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ABSTRACT

Background: The deployment of various networks (e.g., Internet of Things (IoT) and mobile networks) and databases (e.g., nutrition tables and food compositional databases) in the food system generates massive information silos due to the well-known data harmonization problem. The food knowledge graph provides a unified and standardized conceptual terminology and their relationships in a structured form and thus can transform these information silos across the whole food system to a more reusable globally digitally connected Internet of Food, enabling every stage of the food system from farm-to-fork.

Scope and approach: We review the evolution of food knowledge organization, from food classification, food ontology to food knowledge graphs. We then discuss the progress in food knowledge graphs from several representative applications. We finally discuss the main challenges and future directions.

Key findings and conclusions: Our comprehensive summary of current research on food knowledge graphs shows that food knowledge graphs play an important role in food-oriented applications, including food search and Question Answering (QA), personalized dietary recommendation, food analysis and visualization, food traceability, and food machinery intelligent manufacturing. Future directions for food knowledge graphs cover several fields such as multimodal food knowledge graphs and food intelligence.

1. Introduction

As for the food domain, the improvement of digital technology is accompanied by the production of huge volumes of food-related data (e.g., food item barcodes, nutrition and health databases, food images, food ordering data, recipes, and cooking videos). A large amount of multimodal multidisciplinary food data provides a basis for the development of computing technology and artificial intelligence, making digital technology an indispensable part of the food science domain. Benefiting from these data, some downstream food industry processes can be replaced with data-driven automatic technology, such as the use of convolutional neural networks in classifying food and fruits (Liu et al., 2021), and food object detection with mobile devices (Knez and Šajn, 2020). However, when faced with complex issues such as food contamination traceability, exposure assessment, food recommandation, etc., it's important to organize food knowledge extracted from these multi-source heterogeneous data in the food system. Only in this way, we can interchange and easily access food-relevant data all over the world, which benefits different stakeholders, such as food manufacturers, retailers, food distributors, authorities, researchers and consumers. Such a standardized knowledge organization system can facilitate responsible governance via more efficient knowledge utilization and access (Holden et al., 2018).

A key requirement for standardization is to make heterogeneous data from multiple sources interoperable. For that, Internet of Food is proposed to help tackle this problem via defining one lingua franca (Holden et al., 2018; Leone, 2017). Food classification and description systems (Ireland and Møller, 2016) provide basic standards for organizing food in a simple hierarchical way. The ontology is then introduced to describe more complex structures with arbitrary relations and restrictions between concepts (Jurisica et al., 2004), and thus increases the data interoperability between different internet devices and data sources. For these reasons, different food ontologies have been developed, such as Open Food Facts and FoodWiki (Çelik Ertuğrul, 2015). The knowledge graph adopts ontology as its scheme to further model more real-world instances and their relationships in a graph. Following the definition of a knowledge graph

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(Ehrlinger and Wöß, 2016), a food knowledge graph acquires and integrates food-relevant information in a knowledge base, and can apply computational methods to derive new information. It provides a unified and standardized conceptual terminology and their relationships to link various silos related to food, paving the way for Internet of Food.

A global food knowledge graph will have considerable impact in many food-relevant fields. A range of use cases include food safety (e.g., food contamination traceback), food allergy, chemical exposure and nutritional assessment, food regulation, cooking and culinary use. Combined with Artificial Intelligence (AI), it further enables food-oriented semantic retrieval, interpretable recommendation and intelligent understanding to support food computing (Min et al., 2019a).

Some relevant reviews have been done. For example, some works have reviewed existing international food classification and description systems (Ireland and Møller, 2000, 2016) and food ontologies (Boulos et al., 2015). There are also some surveys on knowledge graphs from different perspectives (Paulheim, 2016; Wang et al., 2017; Chen et al., 2020b; Ji et al., 2020). In contrast, this survey seeks to provide a comprehensive summary of current research on food knowledge graphs, the evolution from food-oriented classification, ontology to knowledge graphs, and their representative food-oriented applications. The structure of this review is as follows. First, we briefly review the history of knowledge graphs. Next, we outline the evolution of food knowledge organization, ranging from food classification systems, food ontology to food knowledge graphs. We then review representative applications of food knowledge graphs, and finally close by discussing main challenges and future directions.

2. Knowledge Graph

In this section, we briefly introduce the history of knowledge graphs, and discuss how they are constructed, represented and used.

