GENERATIVE AI FOR COMPUTATIONAL CREATIVITY CONCEPTUALIZATION

Boshko KOLOSKI,[1,2] Senja POLLAK[1],
Geraint Wiggins[3, 4], Nada LAVRAČ[1]
[1]Jožef Stefan Institute, Ljubljana, Slovenia
[2]Jožef Stefan International Postgraduate School, Ljubljana, Slovenia
[3] Vrije Universiteit Brussel, Brussel, Belgium
[4] Queen Mary University of London, London, United Kingdom

Concept Creation Technology is concerned with engineering software for (semi-)automated domain conceptualization. This paper presents an approach to automatizing the conceptualization of the Computational Creativity (CC) domain, exploiting Generative AI (GAI) as a general-purpose Concept Creation Technology tool. The approach is showcased on the task of CC domain conceptualization using all publicly available proceedings from ICCC-2010 to ICCC-2023, as well as on the task of automated table of contents (ToC) structuring of individual Proceedings of the International Conferences on Computational Creativity. The implemented GAI methodology facilitates automated conceptualization of any domain of interest, automated ToC structuring of any proceedings or document corpus, as well as experiment replicability and software reuse.

Keywords: generative AI, computational creativity, natural language processing

1 INTRODUCTION

Computational Creativity (CC) is concerned with engineering software that exhibits creative behavior (Boden, 2004; Colton & Wiggins, 2012). A part of CC research addresses *Concept Creation Technology*, concerned with engineering software that exhibits creative behavior of *conceptualization*. In information science, conceptualization is defined as “an abstract (simplified) view of some selected part of the world, containing the objects, concepts, and other entities that are presumed of interest for some particular purpose and the relationships between them”, usually formalized through ontologies (Gruber, 1993; Smith, 2003). Manual construction, maintenance and updating of ontologies represents a significant investment of human resources, which is not always available and/or needed. More contemporary and less resource-consuming domain categorization approaches are currently available, using methods for automated extraction of domain knowledge from unstructured texts. These include automatic taxonomy construction (Fortuna et al., 2007; Kozareva & Hovy, 2010; Navigli & Ponzetto, 2012), knowledge graph construction (Y. Wei et al., 2023; Ye et al., 2022), and topic modeling that allows for domain conceptualization without explicit relations between concepts (Grootendorst, 2022; Porturas & Taylor, 2021; Yao et al., 2018). As this paper shows, the research vision of developing a fully automated technology for ICCC domain conceptualization has been fulfilled in this work, using novel Generative AI (GAI) methods to support the understanding of the conceptual structure of any research field represented by the papers published in conference proceedings.

This paper explores the potential of Large Language Models and Generative AI (GAI) acting as an advanced Concept Creation Technology tool that can be applied to any domain of interest. The proposed GAI approach facilitates automated conceptualization of any domain of interest, automated proceedings ToC generation for any proceedings or paper corpus.

The paper is structured as follows. After a brief outline of related work on CC domain conceptualization, Large Language Models (LLMs) and Generative AI (GAI), we describe the data used in the study, followed by the presentation of the proposed GAI-based methodology. We then present the results of the methodology on the task of automated CC domain conceptualization, covering all publicly available proceedings from ICCC-2010 to ICCC-2023. Moreover, the approach has been applied also to the table of contents (ToC) structuring of papers published in the ICCC-2023 Proceedings edition. Finally, we discuss experiment replicability and software reuse.

As for every other research community, Computational Creativity (CC) field conceptualization is also an interesting research field. Loughran & O'Neill (2017) have studied the CC domain by analyzing its conference proceedings, where conceptual categorization was conducted subjectively, through the re-view of each paper. This paper addresses automated CC conceptualization, following the line of past research in this area.

2 RELATED WORK

2.1 CC Domain Conceptualization

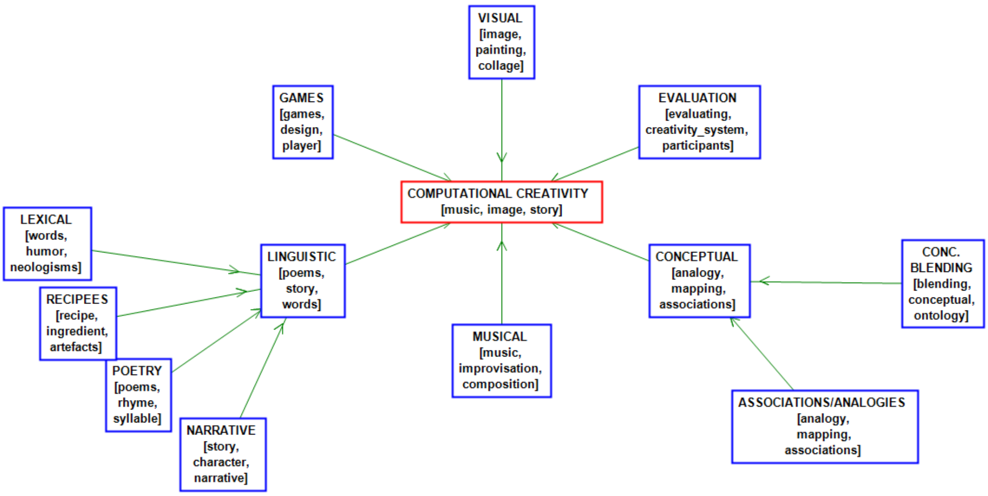

Figure 1: Semi-automatically generated conceptualization of the CC, with semi-automated concept naming and subconcept creation, using papers from 2010–2015 ICCC proceedings.

