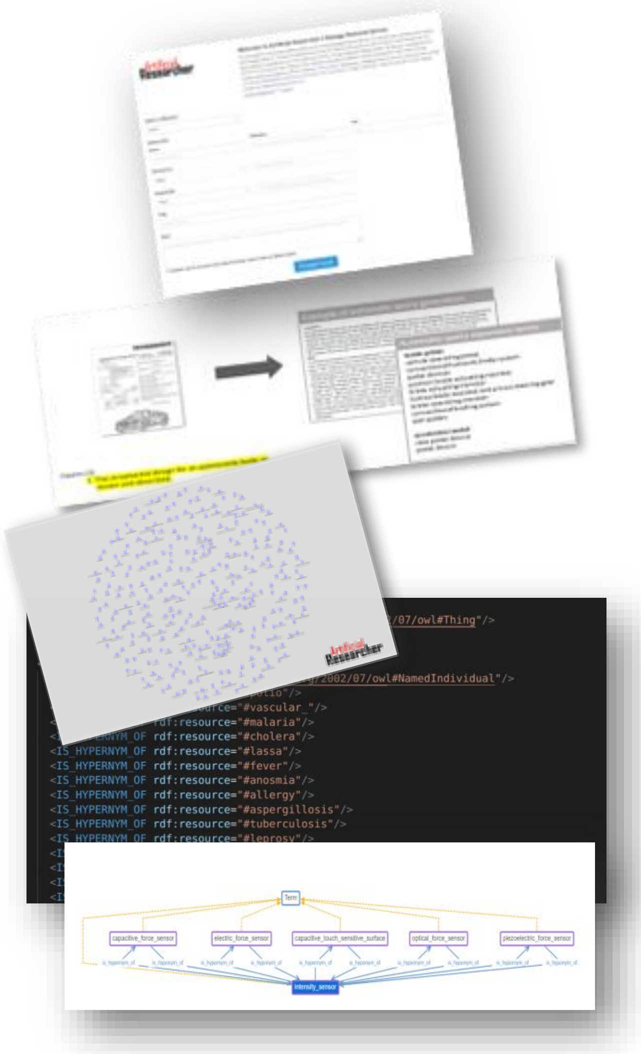
© Artificial Researcher 2023

Artificial Researcher

Artificial Researcher - Services & Products

Test access: API key **b10225791d2a478c9ff3d8cd106ad65a**

- **Artificial Researcher Passage Retrieval Service**
  - Access: rest API, Desktop App Script (Python)
    - https://swagger.artificialresearcher.com/ (developer)
    - https://passageretrieval.artificialresearcher.com/ (demo)
  - SaaS or on-premises software (Docker)
- **Artificial Researcher Ontology Service**
  - Access: rest API, Desktop App Script (Python)
    - https://swagger.artificialresearcher.com/?urls.primaryName=onto-api (developer)
    - Data format OWL or JSON
  - SaaS or on-premises software (Docker)
    - Ontology generator – only SaaS
- **Artificial Researcher NLP-toolkit Services**
  - Access: rest API
    - https://swagger.artificialresearcher.com/?urls.primaryName=unified-nlp-server (developer)
  - SaaS or on-premises software (Docker)
- **Artificial Researcher Graph Search Service**
  - UX: https://graph-demo.artificialresearcher.com/ (demo)



© Artificial Researcher 2023