A Brief History of Knowledge Graphs. Graph-based knowledge representation has a long history in AI. The semantic network was first proposed as a form of knowledge representation¹, and it represents relations between concepts as one graph, which consists of nodes representing concepts, and edges representing semantic relations between concepts. However, there are no standards for the use of values of nodes and edges, and thus it is difficult to apply in practice. Latter, researchers borrowed the term ontology from philosophy as the knowledge specification, and defined ontology as a formal explicit description of concepts within a certain domain, properties of each concept and restrictions on facets. The aim of an ontology is to provide shared understanding to conceptual knowledge and give the definition to mutual relationships between concepts (van Heijst et al., 1995).

An ontology together with a set of individual instances of classes constitutes a knowledge base (For example, a dish is an entity, while Kung Pow Chicken is an instance of dish). Google proposed the term of knowledge graph² in 2012, which mainly describes real world entities and their relations in a graphical representation, and defines possible classes and relations of entities with the ontology as one schema (Paulheim, 2016). It is synonymous with the knowledge base with a minor difference. A knowledge graph can be viewed as a graph when considering its graph structure. When we highlight formal semantics, it can be considered as a knowledge base for interpretation and inference over facts (Ji et al., 2020). Currently, there is no unifying definition of knowledge graphs. Herein we adopt the following definition: a knowledge graph is viewed as a multi-relational graph of data for accumulating and conveying knowledge of the real world, where nodes represent entities and edges represent different types of relations. The focus of knowledge graphs is instances, while the ontology is often used as the schema and plays a minor role in the knowledge graph. The number of instance-level statements from knowledge graphs is generally by a few orders of magnitude larger than that from the ontology (Paulheim, 2016).

Knowledge Graph Construction, Representation and Applications. Knowledge graphs can be constructed either manually or automatically (Nickel et al., 2016). Manual construction methods include curated ones and collaborative ones, where the former creates triples by experts while the latter resorts to volunteers. Manually constructed knowledge graphs have little or no noisy facts, and yet require very large human efforts. For efficiency, auto-constructed methods are explored, and mainly contain two types. The first one utilizes various rules, such as hand-crafted rules and learned ones to exploit semi-structured data, such as Wikipedia infoboxes. However, semi-structured text still covers a small fraction of the information stored on the web, and these repositories are still far from complete. In contrast, the second one extracts facts from tremendous amounts of unstructured text using machine learning and

¹https://en.wikipedia.org/wiki/Semantic_network#cite_note-Quillian1963-7(Accessed June 14, 2021)

²https://www.blog.google/products/search/introducing-knowledge-graph-things-not/(Accessed June 14, 2021)

natural language processing techniques (Dong et al., 2014; Petković et al., 2021; Youn et al., 2020). The knowledge extraction-fusion-refinement pipeline (Paulheim, 2016) is adopted to reduce the noise in the extracted facts. Based on the constructed knowledge graphs, effective representation learning methods for knowledge graphs are explored, such as linear models, neural models and translation models (Lin et al., 2018). The learned feature representation can in turn benefit various tasks, such as relation extraction, entity classification and reasoning (Wang et al., 2017; Chen et al., 2020b), and applications, such as semantic search, recommendation and decision-making.

3. From Food Classification to Food Knowledge Graph

Knowledge graphs allow for potentially interrelating arbitrary entities with each other from various topical domains. Knowledge graphs focusing on the food-relevant domain result in food knowledge graphs. From the aspect of food knowledge organization, it mainly has gone three stages, ranging from food classification, food ontology to food knowledge graphs. Therefore, before we introduce food knowledge graphs, we first describe and summarize existing food classification and ontology systems, which are the basis of food knowledge graphs.

3.1. Food Classification

Food classification generally organizes food concepts in a hierarchical form. For example, "beef" belongs to "meat" while "cake" belongs to "bread". It is relevant to the organization and communication of information within different areas of food science, such as nutrition, health, marketing and microbiology (Torres-Ruiz et al., 2018). Constructing standardized food classification systems can alleviate many problems, such as the food term ambiguity caused by homonyms and synonyms.

Different food classification systems are created for one certain purpose, such as dietary monitoring, nutrient risk assessment, exposure assessment, and regulation of commodities (Ireland and Møller, 2000, 2016). For example, Codex Classification of Foods and Animal Feeds (CCPR) and Codex Alimentarius General Standard for Contaminants and Toxins in Food and Feed (GSCTFF) are created for exposure assessment and monitoring. DAta Food NEtworking (DAFNE) (Lagiou et al., 2001) and Eurocode-2 Food Coding System are created for dietary surveys and comparison. Furthermore, Food Balance Sheet (FBS) and Global Product Classification (GPC) are created for regulation of commodities, while Indian Food Categorization System (IFCS) and Australia New Zealand Food Standards Code (ANZFSC) food standard serve as the references for their countries.

