Prediction and Visualization of Trending Research Topics in Social and Cognitive Robotics

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Abstract

This paper presents the results of a method designed to realize visualization of long-term prediction of trending research topics in the field of social and cognitive robotics. Meaningful topics were identified among the words included in the titles of scientific articles. The longevity of the citation trend growth was the target for the machine learning algorithm CatBoost. We conducted experiments on a dataset including 5 million scientific publications to demonstrate the effectiveness of the proposed model. The accuracy rate of 5-year forecasts for a number of experiments was about 60%. Trending topics are built from trending keywords located closely in the semantic vector space. The following trending topics in the field of social and cognitive robotics have been identified: recognition, deep learning, engagement, disorder, conversation, cognitive computing, attention, robotic platform. Trending keywords and topics are visualized on a semantic map built using the t-SNE method. Visualization helps to see the Big Picture, identify promising directions, understand trending topics and reveals related keywords.

Keywords

Cognitive robotics, social robotics, visualization, long-term prediction, trending research topics, proven forecast accuracy, CatBoost, scientific bibliography, Big Data.

1. Introduction

Currently, research is actively developing in the areas of social robotics and cognitive robotics. These areas are interconnected and have much in common, as include the ability to communicate with people. Cognitive robotics is a field of technology involving robots that can learn from experience, from human teachers, and even on their own, thereby developing the ability to effectively deal with their environment [1]. Social Robotics is the study of robots that are able to interact and communicate among themselves, with humans, and with the environment, within the social and cultural structure attached to its role [2]. A social robot is an artificial intelligence (AI) system that is designed to interact with humans and other robots [3].

This article is a forecasting review of research topics in the field of SOCIAL AND COGNITIVE ROBOTICS. The article describes future long-term trends with proven forecast accuracy. The long-term prediction of trending research topics helps to efficiently navigate and evaluate scientific articles, identify promising directions, find breakthrough ideas, and focus efforts on the most fruitful direction.

The long-term prediction of trending research topics can be done using analyses of bibliographic collections of millions of scientific articles that are freely available on the Internet. We conducted experiments on a scientific dataset called DBLP (Digital Bibliography & Library Project dblp.org) that includes 5,354,309 computer science articles. Meaningful topics were identified among the words included in the titles of scientific articles. The longevity of the citation trend growth was the target for the machine learning algorithm CatBoost [4]. Trending keywords and topics are visualized on a semantic map built using the t-SNE method [13]. Visualization helps to see the Big Picture, identify promising directions, understand trending topics and reveals related keywords.

The contributions of this paper are as follows:

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- A new algorithm for long-term forecasting of future trends in scientific articles has been developed and the forecast accuracy has been determined.
- For the first time, a forecasting review of scientific articles in the field of SOCIAL AND COGNITIVE ROBOTICS was created, describing long-term future trends with proven forecast accuracy.
- A new form of visualization of long-term forecast of future trends in scientific literature has been proposed.

The structure of this paper is as follows. Next section discusses related works in social and cognitive robotics. Section 3 describes the relevant methodology. Section 4 presents empirical results and the last Section 5 concludes the paper.

2. Related works

The research areas of social robotics and cognitive robotics are very popular now. Korn et al. pointed out that artificial intelligence and engineering allow robots with social behaviors to become an everyday phenomenon [5]. They gave the following definition. Social robots are robots interacting with humans not only in collaborative settings, but also in personal settings like domestic services and healthcare. The authors found that the experts consider the basic technologies for emotion recognition as fairly well developed (with the exception of brain computer interaction and facial thermal regions). When it comes to applying emotion sensing in health care, the acceptance increases with the severity of the patients' illness or impairment. Also social robots are rated significantly more acceptable in such areas as 'replacement for pet', 'companion for lonely seniors', and 'anti-terror measures'.

Henschel et al. have argued that careful delineation of the neurocognitive mechanisms supporting human–robot interaction will enable us to gather insights critical for optimising social encounters between humans and robots [6]. Research examining social cognition when interacting with robots offers a promising avenue for understanding how best to introduce robots to complex social settings, such as in schools, hospitals, and at home. The future of social robotics is undeniably exciting, and insights from human neuroscience research will bring us closer to interacting and collaborating with socially sophisticated robots.

