# Unveiling Computer Chess Evolution: Can Machine Learning Detect Historical Trends?

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**Abstract.** Computer Chess and AI are deeply intertwined, addressing similar research issues and proposing solutions that intersect. Even from a historical viewpoint, these two areas are strongly connected. This article presents a historical overview of Computer Chess research segmented in four seasons. Our research goal is to report an experiment of using cutting-edge machine learning tools to extract keywords and topics from a large set of scientific articles on Computer Chess, aiming at singling out the characterizing differences among the seasons. Moreover, we investigate the relationships between topics across seasons and their evolution. Although the seasons can be identified by clear milestones, we observed a lack of distinct boundaries between their topics. Instead, some issues recur across different seasons, albeit adjusted to new contexts, tools, and technologies.

## 1 Introduction

Computer Chess and AI are strongly interconnected, both in terms of the problems they study and the solutions they propose. Even from a historical perspective, there is a parallelism between these two disciplines, which has been highlighted by several authors. For instance [27] traced the parallel evolution of these two fields, showing how advances in one often led to progress in the other. Similarly, [23] explored how Computer Chess served as a testbed for AI techniques, driving innovation in areas such as search algorithms and knowledge representation.

The evolution of AI has been schematized into seasons that repeated cyclically and differ for problems studied, solutions found, and failures asking for new approaches. For instance, a report by the EU commission identified four periods[1]: the foundation of AI algorithms (1950s-1970s), the development of symbolic algorithms and expert systems (1970s-1990s), the explosion of machine learning (1990s-2010s) and later deep learning approaches (2010s-).

The history of Computer Chess can be schematized into historical seasons as well, each characterized by specific issues and solutions, and failures and

[1] https://ai-watch.ec.europa.eu/publications/historical-evolution-artificial-intelligence_en

triumphs, as proposed by [4] and [1]. For instance, in both [12] and in [17] the evolution of Computer Chess was articulated into three seasons. The seasons described in these works largely overlap with those of AI.

This work builds upon historical categorizations to further explore the connection between AI and Computer Chess. Particularly, we introduce four seasons of Computer Chess history and investigate how and to what extent modern AI methods can recognize the relevant differences among these seasons from the scientific literature.

In addition, our study contributes a unique dataset of Computer Chess literature that we have curated to provide a comprehensive overview of the field's evolution.

We divide the history of Computer Chess in four seasons, exploiting some well known milestones; then we study a dataset of 2118 scientific papers, spanning from 1950 to 2021, selected from scientific venues (journals, conference proceedings, technical reports) and collected by a domain expert. The dataset includes mostly published articles, while books and theses were excluded.

We exploited state-of-the-art AI tools for extracting keywords and topics from this collection aiming at exploring possible relations between them within different seasons. Our analysis can be summarized in three research questions:

- RQ1: can we use current AI techniques to identify different seasons of Computer Chess research topics from the input dataset?
- RQ2: which keywords and topics are identified by these techniques to characterize each season?
- RQ3: how the most relevant topics were treated over different seasons? how their relevance changed over time?

Although clear milestones have marked the transition from one season to another, in fact, we did not find a sharp distinction between the topics of each season. Similar issues have been addressed in different seasons, albeit adapted to the new contexts, tools and technologies.

The paper is structured as follows. Section 2 introduces our historical perspective; Section 3 goes into the details of the input dataset and the AI techniques we employed to analyze the documents; our findings are summarized in Section 4, then we answer the Research Questions and conclude with Section 5.

## 2 The Four Seasons of Computer Chess

The history of Computer Chess offers a good perspective for understanding the evolution of scientific methods and technologies. Chess has been considered for long time as an "intelligent" game, meaning it requires some superior kind of cognitive capacity to play well [28].

Building chess-playing machinery has been a target of scientists and engineers since the end of XVIII century, when an automaton able to play chess was exhibited in several European courts. It was called "The Turk" and was an hoax, because inside the automaton a human player was well concealed.