Also, different food classification systems are food level-specific. There are mainly three reporting levels, namely the intake level, ingredient level and commodity level (Ireland and Møller, 2016). Generally, reporting level depends on the purpose of the classification system. Representative food classification systems with intake-level include the national or international food classification for dietary and consumption surveys, like Dutch National Food Consumption Survey (DNFCS), DAta Food NEtworking (DAFNE), Euro-Food Groups Classification System (EFG), What We Eat in America (WWEIA) Food Categories, Eurocode-2 Food Coding System and Individuelle Nationale des Consomations Alimentaires 2 (INCA2). Similarly, food classifications for food composition databases are created with intakelevel, like European Food Information Resource (EUROFIR) Food Composition Databases (FCDBs). Systems like Version 2 of the EFSA Food Classification and Description System for Exposure Assessment (FoodEx2) and Global Environment Monitoring System - Food Contamination Monitoring and Assessment Programme (GEMS/FOODS) are designed for exposure assessment, and they record food at the ingredient-level. The food categorization systems in GSCTFF and Codex Classification of Foods and Animal Feeds record food at the raw commodity level, grouped based on the commodities' similar potential for pesticide residues, and are thus for the exposure risk assessment of food safety and health. For the needs of the import and export trade statistics, some classification and coding systems for goods and productions also include a classification system for commodity-level foods, such as Food Balance Sheet (FBS), Harmonized Commodity Description and Coding System (HS Code), and PRODuction COMmunautaire (PRODCOM).

In contrast with food classification systems, which group foods with similar characteristics, there are different food description systems (such as INFIC/ENFIC System, LanguaL (Ireland and Moller, 2010) and INFOODS Nomenclature System (Truswell et al., 1991)), which describe food as precise as possible in a multidimensional way without necessarily aggregating them. Table 1 lists main food-related classification systems in more details.

[Table 1 about here.]

Food classification systems represent a simple hierarchical relationship between concepts and their relationships. There is no single universal classification system that can serve all the needs of every food composition database. In addition, many national and international food classification systems are incomparable. On the other hand, such hierarchal food concept structures from food classification systems and more metadata from food description systems are basic to develop more complex structures with rich relations and restrictions between concepts, namely food ontology, which will be detailed in the following section.

3.2. Food Ontology

Food ontology uses the shared terminology for types, properties and relationships about food concepts, and thus can help tackle data harmonization problems that span food-relevant domains. Table 2 summaries existing food ontologies from different aspects, where some food ontologies have been reviewed by previous work (Boulos et al., 2015).

[Table 2 about here.]

Different food ontologies focus on different aspects of food and cover different domains. Taaable (Cordier et al., 2014), Cooking Ontology (Batista et al., 2006) and BBC Food Ontology³ are about cooking and recipes. Cooking Ontology contains actions, foods, recipes and utensils with supplementary class units, measures, and equivalencies, and is integrated into a dialogue system to support cooking-oriented Question Answering (QA). These ontologies facilitate cooking recipes based works, such as retrieval, mining and recommendation (Min et al., 2017, 2018; Sajadmanesh et al., 2017). Many food ontologies also serve as an auxiliary structure to help nutrition and healthy advising in various food applications and systems. For example, Personalized Information Platform for Health and Life Services (PIPS) Food Ontology (Cantais et al., 2005) represents an abstract model of different types of foods with nutritional information, including the type and amount of nutrients, and provides nutritional advice for diabetic patients. Similarly, Foods (Diabetes Edition) (Snae and Bruckner, 2008) is designed to provide diet advice for diabetic patients, and Unified Traveler and Nutrition ontology (Karim et al., 2015), and Edamam Food Ontology⁴ are developed to help general users make the food-related choice via the recommendation.

Food ontology can also be used to integrate statistical data, and then used in consumption system statistics and health monitoring applications. For example, FoodWiki (Çelik Ertuğrul, 2015) is used to build an ontology-driven mobile safe food consumption system, monitoring and controlling food intake. HeLiS (Dragoni et al., 2018) provides the representation of both food and physical activity domains and the definition of concepts enabling the monitoring of both users' actions and their unhealthy behaviors.

