Building Model of Additive Manufacturing Based on Knowledge Driven

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Abstract—This paper combines the current mainstream knowledge graph intelligent recommendation algorithm and the first step in the additive manufacturing process: model design, and proposes a knowledge-driven intelligent recommendation algorithm to be applied to model design. Combining the designer’s historical design habits and the relationship between entities and attributes in the knowledge graph can better improve the accuracy of recommendations. It is verified in the third chapter of this article that the knowledge-driven recommendation algorithm is better than other traditional recommendation algorithms.

1. Introduction
Additive manufacturing (AM) has developed into an indispensable manufacturing system in Industry 4.0. Unlike AM production prototypes 30 years ago, current AM applications focus on the production of end-use parts. According to the additive manufacturing financial report [1], by 2020, the market value of additive manufacturing products will exceed US$20 billion. Due to the size of the potential market, additive manufacturing is known as one of the most popular manufacturing processes. However, the different combinations of process parameters will cause products to vary greatly in geometric accuracy [2] and mechanical properties (such as stiffness, strength and toughness) [3]. These instabilities and uncertainties in product performance usually bring new challenges to obtain reliable and high-performance products with customized functions for end-use applications. Due to various difficulties, this makes the sustainability of additive manufacturing a key research topic [4]. Its advantages include custom parts to meet customization requirements and shortened lead times between design and manufacturing stages. Under this interesting theme, many issues have never attracted the attention of researchers [5]. For example, additive manufacturing (AM) can produce complex free shapes. How to quickly design a model to be printed has become one of the hot spots of current researchers.

In 2017, Cataldo Musto et al. proposed a graph-based intelligent recommendation algorithm, which can automatically feed features collected in the LOD (Linked Open Data) cloud into a graph-based recommendation system, and in this recommendation setting Analyze the impact of several widely used feature selection techniques. In 2018, John K. Tarus and others proposed a knowledge-driven e-learning resource recommendation algorithm, which intelligently recommends relevant learning resources for students according to their curriculum requirements. In 2019, Hongwei Wang et al. combined the convolutional neural network and knowledge graph in deep learning to propose a Knowledge Graph-Convolutional Networks algorithm.
Therefore, this paper proposes a knowledge-driven design method, which aims to use artificial intelligence technology to quickly and accurately recommend the rapid design of models in the additive manufacturing process to improve the efficiency of designers. This article intends to solve the following problems:

1) The establishment of knowledge graph based on AM design;
2) The establishment of a knowledge base of user design habits;
3) Application of intelligent recommendation algorithm based on knowledge graph to AM design;
4) Verify the superiority of knowledge-driven algorithms compared with traditional algorithms.

The overall framework of this article is: Chapter 1 is an introduction, focusing on the current domestic and foreign development of knowledge graphs and intelligent recommendation technology; Chapter 2 introduces the relevant content and detailed steps of knowledge graphs and intelligent recommendation algorithms; Chapter 3 verification is based on The superiority of knowledge-driven intelligent recommendation algorithm; Chapter 4 is the summary and outlook.

2. Knowledge-driven intelligent recommendation algorithm

2.1. The Knowledge Graph of AM Model Design

Knowledge Graph, known as knowledge domain visualization or knowledge domain mapping map in the library and information industry, is a series of various graphs showing the relationship between the development process and structure of knowledge. Use visualization technology to describe knowledge resources and their carriers [6], mine, analyze, construct, draw, and display knowledge and their interconnections. The knowledge map combines the theories and methods of applied mathematics, graphics, information visualization technology, information science and other disciplines with metrological citation analysis, co-occurrence analysis and other methods, and uses the visual map to vividly display the core structure and development of the discipline History, frontier fields, and overall knowledge structure to achieve the modern theory of multi-disciplinary integration. It can provide practical and valuable references for subject research [7].

The Knowledge Graph was first released by Google. In order to improve the quality of the answers returned by search engines and the efficiency of user queries, with the aid of the knowledge graph, search engines can gain insight into the semantic information behind the user’s query, and then return more precise and structured information. Thereby it is more likely to satisfy a user's query demand. When we search, the association on the right side of the search result comes from the application of knowledge graph technology. We receive all kinds of recommendations almost every day, from news and shopping to meals and entertainment. As an important means of information filtering, personalized recommendation can recommend suitable services according to our habits and hobbies, and it also comes from the application of knowledge graph technology. Search, maps, personalized recommendations, the Internet, risk control, banking...More and more application scenarios rely more and more on knowledge graphs, which can be said to be ubiquitous.