Babbage also studied the problem of building a programmable machinery to play chess, but never built a prototype. The first machinery able to play a subset of chess (the ending King and Rook against Rook) was built in the XX century by the Spaniard engineer Torre y Quevedo.

Computer chess has a rich and fascinating history that we divide in four seasons. Besides summarizing the key aspects of each season, we discuss their entertainment value and the reaction of the society and market to the different phases of computer chess evolution.

### 2.1 First season: 1950-1977

The study of how to develop a program to play chess - and possibly the simultaneous *ouverture* of Artificial Intelligence research - starts with two papers published in 1950 by Turing [34] and Shannon [30]. Turing also used Chess in his "simulation game" as a benchmark to compare machine intelligence with human intelligence [35]. Turing's and Shannon's papers inaugurated the first season of Computer Chess research, which includes works by scientists of the caliber of Herbert Simon and John McCarthy. These people believed that studying how a general-purpose computer could play chess at the level of the best human grand masters could pave the way to the goal of building intelligent general-purpose machines. An important role in the progress of Computer Chess was played by the institution of World Computer championship, in 1974, by the International Computer Chess Association [16], which followed a series of US tournaments started in 1970 [29]. Year after year, the progress of the playing strength of chess engines has been slow but constant, as witnessed by the constant increase of Elo rating. Introduced in 1970 to assess the playing strength of human chess players, the Elo rating was immediately extended to chess machines [21].

In this seminal paper, Shannon described two architectures for chess playing software, called Type-A and Type-B programs. In the following three decades many research efforts were invested in improving these programs. The best in that epoch were Kaissa [2] and Chess [33].

**Machines Playing Risible Moves.** In the early days of computer chess, machines made moves that were often laughable to human players. During the 1950s and 1960s, computers were in their infancy and chess programs were rudimentary. Due to the limited computational power of the time, these programs were simplistic. For instance, the moves were based on shallow searches of the game tree and lacked sophisticated evaluation functions.

Programs such as the ones run on IBM 701 and later, IBM 704, by pioneers like Alex Bernstein and Allen Newell, displayed a lack of understanding of basic chess strategies, making them easy prey for even novice human players. This period was marked by a general skepticism about the ability of computers to ever compete meaningfully with human players. However, these early attempts laid the groundwork for future advancements.

In fact, the entertainment value of computer chess took a significant leap forward in 1968 when David Levy, an International Master from Scotland, made a famous bet with Marvin Minsky that no computer program would beat him within ten years. This bet spurred a great deal of interest and investment in computer chess. It was both a challenge to computer scientists and a statement of human superiority in complex intellectual tasks.

Levy successfully defended his bet in 1978 against the best programs of the time, including CHESS 4.7, a leading chess program developed at Northwestern University. His victory was seen as a triumph for human intellect over artificial intelligence, and the bet itself generated substantial media coverage and public interest, highlighting the dramatic tension between humans and machines.

### 2.2 Second season: 1977-1997

It took one generation to understand that the role of special hardware could be decisive for building a strong chess machine. Starting from 1977 [3] the introduction of special hardware purposefully designed for chess move generation and position assessment improved dramatically the playing strength of machines.

This season, was inaugurated by Belle, a machine built by J. Condon and K. Thompson at Bell Labs [8]. Another special machine was Cray Blitz [20]. Hitech was another machine built at CMU by Hans Berliner and his group [13].

Also at CMU another machine was designed, DeepThought, later rechristened as DeepBlue by IBM. The DeepThought/DeepBlue machine also was based on special purpose hardware [19]. This season terminates with the famous two matches between Garry Kasparov and DeepBlue, in 1996 and 1997. The latter one was won by Deep Blue. Kasparov was the World Champion of Chess, and possibly the best human player in the history, so his defeat was a milestone in the history of AI.