Most ontologies focus on specific sub-fields of the food domain to better promote related research and industrial applications, like Ontology for Food Processing Experiment (OFPE)⁵ and Agri-Food Experiment Ontology (AFEO)⁶ for food processing, Food Safety Ontology (Qin et al., 2019) for food safety, Food-Biomarker (FOBI) ontology (Castellano-Escuder et al., 2020) for food nutrition and metabolomics, ISO-Food (Eftimov et al., 2019) for food isotopes research, and Ontology for Nutritional Studies (ONS) (Vitali et al., 2018) for food nutritional science. In contrast, there are also some ontologies with broader concepts, like FoodOn (Dooley et al., 2018), RICHIFIELDS ontology (Eftimov et al., 2018) and AGROVOC⁷. FoodOn represents knowledge on both food and food processes comprehensively enough to drive various applications in food safety, farm-to-fork traceability, risk management, etc. Each food product includes the food origin, physical attributes, processing, packaging, dietary uses, and geographical origin. In addition, some ontologies are developed for knowledge database construction, like FOod in Open Data Ontology (Peroni et al., 2016), DBpedia Food class⁸ and Open Food Facts⁹, where Open Food Facts is a global food product database, and allows users to learn about nutritional information, and compare worldwide products.

Food ontologies formally describe food types, their properties and interrelationships between food entities. However, they lack detailed information about more food instances. For these reasons, food knowledge graphs are developed with both food ontology and specific food-relevant instances, where food ontology is generally considered as the schema.

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<sup>3</sup>https://www.bbc.co.uk/ontologies/fo(Accessed June 14, 2021)
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⁴https://www.edamam.com/(Accessed June 14, 2021)

⁵http://agroportal.lirmm.fr/ontologies/OFPE(Accessed June 14, 2021)

⁶http://data.agroportal.lirmm.fr/ontologies/AFEO(Accessed June 14, 2021)

⁷http://agroportal.lirmm.fr/ontologies/AGROVOC(Accessed June 14, 2021)

⁸http://dbpedia.org/data3/Food.ntriples(Accessed June 14, 2021)

⁹https://world.openfoodfacts.org/who-we-are(Accessed June 14, 2021)

3.3. Food Knowledge Graph

[Table 3 about here.]

The proliferation of food-relevant information, such as recipes and nutrition from various sources presents an opportunity for discovering and organizing food-related knowledge into the food knowledge graph. Considering food knowledge graph construction needs a lot of laborious work, there are few constructed food knowledge graphs in the academic field. Basically, food knowledge graphs can serve as knowledge databases to support food data retrieval and search. For example, FOODpedia (Kolchin et al., 2015) is a knowledge graph about Russian food products and their ingredients, with Food Product Ontology as the ontology. Foodbar knowledge graph (Zulaika et al., 2018) consists of different facts that describe ingredients, opinions and ratings, and relates them to users, points of interest, cultural facts and other information. FoodKG (Steven et al., 2019; Haussmann et al., 2019) integrates FoodOn into its ontology and contains food-relevant instances including foods, ingredient information extracted from Recipe1M (Marín et al., 2021) and nutrient records from United States Department of Agriculture (USDA) for recipe recommendation. The food knowledge graphs are also used to construct QA systems. Agricultural Knowledge Graph(AgriKG) (Chen et al., 2019) is an agriculture domain-specific knowledge graph, and covers raw food materials and food products. It aims to integrate this fragmented information for agriculture relevant retrieval and QA. Food safety knowledge graph (Qin et al., 2019) contains the data of unqualified foods officially released in recent years from the Internet. The food safety ontology in this knowledge graph is used to organize concepts, classifications and relationships between food production and food inspection. Based on this food safety knowledge graph, an intelligent food safety QA system is built to help people get information about unqualified foods information.

Because of its vital importance in business (Noy et al., 2019), many companies such as Uber, Meituan and Yummly have constructed their food knowledge graphs to drive many products and make them more intelligent from different specific domains. For example, Uber Eats¹⁰ built a food knowledge graph to enable food-related queries and recommendation. In this food knowledge graph, the nodes consist of heterogeneous entities such as restaurants, cuisines and menu items, and different relations are constructed as edges, such as the association between cuisines and location information. Edamam developed an extensive knowledge graph on food and cooking. This knowledge graph includes recipes, ingredients, nutrition information, measures and allergies. Yummly constructed the recipe-oriented knowledge graph for personalized recipe recommendation and search.