Shimoda et al. pointed out that social demand for robots to be our partners in daily life has been rapidly increasing [7]. Cognitive robotics should play a major role in making robots our partners. The existence of uncertainty in the continuous control loop is a source of the need for cognitive robots and is the key factor that distinguishes cognitive robotics from the cognitive system in other fields. The authors discussed information generalization, active sensing, prediction, and language communication as the necessary functions for future cognitive robots.

For better mutual understanding, robots must be able to look at things, phenomena and events from the point of view of people. Robots should not perceive the world as it is but should have perceptual and cognitive biases for collaboration with humans. It is well known that human brains transform 'real' sensory signals into the information what we want to sense, which is sometimes called 'anthropomorphic lens'. As a result, perception of the temporal and spatial properties of actions or the environment can be inaccurate [8], as demonstrated for instance by visual illusions. However, these processes bring several advantages for collaboration. For instance, when observing a passing action, the human doesn't detect the details of the motion, but naturally understands the features of the action such as the action goal [9], which is more important than the details for good collaboration.

One of the most important benefits of robots to be able to use generalized information well may be the prediction of future events. Prof. Sandini, proposed the concept of 'Beyond Real-time' [10] for cognitive robotics, suggesting that the ability to move with predictions of future events beyond real-time responses is essential for future cognitive robotics. He stated that this capability is expected to lead to the notion of cognitive safety, where humans and robots can live in the same space with a high level of safety if the robots can predict what the human will do or want to do [11].

3. Methodology

3.1. Keywords Trends Prediction

We studied keywords trends via the dynamics of various features/parameters of groups of articles containing these keywords. The most important parameter of a keyword trending is the keyword citation count (KCC). To calculate this parameter, we first find all articles with this keyword in a particular year, and then we count all citing links to those articles. For each keyword, we calculated the duration of its trend growth that is equal to the number of years of continuous growth of its average citation. This duration of trend growth was the target for the machine learning algorithm CatBoost [4].

The CatBoost regression model was trained for 20 trend features of a keyword in the current and previous years, including: current KCC, total number of articles with the keyword, time of growth of the previous trend, total citation growth for the previous trend, time from trend situation to current/base year, the number of citing links between articles with the keyword since the beginning of the trend.

The accuracy and forecast error of the trained model was checked on completely different and later data than in training.

3.2. Trending Research Topic Identification

Trending topics are built from trending keywords whose corresponding semantic vectors are located closely in the semantic vector space. For the construction of semantic vectors corresponding to keywords, the methods based on neural networks such as Word2Vec [12], BERT or SciBERT are used.

The calculation of clusters/topics is based on density in the semantic vector space. Keywords with close semantic vectors that have the same close environment are merged into a cluster/topic. Close environment is a group of nearest keywords. To identify trending topics, the average value of the forecast for the keywords of each cluster/topic is calculated. Trending topics are clusters/topics with high average forecast values.

To explain the meaning and semantics of a topic, examples are used, consisting of fragments of articles titles containing the keywords of the topic. When searching for examples, short titles of fresh articles with a large number of keywords are advantageous.

3.3. Visualization of Research Topic Prediction

After trending keywords are found and their trend forecast is calculated, a similarity matrix is built for these keywords using their semantic vectors. A visual semantic map and coordinates of trending keywords on the plane are calculated using the similarity matrix and t-SNE method [13]. The keywords are marked on the map with dots of different colors depending on their forecast. Trending topics are represented by circles going through the topic keywords.

4. Empirical research

4.1. Data Acquisition

We experimented with the DBLP-Citation-Network V11 dataset which includes 5,354,309 computer science articles from 1936 to 2021, referred to here as the DBLP collection. The DBLP collection was used to calculate and predict the trends of keywords included in the collection more than 5 times, and to calculate semantic vectors for these keywords.

To search for trending keywords in the field of SOCIAL AND COGNITIVE ROBOTICS, a query was formed containing the following specific words related to this topic: (cognit* robot*) or (recognit* robot*) or (social* robot*). The asterisk (*) represents any group of letters. This query returned 5,032 articles from the DBLP collection. These 5,032 articles are referred to here as the Collection-2. This Collection-2 was used to search for trending topics and keywords in the field of SOCIAL AND COGNITIVE ROBOTICS, as well as to visualize these topics on a semantic map.