**The Rise of the Market and Broeader Interest for Chess Machines.** In the 1970s and 1980s, the market for dedicated chess computers began to grow. Companies like Fidelity Electronics, SciSys, and Mephisto produced chess machines that became popular among chess enthusiasts. These machines, such as Fidelity's Chess Challenger series and Mephisto's dedicated chess computers, were designed specifically for playing chess and marketed as serious tools for chess improvement.

This period saw the introduction of microprocessors, which allowed for more powerful and affordable chess machines. The dedicated chess computer market boomed, and products ranged from basic models for beginners to advanced machines for experienced players. These machines were often used for training, entertainment, and even casual competitions, making chess more accessible to the public and fostering a broader interest in the game.

**The Success and Widespread Debate.** The entertainment value of computer chess reached its zenith in the 1990s and 2000s, when grandmasters and world champions began to lose to the best chess machines. Levy finally lost his bet launched in 1968 when he played against DeepThought, a machine which later became Deep Blue [22]. In fact, the most entertaining climax came in 1997, when IBM's Deep Blue defeated Garry Kasparov, the reigning world champion. This historic match captured the world's attention and marked a significant milestone in the development of artificial intelligence and entertainment computing. The match was highly publicized and followed by millions, showcasing the incredible advancements in computer chess. Deep Blue's victory demonstrated that computers had reached a level of strategic sophistication that could rival and even surpass the best human players. This event sparked widespread debate about the future of artificial intelligence and its implications for human society.

### 2.3 Third season: 1997-2017

After DeepBlue's triumph, the development of new special hardware for chess play was oriented to exploit special architectures (like for instance FPGA [6]) in combination with highly distributed infrastructures, like Hydra [11].

However, the third season was dominated by software progresses: programs running on general purpose personal computers and implementing refined search algorithms and complex evaluation functions became stronger and stronger as new heuristics were developed, especially to improve scalability of search when multi-core hardware was available [18].

Interestingly, during this season there was no dominant software. The diffusion of open source engines fostered continuous and incremental improvements, which were recorded by the results of the World Computer Chess Championship [26]. From this seasons no more challenges between human world champions and computers have been played: too large is the difference in terms of strength of play.

**Continuous entertainment and new ways of playing.** In subsequent years after 1997, programs like Fritz, Junior, and Rybka continued to dominate in competitions against human players, culminating in the development of neural network-based engines like AlphaZero and Stockfish, which have set new standards of play. The ongoing development of these engines and their matchups against human grandmasters continue to be a source of great entertainment and fascination for the global chess community.

### 2.4 Fourth season: 2017-today

The fourth season is still in progress and includes scores of papers based on Machine Learning (ML). This approach had been attempted to build chess machines in the past century, see for instance [32], however the available hardware at the time was not powerful enough.

Deep Learning, a variant of ML, showed its power in 2017 when Alpha Zero running on a Google's supercomputer learned to play from scratch, with zero knowledge of chess data or algorithms, and after playing against itself for a few hours, reached a strength level so high to be able to clearly win a match against

Stockfish 8, a strong game-tree based open source program running on general purpose hardware [31].

**Unstoppable fascination and entertainment.** The explosion of ML and DL gave again strength to computer chess and its appeal, and new sophisticated frontiers are being explored.

One of the innovations, for instance, consists in developing chess personas, ie. virtual chess players who can play in the style of champions so that one can train specifically against their style of play [9].

The entertainment value of computer chess has evolved dramatically over the decades, from the early days of laughable machine moves to the era of grandmasters being defeated by supercomputers, to the current era where young players use variants and mimic play by neural networks. Each period has contributed to the allure and excitement of computer chess, captivating audiences and driving interest in both chess and artificial intelligence. This journey not only highlights the advancements in technology but also underscores the enduring appeal of chess as a timeless and intellectually challenging game.

## 3 Methods and Materials

### 3.1 Dataset

The dataset we have curated includes a collection of 2118 scientific papers related to Computer Chess across a period of time of 70 years[2]. Each paper was catalogued by its publication year and season, facilitating temporal analyses. Figure 1 shows how many papers were published each year, highlighting a notable imbalance in dataset representation across different seasons. To address this, we applied data augmentation techniques such as Synthetic Minority Over-sampling Technique [7] (SMOTE) to enhance model training.