In related work by (Pollak et al., 2016), automated CC conceptualization was addressed using a semi-automated topic ontology construction tool OntoGen from 2010–2015 ICCC proceedings papers. The resulting corpus-based categorization of the CC field identified the following main CC subdomains: Musical, Visual, Linguistic creativity, Conceptual creativity, Games and creativity, with a manually added sub-domain of Evaluation through manual query used in the active learning approach to topic ontology creation. For several subdomains, subcategories were detected at a lower level, including Narratives, Poetry, Recipes and Lexical creativity as subdomains of Linguistic creativity, shown in Figure 1, visualized by (Pollak et al., 2016). Later, an extended corpus of 2010–2017 ICCC proceedings papers using k-means clustering and LSI cluster visualization techniques was analyzed (Podpečan et al., 2018). For instance, when analyzing again the ICCC proceedings papers from ICCC 2010–2015, the CC domains are very clearly separated, allowing the expert to easily recognize the topics (e.g., musical creativity, visual creativity, story generation, poetry generation, culinary creativity, conceptual creativity, etc.), where k-means with k=11 proved to provide optimal clusters in terms of the Silhouette score. Nevertheless, automated discovery of the optimal number of clusters using the Silhouette score gave non-conclusive results, as the results did not fully align with human conceptualization based on 2D visual cluster representations.

2.2 NLP, Large Language Models and Generative AI

The field of natural language processing has witnessed a remarkable transformation with the advent of Large Language Models (LLMs), which can be divided into two groups: Masked Language Models (MLMs) such as BERT (Devlin et al., 2019) and generative Causal Language Models (CLMs) such as LLaMa2 (Touvron & et al., 2023). These foundational models have set new standards for understanding and generating text with human-level precision (Min et al., 2023). Building on this groundwork, the sentence transformers (Reimers & Gurevych, 2019) have emerged as a specialized evolution. These models, which are tailored to the task of learning sentence representations, ensure that semantically similar sentences are closely aligned in the vector space. One notable application of sentence transformers is BERTopic (Grootendorst, 2022), which has revolutionized topic modeling with its unique approach. BERTopic clusters sentences based on semantic similarity, providing a refined and context-sensitive thematic analysis that outperforms conventional methods. In a similar vein, KeyBERT (Grootendorst, 2020) advances the field of keyword extraction. Utilizing sentence-transformer technologies, it effectively extracts key terms and phrases from extensive texts (Škrlj et al., 2022; Koloski et al., 2022). A pivotal area of research in the use of these models is domain adaptation. (Wang et al., 2021) proposed an approach for unsupervised domain adaptation, employing sequential denoising auto-encoders to learn from corrupted data. Another approach to domain adaptation involves generative pseudo-labeling (GPL) (Wang et al., 2022), where researchers use a surrogate generative model, such as T5 (Raffel et al., 2020) that is trained to generate queries for specific passages (Thakur et al., 2021). These queries are then ranked by a cross-encoder (Reimers & Gurevych, 2020) and used as downstream fine-tuning data for the sentence transformer. The development of prompting techniques in LLMs (J. Wei et al., 2022), particularly in-context oneshot learning (Lampinen et al., 2022), represents a significant stride in model interaction. This approach involves crafting specific prompts that enable models to learn from a single example within the prompt context, thereby generating more relevant and contextually nuanced responses. This technique is crucial in eliciting accurate and specific outputs from models like LLaMa2 (Touvron & et al., 2023), demonstrating a high level of understanding and flexibility in language generation (Pan et al., 2023).

3 EXPERIMENTAL DATA AND PROBLEM DEFINITION

In this section we present the data acquisition approach, followed by exploratory data analysis over the ICCC proceeding from the period of 2010 to 2023.

3.1 Data acquisition

We have extracted the data from two sources: actual ICCC proceedings in PDF format and the DBLP entries of individual proceedings articles. The ICCC proceedings for all years except for 2011 are available as single PDF files that were easy to process, whereas for 2011, individual articles are downloadable from the ICCC-2011 Proceedings Web page.

To enrich the PDF data available to us, we used DBLP as a resource to utilize the Bibtex metadata references for the ICCC proceedings as a second way of preparing the data for our system. We found dBLp entries for all years except for 2023. Note that by collecting data from dBLp, we have generalized our approach to work not only with the ICCC proceedings papers, but with any available conference proceedings paper collection, so that a specialized table of contents structuring system can be created for any conference of user's interest.