In order to effectively construct the food knowledge graph, one common method is to combine extractions from web content with domain knowledge from existing knowledge repositories. The semi-automatic way is usually adopted with both machine learning methods and manual efforts. Generally, the first step is to construct the food ontology. One effective and feasible method is to reuse existing food ontologies (Helmy et al., 2015). For example, FoodKG (Haussmann et al., 2019) adopts the ontology on food products from the FoodOn ontology as its ontology. In some cases, existing ontologies do not cover what is intended with the target project, and building one food ontology from scratch is thus necessary. The most widely used ontology construction method is to combine top-down and bottom-up approach (Eftimov et al., 2019), where the former starts with defining the classes for the more general concepts in the domain, and continues by defining the subclasses. while the latter starts with a definition of more specific concepts in the domain as subclasses and continues by grouping these classes into more general concepts, such as Wine ontology (Graça et al., 2005). Different types of methodology models are adopted for ontology construction, such as stage-based model Ontology-101 (Noy and McGuinness, 2001), and the evolving prototype model, e.g., Methontology. After food ontology construction, more information on instance items, such as food entities and their relations (Popovski et al., 2019; Popovski et al., 2020; Chi et al., 2018; Petković et al., 2021) should be extracted from various sources, and are added into the food ontology for food knowledge graph construction.

Note that some food ontologies actually belong to food knowledge graphs according to the definition of knowledge graphs (Paulheim, 2016). This is because they contain not only classes and their relations in a schema, but also real world instances, their properties and relationships. For example, FoodWiki and Open Food Facts contain not only the food ontology, but also product instances, their properties and relationships. Therefore, the boundary of food knowledge graphs and food ontology is vague in some cases.

[Figure 1 about here.]

Fig. 1 shows the difference among food classification, food ontology, and food knowledge graphs. In a food classification system, food categories are divided hierarchically. For example, the fuji apple is in the apple category,

¹⁰ https://eng.uber.com/uber-eats-query-understanding/(Accessed June 14, 2021)

and the apple category belongs to the fruit category. In the food ontology, concepts, attributes, and relations are all built. Comparing with simple hierarchical structures, the food ontology further defines various relations between the subjects and objects: for example, the concept of the fruit product can be connected to the fruit concept by the relation named "is made of", like Fig. 1(b). Knowledge graphs use ontology as their schema, and further add instances from web data or experts. Instances like the fuji apple are connected by abundantly predefined relations (like "derives from", "has a", "is made of", etc.) to become the knowledge graph. Compared with the classification system, food knowledge graphs allow us to access more relevant information besides the category.

4. Applications

As illustrated in Fig. 2, we have identified various applications of food knowledge graphs in different domains and summarize them from the following six aspects.

[Figure 2 about here.]

Food Search. Many people suffering from different diseases (e.g., heart disease and diabetes) spend a lot of time searching dietary information. They lack professional knowledge of healthy diet. For example, users do not know what kind of food they should choose or avoid when they feel uncomfortable. Although the Internet has created a search and sharing platform of healthy eating information, it is time-consuming and difficult for users to learn about healthy diets: they need to search data from multiple platforms, integrate different types of information (e.g., food, nutrition, healthcare and medical treatment), and then understand what they have learned. One extensive food knowledge graph provides one way to solve these above-mentioned issues, for it contains comprehensive knowledge about food, nutrition, health and disease. It can understand user's query intent to support semantic search, and thus help to obtain more relevant health and nutrition information to satisfy their personalized needs (Helmy et al., 2015).

Food QA. When queries are questions in natural language, food search is changed to food QA. Food QA can answer food-relevant questions, not just the terms. For example, a diabetic often asks questions like, "How can I increase the fiber content of this cake?" A person with lactose intolerance may ask "What can I substitute for milk in chocolate cake?" Answering these questions is not possible from general knowledge graphs for the incompleteness of domain knowledge. Food knowledge graphs are developed to support natural language QA based on different categories of questions about recipes and nutrition, such as simple queries for nutritional information, comparisons of nutrients between different foods, and constraint-based queries to find recipes matching certain criteria (Steven et al., 2019). Food knowledge graph based QA systems can describe recipes, nutrients in foods and the interaction between nutrients and prescribed drugs, disease and general health to satisfy users' specific information need. For example, cooking QA (Manna et al., 2017; Semih et al., 2018) is intended to satisfy the user's information need in the cooking domain, and is helpful to people, such as housewives and nutritionists.