The current application areas of Knowledge Graph include: intelligent search, risk avoidance of group fraud, abnormal analysis, and precision marketing. As long as the characteristics of the knowledge graph are:

1. The more users search and the wider the scope, the more information and content the search engine can obtain.
2. Give new meaning to strings, not just strings.
3. It integrates all disciplines to facilitate user search continuity.
4. Find more accurate information for users, make a more comprehensive summary and provide more in-depth relevant information.
5. The knowledge system related to keywords is systematically displayed to users.
6. Users only need to log in to one of more than 60 online services under Google to obtain information and data retained on other services.
7. Google draws useful information from the entire Internet so that users can obtain more relevant public resources.

2.2. Intelligent Recommendation Algorithm for AM Design

At present, the more popular recommendation algorithms include content-based recommendation, collaborative filtering recommendation, recommendation based on knowledge graph, and recommendation algorithm based on machine learning\(^8\).

1) Content-based recommendation algorithm: extract some features from the content of each historical item of the user, and then use the item feature set that the user likes or dislike in the history to learn the user's interest feature representation, and compare the user's interest feature with the candidate item Features, select the n items with the highest correlation for recommendation;

2) Recommendation algorithm based on collaborative filtering: including recommendation based on the similarity of user preferences and recommendation based on the similarity of user preferences;

3) Recommendation system based on knowledge graph: use the characteristics of entities and relationships in the knowledge graph to make recommendations\(^9\);

4) Recommendation algorithm based on machine learning: use artificial intelligence algorithms such as K-means and Naive Bayesian to predict user interests\(^10\).

2.3. Knowledge-driven 3D model design recommendation algorithm

Based on the knowledge-driven intelligent recommendation algorithm, the knowledge graph of the model design is first established, and then the content-based and collaborative filtering recommendation algorithm is combined for intelligent recommendation. The detailed process is:

1) The present invention will be applied to 6 knowledge bases: the knowledge base KD\(_M\) of mechanical structure decomposition, Users A, B, C, D, and E used the knowledge base KD\(_M\) in the past and searched the knowledge base KD\(_A\), KD\(_B\), KD\(_C\), KD\(_D\), KD\(_E\). User E is the user to be recommended;

2) The knowledge base KD\(_M\) contains the structural decomposition of the assembly, the attributes of the assembly and its split structure (for example: color, size, manufacturing materials, etc.), the number of user citations of the assembly, and the number of user views of the assembly;

3) The knowledge base KD\(_A\), KD\(_B\), KD\(_C\), KD\(_D\), KD\(_E\) contains mechanical records designed by the user, reference records and browsing records of the knowledge base KD\(_M\);

4) Use formula (1) to calculate user X (X may be more than one) whose similarity to user E is higher than 0.5 among users A, B, C, and D;

\[
W_{u,v} = \frac{|N(u) \cap N(v)|}{\sqrt{|N(u)| \cdot |N(v)|}}
\] (1)

Among them, u,v are two users, N(u) N(v) is the set of items cited by the two users, the value range of W\(_{u,v}\) is [-1,1], the closer the calculation result is to 1, it represents two The higher the user similarity.

5) User X's citation record and the organization list of browsing records more than 3 times L1;

6) According to the union of the citation records of user X and user E, search for the 5 institutions of the same type and the most citations in the knowledge base KD\(_M\) to form a list L2;

7) According to the union of the reference records of user X and user E, relevant attributes are extracted, sorted according to the number of the same attributes, (for example: 8 institutions are all silver in color), and the number less than 3 is excluded. Find institutions with three or more attributes in the library KD\(_M\) to form a list L3;

8) According to the citation and browsing records of user E in the past three days, search the 5 institutions of the same type and the most citations in the knowledge base KD\(_M\) to form a list L4;

9) Since the citation and browsing records of the past 3 days can well reflect the theme that the user is designing, in L4, select the two most cited by users result1, result2, and then take the union of L1, L2, and L3, and select The three most cited by users, result3, result4, and result5, store result1 ~ result5 in the list result in the above order, result is the combination of institutions to be recommended, generally, there will be 10 objects to be recommended in result.
Figure 1. The structure decomposition diagram of the knowledge base KDM.