The imbalance in the dataset is naturally due to the inclusion of articles that have defined the field. This targeted selection ensures that our analysis captures key developmental milestones in computer chess, providing a solid foundation for understanding its evolution. The concentration on these peer-reviewed works guarantees that our review reflects the most critical and influential research, thereby maintaining the integrity and depth of our study.

### 3.2 Extracting keywords and topics

**Preprocessing** The text content was extracted from PDF papers, resulting in occasional lexical discrepancies, like broken words, due to conversion errors. Our pre-processing routine involved removing numerals and punctuation, and normalizing words to their lemma form. Due to our models constraints, we processed either the first five pages or those containing the abstract of each paper.

[2]The list of authors and titles of the documents in the dataset is currently available on request and will be made public.

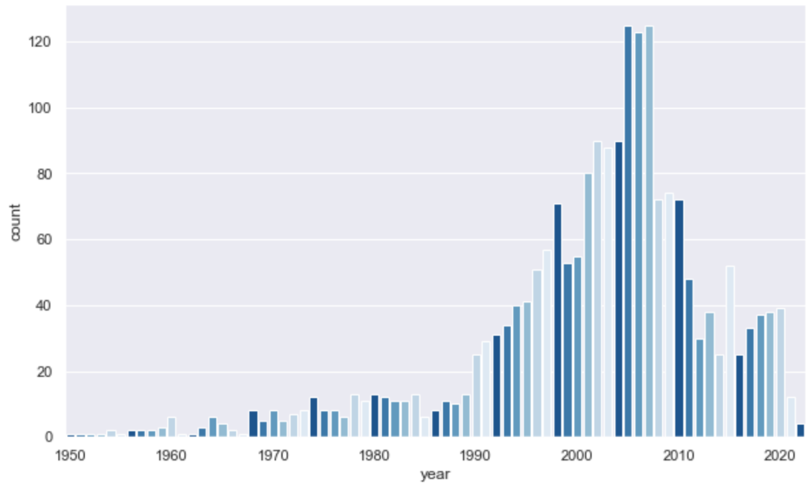


**Fig. 1.** Distribution of articles in years

**Extracting keywords with ChatGPT** Utilizing OpenAI's GPT-3.5-Turbo, we extracted 10 keywords from each paper through the following prompt:

> "Extract the 10 most relevant keywords from this paper that is part of a Computer Chess papers collection. Each keyword must be 1 word in singular form. Ignore people names and generic words like "*chess*" or "*game*". Sort them by relevance and return them as a CSV file. TEXT: text"

These keywords were functional in clustering the papers and discerning thematic alignments with their respective seasons.

**Extracting topics with LDA** The LDA algorithm[5] is a type of unsupervised learning used to find different topics (set of words) within a collection of documents. It works by figuring out the likelihood of words appearing together to form topics. At the same time, each document is associated to a set of those topics. We have adjusted the model hyper-parameters to encourage the emergence of specific, less generic topics.
The topics identified by the LDA model were initially made of generic keywords that recurred across different seasons, as detailed in the following section and illustrated in Table 4. To improve the clarity and evaluability of the results, we removed with the application of the TF-IDF method [10], an unsupervised technique to score the relevance of terms, a set of irrelevant commonly used words from the keywords before using LDA. After several iterations, LDA finalized the following list:

> game, chess, piece, player, structure, skill, position, computer, history, book, journal, referee, problem, program, tournament, chessboard, func-

tion, analysis, board, pawn, bishop, knight, championship, algorithm, play, communication, community, membership, newsletter, search, rank, ranking, endgame, committee, competition, publication, rating, round, organization, evaluation

We adopted two distinct approaches to extract and analyze topics using LDA: (i) initially, the LDA model was applied on the entire dataset to identify 8 topics; (ii) afterwards, we refined this approach by generating separate LDA outputs with the papers from each season individually to extract 5 distinct topics per season. We plan to integrate techniques to identify more sophisticated topics derived from recurring and implicitly hidden knowledge [15].