4.2. Keywords Trends Prediction

The CatBoost regression model and DBLP collection were used to calculate the duration of keyword trend growth. The CatBoost regression model was trained for 20 trend features of the word/keyword (see section 3.1). As a result of a predictive experiment, 5587 trending keywords were identified. The most long-lasting forecast of the trend growth duration (over 10 years) had the following keywords: artificial intelligence, AI, convolutional networks, CNN, deep network, explainable.

4.3. Assessment of the Forecast Accuracy

The forecast accuracy of the trained model was checked on completely different and later data than in training. Forecast accuracy has been measured hundreds of times for different forecast durations in different years and for thousands of different keywords. The error rate of 5-year forecasts for a number of experiments was about 40%, whereas the accuracy rate was 60%. With this accuracy, the average time for the actual growth of the trend is 3 years, if the forecast was 5 years.

4.4. Trending Research Topic Identification

The semantic vector space and semantic vectors of keywords were built on the basis of the DBLP collection using the Word2Vec method [12]. Clusters/topics in the semantic vector space were calculated using keywords of Collection-2. Trending topic identification was done using keywords trends prediction data. The list of trending topics and their keywords is presented in Table 1.

Table 1

Topic keywords

Number	Topic	Keywords
1	Recognition	recognition, deep learning, image recognition, detection recognition, recognition algorithm; emotion recognition, emotion detection, person recognition
2	Deep learning	deep learning, deep
3	Engagement	engagement, engaging, preschool; educational robotics
4	Disorder	disorder, mild, impairment
5	Conversation	conversation, conversational, personality; emotion detection
6	Cognitive computing	cognitive computing, brain-inspired, neuroscience; AI
7	Attention	attention, attentional; episodic
8	Robotic platform	robotic platform, robot hand, rehabilitation robot

The time series graph of the popularity of topics in the field of SOCIAL AND COGNITIVE ROBOTICS is shown in Figure 1.

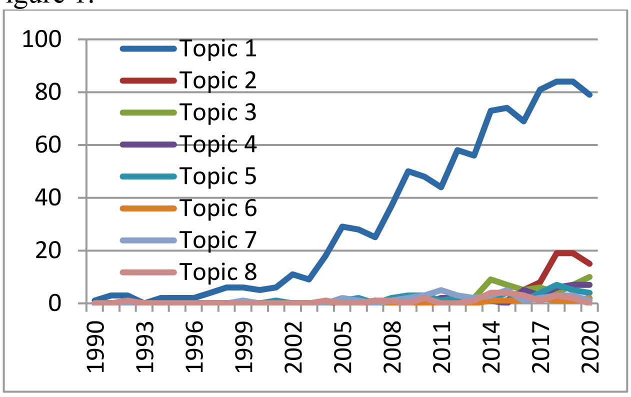

Figure 1: Time series chart of topics popularity in the field of SOCIAL AND COGNITIVE ROBOTICS

4.5. Examples to Explain Topics

To explain the meaning of trending topics, examples are used, consisting of fragments of articles titles from Collection-2.

Topic 1. Recognition (keywords: recognition, deep learning, image recognition, detection recognition, recognition algorithm; emotion recognition, emotion detection, person recognition). Examples:

- 2021. **Emotion detection** for **social robots** based on NLP transformers and an emotion ontology.
- 2020. Semantic visual **recognition** in a **cognitive** architecture for **social robots**.

Topic 2. Deep learning (deep learning, deep). Examples:

- 2021. A **deep learning** short commands recognition for MCU in **robotics** applications.
- 2019. **Deep learning** application to learn models in **cognitive robotics**.

Topic3. Engagement (keywords: engagement, engaging, preschool; educational robotics). Example:

- 2020. **Social robots** that can sense and improve student **engagement**.

Topic 4. Disorder (keywords: disorder, mild, impairment). These keywords are often found together with the following words: older adults, older, people dementia, autism, spectrum disorder, ASD, autistic, therapy children, preschool, children autism. Example:

- 2021. The impact of serious games with humanoid **robots** on **mild cognitive impairment** older adults.