Personalized Dietary Recommendation. The goal of food recommendation is to recommend not only palatable foods, but also healthful ones (Min et al., 2020), which can be a daunting task for many individuals, partly due to the problem of knowledge silos across multiple sources with large amounts of food data. In addition, different from other types of recommendation, we should consider many nutritional parameters, such as caloric and different macronutrient intake when applying food recommendation in practice. A natural solution to this problem is to provide an intelligent semantic food recommender system based on the food knowledge graph. Food knowledge graphs provide formal, uniform and shareable representations about food. They can benefit recommendation from different aspects, such as improving the precision of recommended items via semantic relations among food and user items, increasing the diversity of recommended items for various types of relations and bringing better explainability (Wang et al., 2018). Personalized dietary recommendation based on food knowledge graphs can benefit different types of population, such as diabetics (Chang-Shing Lee et al., 2008), weightlifting athletes (Tumnark et al., 2013) and older adults (Espín et al., 2013). As one use case, the task of personalized food recommendation is considered as constrained QA over the constructed food knowledge graph FoodKG (Haussmann et al., 2019) with recipes, ingredients and nutrients (Chen et al., 2021). Given a user query (e.g., "what is a good lunch that contains meat?") as the input, the system retrieves all recipes from FoodKG for recommendation. They also append personalized requirements as additional constraints, such as user's unique health conditions (e.g., allergies) and health guidelines (e.g., nutrition needs) to the raw user query. In addition, many companies, such as Uber, Meituan and Yummly have built their food knowledge graphs for food recommendation.

Food Analysis and Visualization. Knowledge graphs can also be vectorized and combined with machine learning algorithms for visual analysis, such as image recognition and object detection (Marino et al., 2017; Fang et al., 2017; Knez and Šajn, 2020). Similarly, we can also explore richer knowledge from food knowledge graphs, such as ingredients and their relations to improve the performance of visual food recognition (Min et al., 2019b; Jiang et al., 2019; Chen et al., 2020a). On the other hand, after visual food recognition, we further resort to the food knowledge graph to obtain more detailed information, such as their types, properties, interrelationships, macronutrients and ingredients. This is very useful for automatic dietary assessment (Ruede et al., 2020), since taking one food image using mobile devices is very easy nowadays.

Another application scenario is recipe analysis. Food knowledge graphs enable the link of recipes to nutrition, chemical exposure, food-drug interactions and evolution of food preferences. For example, understanding the chemical composition of foods is important to understand nutrition and evaluate the risk of toxicity. Ingredients of recipes can reveal cultural food preference and possibly provide a link to disease incidence and prevalence within particular populations (Dooley et al., 2018). Some works extract semantic representation about ingredients or recipes from the food knowledge graph to identify ingredient substitutions (Shirai et al., 2021), recipe classification and region prediction (Li and Zaki, 2020). The food knowledge graph can also enhance the quality of mappings between cooking recipes and food composition tables for more accurate nutritional qualification of recipes (Azzi et al., 2020). In addition, visualization plays a key role in food data exploration and analysis (Gómez-Romero et al., 2018). For example, food knowledge graphs can better summarize relevant content around food-relevant concepts and topics in the form of knowledge cards, and present complex data structures and rich information in an easy-to-understand way.

Food Traceability. Food traceability is attracting more attention due to its important impact in society and its relevance in both foodborne pathogen surveillance and outbreak investigations. Food knowledge graphs accurately and consistently describe foods commonly known in cultures from around the world to address food product terminology gaps. It can thus aid in the traceability of investigations, such as the tracing of contaminated foods, especially those that occur across borders, by providing standardized identifiers for suspected foods.

Food Machinery Intelligent Manufacturing. With continuous evolution of technologies, the innovation of IoT sensors also makes its way in food-relevant industries like health, wellness and food. For example, in intelligent kitchens, smart refrigerators with the cameras can reason with recognized food and drink items, ingredients and quantities/portion sizes, and even estimate their shelf-life and timely use in recommended recipes via the embedded food knowledge graph. Smart microwaves with the cameras can recognize the food type and then automatically choose the way and time of heating via the embedded food knowledge graph. AI systems like a cooking robot require food knowledge graphs from multiple domains and sources.

5. Future Directions

Based on comprehensive discussions on existing efforts, we now articulate key open challenges and future research directions for food knowledge graphs.

Internet of Food (IoF). IoF is designed to make the data from different devices and sources interoperable and to be able to compute across the data set they create. However, a notable limitation is lack of integration caused by the current mix of data from different sources and hardware standards. Food knowledge graphs can provide standards (food ontologies) about all food information, such as how we describe food attributes, and how it is cooked, processed or consumed, and make all food-relevant data and information (instances) connected. Therefore, it will foster the development of IoF. However, food knowledge graphs involve complex technologies, such as knowledge aggregation, complex storing and index technologies, bringing about great challenges. In addition, considering using knowledge graphs to integrate food data from diverse sources at large scale is necessary (Nguyen et al., 2020), developing scalable scientific and engineering methods to keep scale with little cost explosion is an obvious requirement for the successful application of food knowledge graphs. Once IoF is constructed based on food knowledge graphs, it enables all known food-relevant information to be accessible by machines, consumers and companies to further support sustainable food systems (Holden et al., 2018) and Agri-food 4.0 (Lezoche et al., 2020).