# 4 Results

## 4.1 Keywords in Seasons

Table 1 shows the 15 most frequent keywords in each season. For each keyword, the table also shows the number of papers that are associated to that keyword (in that season). For instance, the keyword "*program*" was the most used in Season 1, associated to 19 papers.

**Table 1.** Most 15 used keywords in each season.

| # | Season 1 | #papers | Season 2 | #papers | Season 3 | #papers | Season 4 | #papers |
|---|---|---|---|---|---|---|---|---|
| 1 | program | 19 | search | 103 | algorithm | 240 | learning | 23 |
| 2 | search | 15 | algorithm | 83 | search | 214 | algorithm | 22 |
| 3 | heuristic | 13 | program | 65 | strategy | 169 | performance | 15 |
| 4 | evaluation | 12 | performance | 52 | evaluation | 156 | move | 14 |
| 5 | structure | 10 | knowledge | 47 | move | 139 | neural | 13 |
| 6 | analysis | 10 | evaluation | 46 | learning | 127 | network | 13 |
| 7 | language | 9 | strategy | 45 | performance | 124 | search | 11 |
| 8 | algorithm | 9 | position | 43 | intelligence | 108 | cognitive | 10 |
| 9 | machine | 9 | learning | 43 | analysis | 108 | strategy | 10 |
| 10 | performance | 9 | tree | 41 | program | 95 | reinforcement | 9 |
| 11 | move | 9 | move | 41 | cognitive | 91 | tree | 9 |
| 12 | tournament | 8 | system | 30 | memory | 87 | position | 9 |
| 13 | memory | 8 | memory | 29 | position | 85 | analysis | 9 |
| 14 | learning | 7 | heuristic | 29 | endgame | 83 | training | 9 |
| 15 | tree | 7 | minimax | 24 | model | 80 | machine | 8 |

In season 1 the focus appears on developing and evaluating chess programs, utilizing search algorithms and heuristics, analyzing program structures, and evaluating their performance. In season 2 the emphasis is on refining search algorithms and programs, improving performance through evaluation, incorporating knowledge-based approaches, and analyzing strategic knowledge. In season 3 the concentration is on developing advanced algorithms and search techniques, refining strategic approaches, evaluating moves and strategies, and enhancing game analysis. Finally, in season 4 appears a shift towards incorporating machine learning and neural networks into chess algorithms, focusing on improving search performance, and leveraging cognitive models for chess intelligence.

Overall, the progression from Season 1 to Season 4 suggests a transition from traditional program-based approaches towards more sophisticated algorithms, strategies, and learning techniques, reflecting advancements in AI research.

Table 2 shows the position of each keyword in the ranking of each season. For instance, the keyword "*algorithm*" was in 8th position in the first season, then upgraded to 2nd position, then up to 1st and then back to 2nd.

**Table 2.** Raking of relevant keywords over seasons

| Term | Season 1 | Season 2 | Season 3 | Season 4 |
|---|---|---|---|---|
| algorithm | 8 | 2 | 1 | 2 |
| evaluation | 4 | 6 | 4 | 29 |
| heuristic | 3 | 14 | 21 | - |
| knowledge | 40 | 5 | 17 | 34 |
| learning | 14 | 9 | 6 | 1 |
| move | 11 | 11 | 5 | 4 |
| neural | - | - | 44 | 5 |
| performance | 10 | 4 | 7 | 3 |
| program | 1 | 3 | 10 | 21 |
| search | 2 | 1 | 2 | 7 |
| strategy | 18 | 7 | 3 | 9 |
| structure | 5 | 33 | 43 | - |

In Season 1, the ranking shows emphasis on program development and search algorithms. Heuristic techniques are also prominent, suggesting a focus on heuristic search methods. However, there's a notable absence of neural-related terms, indicating a lack of emphasis on machine learning approaches at this stage.