Topic 5. Conversation (keywords: conversation, conversational, personality; emotion detection). Example:

- 2021. **Conversational** interaction with **social robots**.

Topic 6. Cognitive computing (keywords: cognitive computing, brain-inspired, neuroscience; AI). Examples:

- 2020. **Robots, AI**, and **cognitive** training in an era of mass age-related **cognitive** decline.
- 2020 …belief network and linear perceptron based **cognitive computing** for collaborative robots.
- 2015. **Cognitive** learning methodologies for **brain-inspired cognitive robotics**.

Topic 7. Attention (keywords: attention, attentional; episodic). Examples:

- 2020. The impact of a **social robot** public speaker on audience **attention**.
- 2020. **Robotic episodic cognitive** learning inspired by hippocampal spatial cells.
- 2019. Learning **attentional** regulations for structured tasks execution in **robotic cognitive** control.

Topic 8. Robotic platform (keywords: robotic platform, robot hand, rehabilitation robot). These keywords are often found together with the following words: intelligent robotic, robot-assisted. Example:

- 2019. A **socially** assistive **robotic platform** for upper-limb rehabilitation.

4.6. Visualization

The methods Word2Vec and t-SNE were used to visualize the forecast in the field of SOCIAL AND COGNITIVE ROBOTICS. A visual map was built and keywords were marked on it with dots of different colors, depending on their forecast. Trending topics were represented by circles going through the topic keywords (see Figure 2).

Figure 2 shows the semantic map developed by this method in the field of SOCIAL AND COGNITIVE ROBOTICS. Semantically similar keywords are grouped into clusters on the semantic map. These clusters mainly consist of keywords of the same color with similar trend durations. Thus, trending keywords on the semantic map confirm each other and help to more accurately identify promising directions. Visualization helps to understand trending topics and reveals related keywords. For example, the circle of the Topic 4 (disorder, mild, impairment) contains the following keywords: eldery, autism, autism spectrum disorder, ASD. These keywords are relevant to the topic and explain it. Also, visualization helps to see the Big Picture, understand topic relationships and identify promising directions.

Figure 2: Visualization of keywords in the field of SOCIAL AND COGNITIVE ROBOTICS based on t-SNE projections of the Word2Vec similarity matrix between keywords and a forecast of the growth time of their trends (red: keywords with long-term trends, blue: medium trends, black: shortest trends)

Promising directions are usually presented as clusters/topics with a large number of red trending keywords. Sometimes promising directions are presented as intersections or combinations of such topics. An example of a promising direction is the combination of topic 5 (conversation, conversational, personality; emotion detection) and topic 3 (engagement, engaging, preschool; educational robotics) which contains many red terms (conversational, emotion detection, engagement). This promising direction has a long-term forecast of citation growth and can be called emotional engagement. The 2018 paper "Adaptive framework for emotional engagement in child-robot interactions for autism interventions" belongs to this promising direction.

5. Conclusion

This work has several key contributions. To the best of our knowledge, we are the first to study the problem of the long-term prediction (with proven accuracy) of thousands of research trending topics from academic big data. Such long-term predictions help to efficiently navigate and evaluate research topics, identify promising directions, and focus efforts on these directions.

We experimented with the dataset including 5 million scientific publications to demonstrate the effectiveness of the proposed model. The error rate of 5-year forecasts of research trending topics in a number of experiments was about 40%, whereas the accuracy rate was 60%. According to the results of the forecast in the field of SOCIAL AND COGNITIVE ROBOTICS, the longest-growing trends have the topics: recognition, deep learning, engagement, disorder, conversation, cognitive computing, attention, robotic platform.

Trending keywords and topics were visualized on a semantic map using the t-SNE method. The keywords with different predictions were indicated in different colors. A very interesting result of this work is that semantically similar keywords are grouped into clusters which mainly consist of keywords of the same color with similar trend durations. Thus, trending keywords on the semantic maps confirm each other and help to more accurately identify promising directions. The visualization presented in this paper serves as a proposed analytical method that helps to see the Big Picture, identify promising directions, understand trending topics and reveals related keywords.

Our plan for future research is to improve the accuracy of long-term forecasts using information about authors and journals.

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