Data acquisition resulted in the ICCC corpus, which consists of the articles from all the Proceedings of the International Conference on Computational Creativity, published in 2010–2023. The entire 2010–2023 ICCC Proceedings corpus consists of 689 articles (see Figure 2).[1]

[1] Please note that there may be slight differences between the number of articles in the corpus and the actual proceedings, as the PDF corpus from 2010 to 2023 was collected manually and

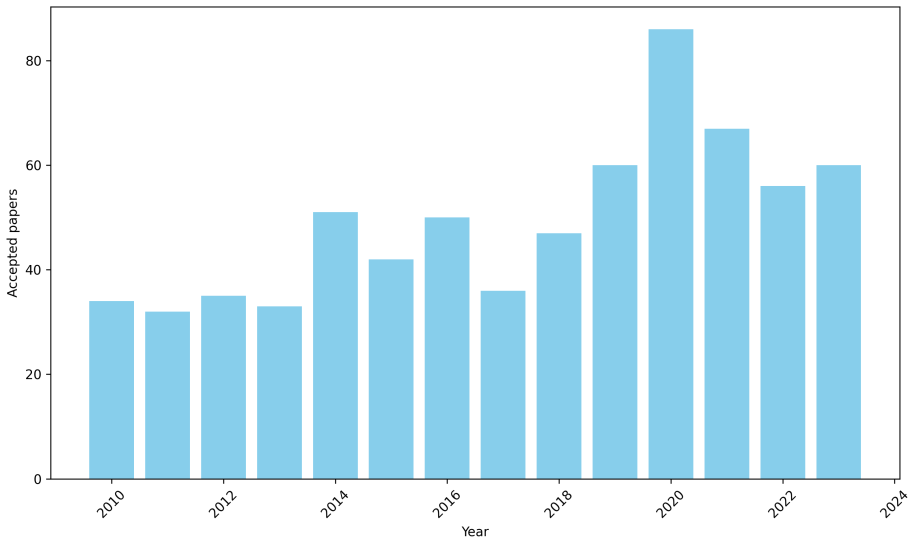

Figure 2: Distribution of articles per year.

3.2 Problem definition and motivation

Let us define the addressed problem, followed by a real-world instance of the problem.

Problem definition: The problem addressed in this paper is defined as follows: Given a set of proceedings papers, propose the topics and the structure of the Table of Contents.

Motivation: ICCC Proceedings editors have a tradition of structuring the proceedings table of contents (ToC) into Parts, containing articles on individual research topics. For example, in the ICCC-2010 Proceedings, there were 12 topics: Music – Patterns and Harmony; Visual Art; Analogy and Metaphor; Stories; Social Aspects; Foundations; Music – Creation/Generation; Creativity Support: Tools; Creativity Support: Applications; Music – Improvisation and Interaction; Evolution and Design; Linguistics; Show and Tell Session. In the ICCC-2022 Proceedings, there were 7 topics: Generating narratives; Co-creative systems;

we cannot exclude human errors, while the remaining years we used the bibtex metadata for automatic crawling, but we found a few minor inconsistencies.

Theory and problem solving; Generative art; Music and applications; Creative meaning; Social aspects and evaluation.

4 DOMAIN CONCEPTUALISATION METHODOLOGY

We closely followed the work of Koloski et al. (2024) for applying contextual large language model technologies for domain conceptualization. The methodology consists of the following steps:

1. Data pre-processing and normalization,
2. Domain adaptation using the model T5,
3. Topic modeling using BERTopic, and
4. Topic naming using LLaMa2.

The individual steps are briefly outlined below.

4.1 Data pre-processing and normalization

For each year (14 data points in total), we scraped the ICCC proceedings articles metadata from dBLp via BeautifulSoup.[2] We analyzed the articles PDFs with the fitz library, and parsed the text with regex to obtain only printable word forms (this dataset is not made available for IPR reasons). On the other hand, we have made available the entire dBLp ICCC proceedings dataset.[3] Note, DBLP did not contain an entry for 2023 proceedings of the ICCC and we mined them by hand, with the exception of demo articles. We combine the information of the start and the end of an article from the dBLP bibtex entries to navigate through the PDF articles, automating the process of data preparation.

4.2 Domain adaptation

Domain adaptation was performed through generative pseudo-labeling (GPL) (Wang et al., 2022) using a surrogate generative model T5 (Raffel et al., 2020) that has been trained to generate queries for specific passages (Thakur et

[2] https://pypi.org/project/beautifulsoup4/
[3] https://dblp.org/db/conf/icccrea/index.html

al., 2021). These queries are then ranked by a cross-encoder (Reimers & Gurevych, 2020) and used as downstream fine-tuning data for the sentence transformer. Following the work of Koloski et al. (2024) we train the *all-mini-LM-v12* sentence-transformer on 100000 steps on the combined corpora consisting of our ICCC corpus and the ArXiV corpus (Muennighoff et al., 2023). We save evaluation checkpoints at every 10,000 steps. Note that input only the first 500 words of individual articles were used as input to the sentence-transformer model as the model is limited on the input size due to its transformer-based architecture.

4.3 Topic modeling

Topic modeling was performed with BERTopic (Grootendorst, 2022) to cluster sentences based on their semantic similarity. BERTopic starts with dimensionality reduction of the underlying sentence transformer embeddings using UMAP (McInnes et al., 2018), followed by the application of a clustering algorithm. We explored two families of algorithms to identify unique clusters:

- HDBSCan (McInnes et al., 2017), where the number of clusters was inferred from the data by utilizing the cluster density heuristic.
- KMeans (MacQueen, 1967), where the number of clusters was fixed to 10, to align our results with related work (Podpečan et al., 2018).