Season 2 sees a significant rise in the prominence of algorithm-related terms, indicating a shift towards refining and optimizing search algorithms. There's also continued emphasis on program development and performance evaluation. Knowledge-related terms emerge, suggesting an increasing focus on incorporating domain knowledge into chess programs.

Season 3 marks a consolidation of algorithm-related terms at the forefront, highlighting continued advancements in search algorithms and techniques. Strategy-related terms gain prominence, indicating a heightened focus on strategic aspects of chess playing and analysis. Evaluation and move-related terms remain important, reflecting ongoing efforts to improve performance and analyze game moves.

Season 4 witnesses a notable shift towards learning-related terms, suggesting a growing interest in machine learning approaches for chess. Performance and move-related terms maintain their importance, indicating ongoing efforts to enhance game performance and analysis. The emergence of neural-related terms reflects the increasing integration of neural network models into Computer Chess research, potentially for strategic decision-making and game analysis.

Overall, the evolution from Season 1 to Season 4 demonstrates a progression from traditional heuristic and algorithmic approaches towards more sophisticated strategies, incorporating machine learning and neural network techniques for improved performance and analysis in Computer Chess.

### 4.2 Topics Over Time

Table 3 shows the topic extracted by LDA on the keywords extracted in the previous step. For each topic, it also reports the labels identified by LDA.

**Table 3.** LDA Topics

| |
|---|
| Topic 0: memory expertise expert knowledge cognitive |
| Topic 1: performance parallel table tree depth |
| Topic 2: strategy tree opponent information value |
| Topic 3: minimax alpha heuristic beta strategy |
| Topic 4: learning machine intelligence network neural |
| Topic 5: decision software solving development language |
| Topic 6: performance rule experiment study strategy |
| Topic 7: cognitive learning strategy intelligence genetic |

Figure 2 shows how the previous topics were discussed over the fourth season.

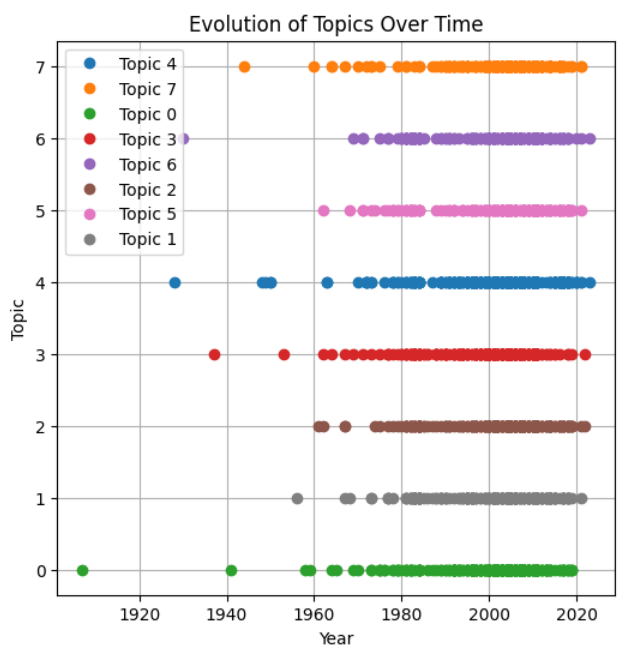


**Fig. 2.** Topics extracted with LDA over time

The X axis indicates the years, while Y axis indicates topics. Each point corresponds to a paper. The plot clearly shows that the same topics were discussed over different seasons. The articles are clustered in the third seasons as expected from the (unbalanced) dataset.

### 4.3 Topics Extracted with LDA within Separate Seasons

Tables 4 and 5 summarize the topics extracted by LDA by considering each season separately, with and without filtering out generic words (as explained in the method section). The algorithm was executed only on the keywords of the articles within the same season and tuned to output three labels for each topic.