Multimodal Food Knowledge Graph. Most of existing food knowledge graphs focus on organizing verbal knowledge extracted from text. However, the proliferation of edge devices, such as mobile and IoT devices in the food system generates large volumes of visual data, e.g., images and videos, which contain another important type of knowledge, namely visual knowledge (Perona, 2010). From the narrow perspective of computer vision, visual knowledge is any information that can be useful for improving vision tasks like recognition. Such visual knowledge

includes different forms, such as labeled examples of different categories (e.g., food categories and rich attributes) and relationships, such as object-object relations (e.g., Chicken is part of Kung Pow Chicken) (Chen et al., 2013). Large-scale efforts, such as visual attribute learning (Ferrari and Zisserman, 2007), visual relationship detection (Lu et al., 2016) and scene graph generation (Xu et al., 2017) are under way to extract a body of visual knowledge. Visual knowledge and verbal knowledge constitute multimodal knowledge. There are some initial attempts to incorporate visual information into knowledge graphs by linking images to text via hyperlinks (Liu et al., 2019). In this case, visual information (e.g., entity images) can only be used for visual demonstration. Most of existing food knowledge graphs don't contain visual knowledge and thus can not support food-oriented visual search, visual QA and visual illustration. It is the right time to start building multimodal food knowledge graph, where searching, indexing, organizing and hyperlinking multimodal knowledge is necessary. Such multimodal food knowledge graph can help food-oriented multimodal learning technologies to support many cross-modal tasks, such as cross-modal recipe-food image retrieval and generation (Marín et al., 2021; Papadopoulos et al., 2019; Wang et al., 2020). The downstream applications are various, such as automatically illustrating a given recipe using semantically corresponding images, and supporting food-oriented multimodal dialogue systems. However, due to different statistical properties between visual knowledge and verbal knowledge, how to reasonably and effectively build multimodal food knowledge graphs is worth further study.

Representation and Reasoning on Food Knowledge Graphs. The first step of using food knowledge graphs is to represent them and conduct complex reasoning on them. Numerical computing for knowledge representation and reasoning requires a continuous vector space to capture the semantic of entities and relations (Wang et al., 2017). While embedding-based methods have limitations on complex logical reasoning, some recently proposed methods, especially Graph Neural Networks (GNN) (Wu et al., 2020) on knowledge graph reasoning are very promising for handling complex reasoning. The GNNs learn a target node's representation by propagating neighbor information in an iterative manner until a stable fixed point is reached. With the help of GNNs, it is possible to extract both entity characteristics and relations from knowledge graph, which is an essential factor for food knowledge graph-based applications, such as compound-food relation prediction (Park et al., 2021) and food recommendation (Wu et al., 2020).

Adaptive Food Knowledge Graphs. Current food knowledge graph research mostly focuses on static knowledge graphs where facts are not changed with time, while the temporal dynamics of a knowledge graph is less explored. In real world, knowledge graphs are dynamic and evolve over time with addition or deletion of knowledge items, because a lot of structured knowledge only holds within a specific period. Similarly, food systems are dynamic, diverse and complex, involving everything from subsistence farming to multinational food companies. In such a climate, an evolving interdisciplinary food knowledge graph is vital (Editorial, 2020). Correspondingly, the representation and reasoning on time-evolving food knowledge graph is different and needs new technologies to handle these problems. Researchers have started to build adaptive knowledge networks from incoming real-time multimodal spatiotemporally evolving data (Trivedi et al., 2017). With the increase in the amount of food-relevant data generated by various networks, more sophisticated models are necessary to take full advantage of such data for effective knowledge extraction and knowledge graph construction.

Food Knowledge Graphs for Human Health. To meet the people's pursuit of better health, the essential demand is for better, more nutritious and safer food. To achieve this goal, building one human health platform is necessary. The food knowledge graphs provide one opportunity to build such platform via large-scale structured food knowledge organization. As the core of this platform, food knowledge graphs can support tracking and monitoring of the dietary behaviors, health-relevant search and recommendation for people. To achieve this goal, the food knowledge graph should satisfy some characteristics. For example, a more complete and accurate interdisciplinary food knowledge graph is one basic requirement, and joint efforts from world-wide experts in nutrition, health and other relevant domains are thus needed. More challenges should also be solved. For example, there exist different culinary cultures and health beliefs in the world, which probably leads to the contradiction when adding these knowledge into the food knowledge graphs. Although existing machine learning and nature language processing methods can make food knowledge graph construction automatically, the multi-source of food data introduces the noise inevitably. To make the knowledge accurate, correct and reliable, various error detection methods can be utilized (Paulheim, 2016). In addition, as mentioned before, such big food knowledge graphs should support dynamic adaptation. For example, currently we should update the food knowledge graphs by adding relevant concepts of COVID-19 and its relations with nutrition and health into this food knowledge graph. Only in this way, people can search what they should eat or drink during the pandemic of COVID-19 to ensure a good nutritional status.