Finally, for each cluster, the KeyBERT (Grootendorst, 2020) keyword extraction technique was applied to find and evaluate relevant keywords and phrases that best describe each cluster.

4.4 Using Generative AI for topic naming

Using the extracted keywords and the most central documents in each thematic cluster, the language model LLaMa2 (Touvron & et al., 2023) was used to generate meaningful semantic labels for each cluster. The crucial component of this methodology was the prompting instructions given to the LLaMa2 language model. Li et al. (2023) found that the way a particular prompt is phrased has a direct impact on performance.

4.4.1 CRAFTING OF THE TOPIC EXTRACTION PROMPTS

Next we show how the topic extraction prompts were designed as combination of system, examples and query parts:

- **System Prompt**

  You are a helpful, respectful and honest assistant that is helping Program Chair of a Conference on computational creativity for creating Table of Contents topics for conferences.

- **Examples Prompt**
  - **Example 1**

    I have a topic that contains the following documents:
    - Computational Filling of Curatorial Gaps in a Fine Arts Exhibition
    - Visual Conceptual Blending with Large-Scale Language and Vision Models
    - What Does it Take to Cross the Aesthetic Gap? The Development of Image Aesthetic
    The topic is described by the following keywords: 'computational, images, language, aesthetic, curation'.
    Based on the information about the topic above, please create a short and concise table of content label of this topic.
    Make sure that you exclude the following terms: 'innovation, creativity'.
    Make sure you to only return the label and nothing more.
    LABEL Art & Aesthetics

- **Example 2**

  Another example:
  I have a topic that contains the following documents:
  - LyricJam: A System for Generating Lyrics for Live Instrumental Music
  - Being Creative: A Cross-Domain Mapping Network
  - Melody Similarity and Tempo Diversity as Evolutionary Factors for Music Variations by Genetic Algorithms
  The topic is described by the following keywords: ’creative, music, cross-domain, generation’.
  Based on the information about the topic above, please create a short and concise table of content label of this topic.
  Make sure that you exclude the following terms: ’innovation, creativity’.
  Make sure you to only return the label and nothing more.
  LABEL Musical Creativity

- **Query Prompt**

  I have a topic that contains the following documents: [DOCUMENTS]
  The topic is described by the following keywords: ’[KEYWORDS]’.
  Based on the information about the topic above, please create a short and concise table of content label of this topic.
  Make sure that you exclude the following terms: ’innovation, creativity’.
  Make sure you to only return the label and nothing more.

5 RESULTS OF ICCC DOMAIN CONCEPTUALIZATION

We evaluated the results of the methodology on all domain adaptation checkpoints (10 checkpoints, 1 on each 10,000 step of the 100,000 adaptation steps), for both clustering algorithms.

As HDBScan generated a large family of not fully consistent clusters, which were of not great quality according to the domain expert’s opinion, we decided to use KMeans in our further analysis.

We found that the best clustering results were obtained by the KMeans algorithm fixed at 10 neighbors for 20,000 adaptation steps.

The output of the used methodology is a list of topics. We propose these topics shall be used as categories for the structuring of further table of contents lists of ICCC proceedings.

In the following subsections, we first describe the topic modeling results for table of contents generation, followed by the analysis of the hierarchy that emerged between the topics, and finally, we explore how the topics evolved through time.

Table 1: Topics inferred from the data and their corresponding representative documents and keywords.

Topic Name	KeyBERT	Representative Document
Visual Conceptual Blending	['blending', 'visual', 'concepts']	Cunha, Joao M., et al. "A pig, an angel and a cactus walk into a blender: A descriptive approach to visual blending."
Computational Creativity Review	['creativity', 'research', 'design']	Mumford, Martin, and Dan Ventura. "The man behind the curtain: Overcoming skepticism about creative computing."
Creative Systems and Approaches	['emoji', 'based', 'data']	Agres, Kat, et al. "Conceptualizing Creativity: From Distributional Semantics to Conceptual Spaces."
Computer Vision and Machine Learning	['generative', 'generation', 'casual']	Compton, Katherine. "Casual creators"
Computational Creativity Frameworks	['surprise', 'images', 'self']	Mondol, Tiasa, and Daniel G. Brown. "Incorporating Algorithmic Information Theory into Fundamental Concepts of Computational Creativity."
Poetic Expressions	['poetry', 'creativity']	Toivanen, Jukka, et al. "Corpus-based generation of content and form in poetry."
Narrative and Storytelling Technologies	['stories', 'narrative']	Mckeown, Lewis, and Anna Jordanous. "An evaluation of the impact of constraints on the perceived creativity of narrative generating software."
Architecture and Design	['humor', 'computational', 'musical']	Brown, Daniel, and Dan Ventura. "Ethics, Aesthetics and Computational Creativity."
Computerized Art and Design	['metaphor', 'style', 'creative', 'art']	Righetti, Guendalina, et al. "A Game of Essence and Serendipity: Superb Owls vs. Cooking-Woodpeckers."
Philosophical Perspectives on Computational Creativity	['creativity', 'research', 'design', 'evaluation']	Llano, Maria Teresa, et al. "Explainable computational creativity."