Again, there are no distinct boundaries between seasons and several topics recur across different seasons.

**Table 4.** LDA Topics within separate seasons without removing generic words

| | Season 1 | Season 2 |
|---|---|---|
| 1 | search chess program | program tournament player |
| 2 | player model problem | search algorithm performance |
| 3 | game player chess | strategy learning knowledge |
| 4 | memory performance learning | program problem method |
| 5 | language tournament program | piece chess structure |
| | Season 3 | Season 4 |
| 1 | chess algorithm game | analysis skill algorithm |
| 2 | game tournament computer | chess cognitive intelligence |
| 3 | cognitive expertise chess | chess player game |
| 4 | player game position | position language chess |
| 5 | search algorithm game | learning algorithm strategy |

**Table 5.** LDA Topics after removing generic words

| | Season 1 | Season 2 |
|---|---|---|
| 1 | machine learning performance | minimax alpha beta |
| 2 | dynamic tree heuristic | depth rule table |
| 3 | memory task pattern | intelligence artificial research |
| 4 | heuristic evaluation strategy | evaluation learning knowledge |
| 5 | language science model | performance tree evaluation |
| | Season 3 | Season 4 |
| 1 | strategy learning tree | learning machine model |
| 2 | memory cognitive expertise | network neural learning |
| 3 | evaluation strategy minimax | strategy information decision |
| 4 | strategy intelligence solution | cognitive development intelligence |
| 5 | performance learning expertise | performance tree method |

## 5 Conclusions

This is an ongoing research, that we intend to extend enlarging the document dataset and experimenting on other AI techniques. Though, it gave us valuable insights and answers to the initial research questions, summarized are as follows:

- RQ1: can we use current AI techniques to identify different seasons of Computer Chess research topics from the input dataset? Answer: not completely, as several topics are found in more than one season.
- RQ2: which keywords and topics are identified by these techniques to characterize each season? Answer: Table 1 shows the most frequent keywords for each season.
- RQ3: how the most relevant topics were treated over different seasons? how their relevance changed over time? Answer: Table 2 shows the ranking of each term within each season.

Before concluding, it is worth summarizing some limitations of the current work. First of all, the distribution of the documents in our dataset was unbalanced. This affected our results but we were able to get meaningful indications about keywords and topics despite the challenges posed by the unbalanced data distribution. Note also that the fourth season includes articles up to 2021 and therefore it misses a lot of recent works. We are including in our dataset more recent articles, in order to increase the coverage and accuracy of the results.

Another issue is about the content extraction techniques. In this first iteration, we only extracted the first three seasons of each article, with some exceptions, but we could use more sophisticated techniques to obtain more precise results. For instance, we plan to consider titles and abstracts as separate entities, as well as to differentiate between various sections. Identifying the related works section, for instance, would allow us to exclude that content from the analysis and, thus, to focus more on the new themes developed in each article.

The construction of the dataset is another critical point: we only considered papers published in journal and conference proceedings, or technical reports, excluding books and theses. This choice was made to align results when extracting only three seasons per document; such an amount could be less significant for longer documents, which need specific content extraction techniques instead.

It could also be argued that the dataset is subjective and does not cover the entire literature. This is true, but our goal here was not to be exhaustive, rather to verify the feasibility of the approach on a rich and well-curated dataset.

Finally, there are some limitations in the application of AI techniques. For instance, we used a fixed prompt for ChatGTP and a fixed list of stop-words and parameters for LDA. Again, our goal was not to validate these specific techniques but to experiment such an approach and collect preliminary feedback. In a forthcoming study, we plan to test other techniques, parameters, and thresholds. In particular we will evaluate state-of-the-art multi-retrieval-augmented generation transformers in [14], as well as bibliographic-based solutions for the clustering and retrieval of semantically similar papers in [25]. Additionally, we will explore long input efficient transformers to capture distant relations in large inputs [24].

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