Figure 2. Recommendation algorithm flowchart.

Establish knowledge base KDM, KDA, KDB, KDC, KDD, KDE

Use Euclidean distance to calculate the similarity between users A, B, C, D and user E, and get user X with similarity higher than 0.5

User X’s citation record and the organization list of browsing records more than 3 times L1

According to the union of the citation records of user X and user E, search for the 5 institutions of the same type and the most citations in the knowledge base KDM to form a list L2

According to the union of the reference records of user X and user E, extract relevant attributes, search for institutions with three or more attributes in the knowledge base KDM, and form a list L3

According to the citation and browsing records of user E in the past three days, search the 5 institutions of the same type and the most citations in the knowledge base KDM to form a list L4

Combine L1, L2, L3 and the browsing records of the past three days to form a list result
3. Result
This experiment collects the usage record data of 100 users after using the knowledge base KDM as the experiment, 80 users as the training set, and 20 users as the test set, to recommend the AM model to be designed by the designer, and compare the recommended and actual Euclidean distance. And compare with latent semantic model, decision tree, XGBoost, deep learning algorithms. The algorithm evaluation index is:

1) The number of people whose maximum Euclidean distance is greater than or equal to 0.8 in the test set;
2) Recommend the number of people whose Euclidean distance is less than or equal to 0.2 and greater than or equal to 3;
3) Recommend the number of people whose Euclidean distance is greater than or equal to 0.8 and greater than or equal to 3;
4) Recommend the number of people whose variance is less than 0.1.

TABLE I. THE NUMBER OF PEOPLE WITH THE HIGHEST EUCLIDEAN DISTANCE GREATER THAN OR EQUAL TO 0.8

| Algorithm          | Knowledge-driven | Implicit semantic | Decision tree | XGBoost | Deep Learning |
|--------------------|------------------|-------------------|---------------|---------|---------------|
| People             | 15               | 15                | 13            | 13      | 16            |

TABLE II. THE NUMBER OF PEOPLE WHOSE EUCLIDEAN DISTANCE IS LESS THAN OR EQUAL TO 0.2 AND GREATER THAN OR EQUAL TO 3

| Algorithm          | Knowledge-driven | Implicit semantic | Decision tree | XGBoost | Deep Learning |
|--------------------|------------------|-------------------|---------------|---------|---------------|
| People             | 0                | 1                 | 3             | 2       | 2             |

TABLE III. THE NUMBER OF PEOPLE WHOSE EUCLIDEAN DISTANCE IS GREATER THAN OR EQUAL TO 0.8 IS GREATER THAN OR EQUAL TO 3

| Algorithm          | Knowledge-driven | Implicit semantic | Decision tree | XGBoost | Deep Learning |
|--------------------|------------------|-------------------|---------------|---------|---------------|
| People             | 15               | 13                | 10            | 12      | 14            |

TABLE IV. NUMBER OF PEOPLE WITH VARIANCE LESS THAN 0.1

| Algorithm          | Knowledge-driven | Implicit semantic | Decision tree | XGBoost | Deep Learning |
|--------------------|------------------|-------------------|---------------|---------|---------------|
| People             | 17               | 14                | 13            | 12      | 16            |

Table I is the number of people whose Euclidean distance is greater than or equal to 0.8 in the test set. The larger the Euclidean distance, the more relevant it represents. It can be seen from Table I that in the test set of 20 users, the number of people with the highest value greater than or equal to 0.8 has the most deep learning algorithms, followed by knowledge-driven algorithms and implicit semantic algorithms. However, it can be seen from Table II that the number of people whose Euclidean distance is less than or equal to 0.2 is greater than or equal to 3, and the number of knowledge-driven recommendation algorithms is 0. This table shows that the more the number of people, the more irrelevant results are recommended to users. It can be seen from Table III that the knowledge-driven recommendation algorithm performs better. The more people in Table III, the more highly relevant results are recommended to users. Table IV represents the stability of the recommended results. The larger the number of people, the smaller the correlation fluctuation in the recommended results.

4. conclusion
From the comparison of the results in the previous chapter, it can be seen that the overall performance of the knowledge-driven recommendation algorithm is better than other algorithms. The main reason is that the algorithm digs out the correlation between hobbies from the user’s historical hobby records and
considers the relationship between entities and attributes. Therefore, the algorithm can greatly improve the work efficiency of AM model designers.

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