5.1 Topic results

In Figure 3 we present the resulting 10 topics produced by the model from all the 2010-2023 ICCC proceedings papers. For example, the most prominent topics were Architecture and Design (15% of the articles), followed by Computational Creativity Review (13%), Philosophical Perspectives on Computational Creativity (12%) and Creative Systems and Approaches (11%). Table 1 presents the ten topics together with the respective keywords generated by KeyBERT, and the most central document representing the document cluster. Figure 4 shows a visual representation of the resulting clustering, while Figure 5 presents the distribution of detected concepts per year.

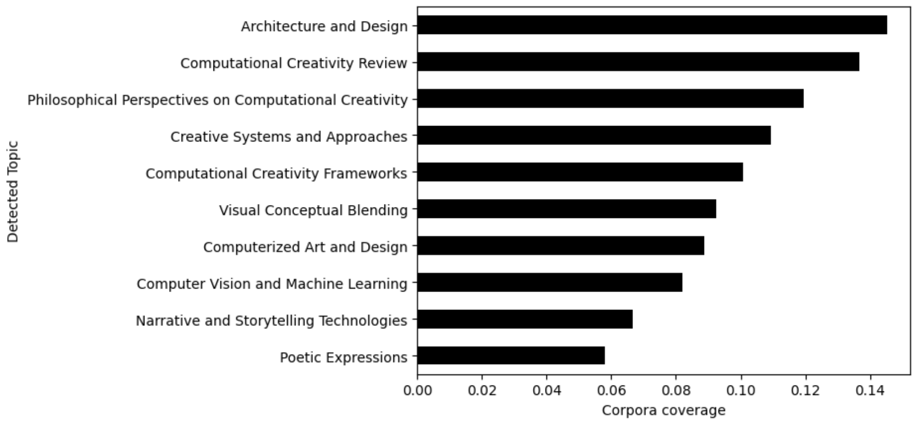

Figure 3: Detected topics and corpora coverage.

5.2 Time evolution of CC field conceptualization

Next, we analyze how the 10 derived topics of ICCC publications evolve over time (Figure 6). For each year in the 2010–2023 period, we measured the distribution of topics across articles. We found out that there were two disruptive periods. The first was in 2015, when the prominence of Philosophical Perspectives on Computational Creativity began to wane, and remained low until 2023. In the same year, Visual Conceptual Blending became very prominent, but fell back to its previous level over the following two years. We speculate that this was due to the emergence of computational frameworks for the massive analysis and generation of computational visual perspectives – the disruptive impact of AlexNet: a few years earlier (Krizhevsky et al., 2012). A change point analysis suggests that a second disruption came in 2020. We speculate that this could be due to the advent of pre-trained, transformer-based, large-scale language models such as the discriminative BERT (Devlin et al., 2019) and generative GPT (Radford et al., 2018). However, in this year there were certainly also some effects of the COVID-19 pandemic, therefore it is difficult to draw firm conclusions.

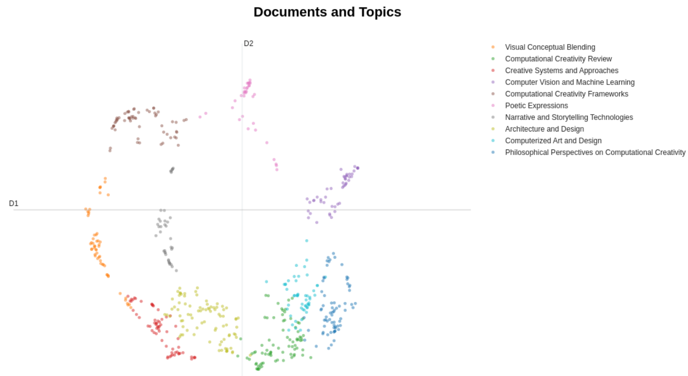

Figure 4: Spatial distribution of the articles for different years.

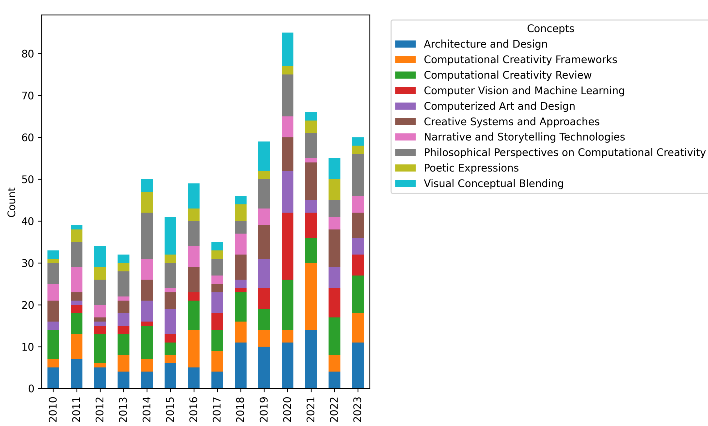

Figure 5: Distribution of detected concepts per year.

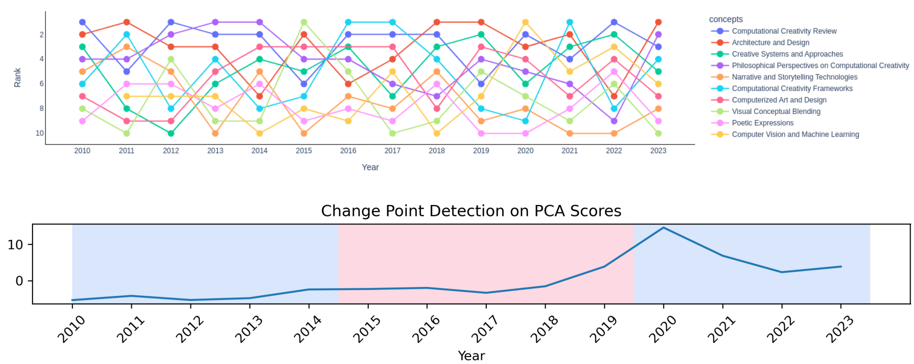

Figure 6: Above: Ranking of topics through the 14 years of ICCC proceedings. Below: Principle component analysis for change point detection over the distribution of ranks of topics through the years.

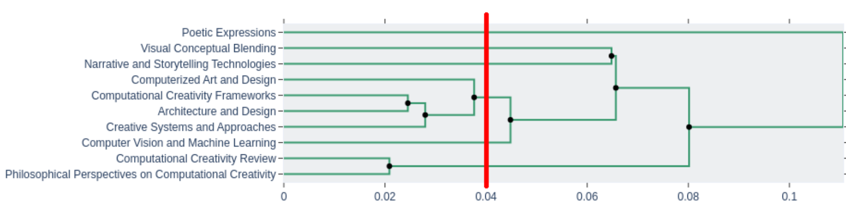

Figure 7: Hierarchical clustering of the inferred concepts.

5.3 Emergence of topic hierarchy

Next, we show the results of hierarchical clustering, i.e. the emergence of hierarchies between the inferred topics (see Figure 7). Since we began with a fixed number of topics resulting from 10-means clustering (k=10), we initially extracted 10 different topics. However, we subsequently grouped them by cluster similarity and decided to put them into 6 final topic categories (as suggested by the domain expert when inspecting the individual cluster names, and as suggested by increased cluster dissimilarities after the hierarchy cut-point at level 0.04). Cluster merging and merged cluster naming was performed as follows:

We merged the 'Computational Creativity Review' topic and the 'Philosophical Perspective on Computational Creativity' topic into a joint topic category. We then asked the LLaMa2 GAI model to name this cluster (after being prompted by the above two topic names). LLaMa2 proposed the following top-3 topic names: 'Computational Aesthetics', 'The Philosophy of Creative Machines' and 'AI-Powered Artistic Expression'. Among these, the expert's choice was the following concept name:

- The Philosophy of Creative Machines

Next, based on cluster similarity, the 'Architecture and Design' topic was coupled with the 'Computational Creativity Frameworks', followed by the 'Creative Systems and Approaches', the 'Computerized Art and Design' topic, showcasing the interactions between different layers of creativity with the different frameworks, resulting in various different downstream applications. Top-3 topic names proposed by the LLaMa2 GAI model (after being prompted by the above four topic names) were: 'Computational Creativity in Practice', 'Creative Systems and Techniques', and 'Innovation and Collaboration in Computational Creativity'. Among these, the expert's choice was the following concept name:

- Creative Systems and Techniques

The remaining topics were considered being relatively independent, and could actually be used as such in the proceedings ToC structure.

- Computer Vision and Machine Learning
- Narrative and Storytelling Technologies
- Visual Concept Blending
- Poetic Expression

5.4 Use Case: Structuring the ICCC-2023 Proceedings

Let us compare the above results obtained by the proposed GAI-based approach with the actual ICCC-2023 Proceedings structure, which was struc-tured by the Proceedings editors into the following 8 topics:[4]

- Language and Storytelling
- Co-creativity
- Evaluation
- Image Generation and Processing

[4] Note that in dataset preparation, we decided not to include the Demo section papers, as the Demo proceedings subpart refers to paper type and not to the topic contents.

- Sound and Music
- Climate Change, Diversity, Equity, and Inclusion
- Interaction and Collaboration
- Demo

The expert comparison and the evaluation of the actual ICCC-2023 structuring into 8 categories (7 content-based topics + Demo) and the ICCC-2023 proceedings structure into 10 categories proposed by our GAI-based system, or alternatively, into the 6 categories proposed above, obtained after merging the most similar topic clusters, is a matter of further work, to be evaluated by human annotators. It should be noted, however, that there is an interesting tension between choosing a ToC structure that directly reflects the paper content, and choosing one that reflects the editors' perception of the important issues in the field as a whole.

In the future, e.g., when structuring the papers accepted for ICCC-2024, the proposed GAI-based ToC structuring technology could be readily applied, by learning the clustering from 2010-2023 ICCC proceedings (or from a different training subset, defined by the editor), and applied to categorization and topic naming of the ICCC-2024 proceedings. A similar analysis over the whole range of ICCC proceedings might yield interesting insights regarding the key areas of interest in the field as a whole.

6 EXPERIMENT REPLICABILITY AND SOFTWARE REUSE

We intend to publish our code for further structuring and generating tables of contents. Since our approach is based on pretrained models, only a few steps of optional domain adaptation are required. Moreover, our approach leverages open data sources such as DBLP, further generalizing the method for structuring and conceptualizing any conference.

7 CONCLUSIONS AND FUTURE WORK

In this work, we focused on the application of contextual large language models to conceptualize a corpus of documents from proceedings and generate tables of contents. We improve on previously published work both in terms of technology (we exploit contextual embeddings and use generative models supported by in-context learning for document labeling) and in terms of scope (we develop a method that is generalizable beyond ICCC conference proceedings and can be used to analyze any conference accessible via dBLP). We analyze the ICCC domain through both the temporal evolution of the core topics defined by the model and the qualitative analysis of the generated topics.

For further work, we propose to explore LLMs for document summarization, since transformer-based models that we use for document representation, have limited input size. We believe that exploring LLMs for both document summarization and large-scale qualitative analysis of topics at different time points can provide interesting insights into how to analyze a given scientific domain at scale. Next, we want to explore the interrelationships and evolution of collaboration networks within conference communities.

8 ACKNOWLEDGMENTS

The authors acknowledge financial support from the Slovenian Research and Innovation Agency through research core funding (No. P2-0103) and project No. PR-12394.

REFERENCES

Boden, M. A. (2004). *The creative mind: Myths and mechanisms*. Routledge.

Colton, S., & Wiggins, G. A. (2012). Computational creativity: The final frontier? In *Proceedings of the 20th european conference on artificial intelligence* (pp. 21–26). IOS Press. https://doi.org/10.3233/978-1-61499-098-7-21 doi: 10.3233/978-1-61499-098-7-21

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019, June). BERT: Pre-training of deep bidirectional transformers for language understanding. In J. Burstein, C. Doran, & T. Solorio (Eds.), *Proceedings of the 2019 conference of the north American chapter of the association for computational linguistics: Human language technologies, volume 1 (long and short papers)* (pp. 4171–4186). Association for Computational Linguistics.

Fortuna, B., Grobelnik, M., & Mladenić, D. (2007). Ontogen: Semi-automatic ontology editor. In *Human computer interface (part ii) (hci 2007), lncs 4558* (Vol. 4558, p. 309–-318).

Grootendorst, M. (2020). *Keybert: Minimal keyword extraction with bert.* Zenodo.

Grootendorst, M. (2022). *Bertopic: Neural topic modeling with a class-based tf-idf procedure.*

Gruber, T. R. (1993). A translation approach to portable ontology specifications. *Knowledge Acquisition*, *5*(2), 199–220.

Koloski, B., Lavrač, N., Cestnik, B., Pollak, S., Škrlj, B., & Kastrin, A. (2024). AHAM: Adapt, Help, Ask, Model - Harvesting LLMs for literature mining. In *Proceedings of IDA 2024.*

Koloski, B., Pollak, S., Škrlj, B., & Martinc, M. (2022). Out of thin air: Is zero-shot cross-lingual keyword detection better than unsupervised? In *Proceedings of the thirteenth language resources and evaluation conference* (pp. 400–409). European Language Resources Association.

Kozareva, Z., & Hovy, E. (2010). A semi-supervised method to learn and construct taxonomies using the web. In *Proceedings of the 2010 conference on empirical methods in natural language processing* (pp. 1110–1118).

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*.

Lampinen, A., Dasgupta, I., Chan, S., Mathewson, K., Tessler, M., Creswell, A., ... Hill, F.(2022). Can language models learn from explanations in context? In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Findings of the association for computational linguistics: Emnlp 2022* (pp. 537–563). Association for Computational Linguistics.

Li, C., Wang, J., Zhang, Y., Zhu, K., Hou, W., Lian, J., ... Xie, X. (2023). Large language models understand and can be enhanced by emotional stimuli. *arXiv preprint arXiv:2307.11760*.

Loughran, R., & O'Neill, M. (2017). Application domains considered in computational creativity. In *Proceedings of iccc 2017.*

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the 5th berkeley symposium on mathematical statistics and probability* (Vol. 1, pp. 281–297).

McInnes, L., Healy, J., & Astels, S. (2017). hdbscan: Hierarchical density based clustering. *J. Open Source Softw.*, *2*(11), 205.

McInnes, L., Healy, J., Saul, N., & Großberger, L. (2018). Umap: Uniform manifold approximation and projection. *Journal of Open Source Software*, *3*(29), 861.

Min, B., Ross, H., Sulem, E., Veyseh, A. P. B., Nguyen, T. H., Sainz, O., ... Roth, D. (2023). Recent advances in natural language processing via large pre-trained language models: A survey. *ACM Computing Surveys*, *56*(2), 1–40.

Muennighoff, N., Tazi, N., Magne, L., & Reimers, N. (2023, May). MTEB: Massive text embedding benchmark. In A. Vlachos & I. Augenstein (Eds.), *Proceedings of the 17th conference of the european chapter of the association for computational linguistics* (pp. 2014–2037). Dubrovnik, Croatia: Association for Computational Linguistics. https://aclanthology.org/2023.eacl-main.148 doi: 10.18653/v1/2023.eacl-main.148

Navigli, R., & Ponzetto, S. P. (2012). Babelnet: The automatic construction, evaluation and application of a wide-coverage multilingual semantic network. *Artificial intelligence*, *193*, 217–250.

Pan, J., Gao, T., Chen, H., & Chen, D. (2023). What in-context learning "learns" in-context: Disentangling task recognition and task learning. In A. Rogers, J. Boyd-Graber, & N. Okazaki (Eds.), *Findings of the association for computational linguistics: Acl 2023* (pp. 8298–8319). Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-acl.527

Podpečan, V., Lavrač, N., Wiggins, G., & Pollak, S. (2018). Conceptualising computational creativity: Towards automated historiography of a research field. In C. L. François Pachet Anna Jordanous (Ed.), *Proceedings of iccc 2018* (pp. 288–295).

Pollak, S., Boshkoska, B., Miljkovic, D., Wiggins, G., & Lavrac, N. (2016). Computational creativity conceptualisation grounded on iccc papers. In F. Pachet, A. Cardoso, V. Corruble, & F. Ghedini (Eds.), *Proceedings of the international conference on computational creativity* (pp. 123–130). (International Conference on Computational Creativity ; Conference date: 25-06-2018 Through 29-06-2018)

Porturas, T., & Taylor, R. A. (2021). Forty years of emergency medicine research: Uncovering research themes and trends through topic modeling. *The American Journal of Emergency Medicine*, *45*, 213–220.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. *OpenAI Blog*. https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., ... Liu, P. J. (2020). Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, *21*(140), 1–67.

Reimers, N., & Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 conference on empirical methods in natural language processing.* Association for Computational Linguistics.

Reimers, N., & Gurevych, I. (2020). Making monolingual sentence embeddings multilingual using knowledge distillation. In *Proceedings of the 2020 conference on empirical methods in natural language processing.* Association for Computational

Linguistics.

Škrlj, B., Koloski, B., & Pollak, S. (2022). Retrieval-efficiency trade-off of unsupervised keyword extraction. In P. Pascal & D. Ienco (Eds.), *Discovery science* (pp. 379–393). Springer Nature Switzerland.

Smith, B. (2003). Chapter 11: Ontology. In L. Floridi (Ed.), *Blackwell guide to the philosophy of computing and information* (Vol. 7250, p. 155–-166). Blackwell.

Thakur, N., Reimers, N., Rücklé, A., Srivastava, A., & Gurevych, I. (2021). BEIR: A herogeneous benchmark for zero-shot evaluation of information retrieval models. In *Thirty-fifth conference on neural information processing systems datasets and benchmarks track (round 2).*

Touvron, H., & et al. (2023). *Llama 2: Open foundation and fine-tuned chat models.*

Wang, K., Reimers, N., & Gurevych, I. (2021). Tsdae: Using transformer-based sequential denoising auto-encoderfor unsupervised sentence embedding learning. In *Findings of the association for computational linguistics: Emnlp 2021* (pp. 671–688). Association for Computational Linguistics.

Wang, K., Thakur, N., Reimers, N., & Gurevych, I. (2022). GPL: Generative pseudo labeling for unsupervised domain adaptation of dense retrieval. In *Proceedings of the 2022 conference of the north american chapter of the association for computational linguistics: Human language technologies* (pp. 2345–2360). Seattle, United States: Association for Computational Linguistics.

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., Le, Q., & Zhous, D. (2022). Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, *35*, 24824–24837.

Wei, Y., Huang, Q., Zhang, Y., & Kwok, J. (2023). KICGPT: Large language model with knowledge in context for knowledge graph completion. In H. Bouamor, J. Pino, & K. Bali (Eds.), *Findings of the association for computational linguistics: Emnlp 2023* (pp. 8667–8683). Singapore: Association for Computational Linguistics. https://aclanthology.org/2023.findings-emnlp.580 doi: 10.18653/v1/2023.findings-emnlp.580

Yao, L., Zhang, Y., Wei, B., Zhang, W., & Jin, Z. (2018). A topic modeling approach for traditional chinese medicine prescriptions. *IEEE Transactions on Knowledge and Data Engineering*, *30*(6), 1007–1021.

Ye, H., Zhang, N., Chen, H., & Chen, H. (2022). Generative knowledge graph construction: A review. In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Proceedings of the 2022 conference on empirical methods in natural language processing* (pp. 1–17). Association for Computational Linguistics. https://aclanthology.org/2022.emnlp-main.1 doi: 10.18653/v1/2022.emnlp-main.1

GENERATIVNA UMETNA INTELIGENCA ZA KONCEPTUALIZACIJO RAČUNALNIŠKE KREATIVNOSTI

Tehnologija ustvarjanja konceptov se ukvarja z inženiringom programske opreme za (pol)avtomatizirano konceptualizacijo domene. Ta članek predstavlja pristop k avtomatizaciji konceptualizacije domene računalniške kreativnosti z izkoriščanjem generativne umetne inteligence (GAI) kot splošnega orodja za tehnologijo ustvarjanja konceptov. Pristop je prikazan na nalogi konceptualizacije domene (computational creativity, CC) z uporabo vseh javno dostopnih zbornikov od ICCC-2010 do ICCC-2023, pa tudi na nalogi avtomatiziranega strukturiranja kazala posameznih zbornikov Mednarodnih konferenc o računalniški kreativnosti. Implementirana metodologija GAI omogoča avtomatizirano konceptualizacijo katere koli domene, avtomatizirano strukturiranje kazala katerega koli zbornika ali dokumentnega korpusa ter ponovljivost eksperimentov in ponovno uporabo programske opreme.

Keywords: generativna AI, računalniška kreativnost, obdelava naravnega jezika