Food Intelligence. Driving by fast development of both AI and food knowledge graphs, there is a stringent need

to pushing the AI frontier to the food domain. To fulfill this trend, food computing (Min et al., 2019a) has received tremendous amounts of interest for its multifarious applications in health, culture and medicine. It acquires and analyze heterogeneous food data from different sources for food-oriented perception, recognition, retrieval, recommendation, and monitoring via computational approaches. The nexus between food computing and AI gives birth to the novel paradigm of food intelligence. Food knowledge graphs can enhance already very popular techniques of computer vision and natural language processing, such as image recognition (Marino et al., 2017; Knez and Šajn, 2020), object detection (Fang et al., 2017) and QA (Zhang et al., 2018), and thus can aid food computing tasks. We can also make decisions and reasoning on food knowledge graphs (Chen et al., 2020b) in combination with advanced AI technologies for many intelligent services in various fields, such as smart kitchen (Krieg-Brückner et al., 2015) and smart agricultures. Therefore, food knowledge graphs will play important roles in realizing food intelligence.

Declaration of competing interest

There is no conflict of interest in this article.

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Figure Captions

Figure 1 Demonstration of (a) food classification, (b) food ontology and (c) food knowledge graph

In a food classification system, food categories are divided hierarchically. In the food ontology, concepts, attributes, and relations are all built. Comparing with simple hierarchical structures, the food ontology further defines various relations between the subjects and objects. Knowledge graphs use ontology as their schema, and further add instances from web data or experts. Compared with the classification system, food knowledge graphs allow us to access more relevant information besides the category.

Figure 2 Applications of food knowledge graphs

Various applications of food knowledge graphs in different domains can be summarized from the following six aspects, respectively food search, food QA, personalized dietary recommendation, food analysis and visualization, food traceability, and food machinery intelligent manufacturing.

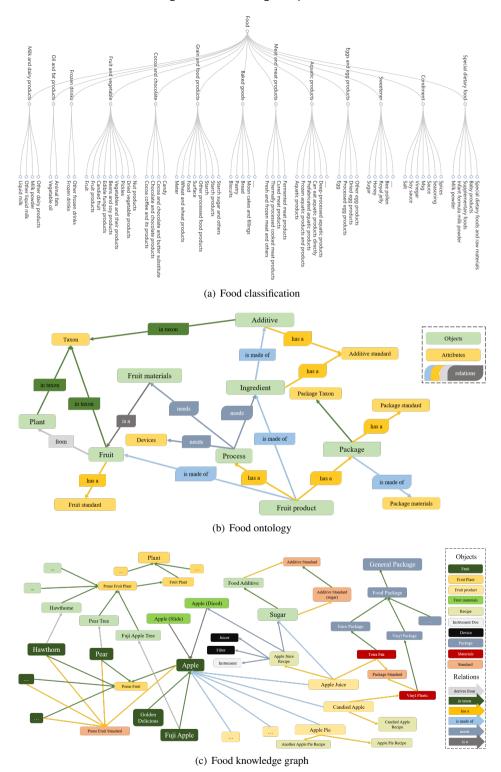


Figure 1: Demonstration of (a) food classification, (b) food ontology and (c) food knowledge graph

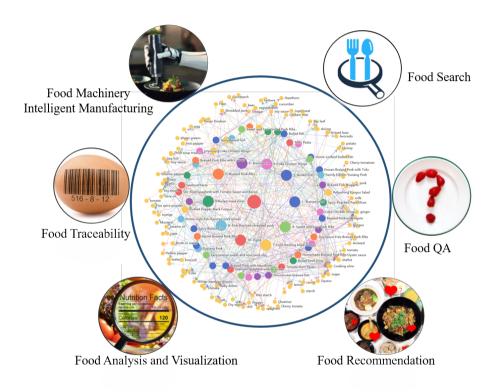


Figure 2: Applications of food knowledge graphs

Table 1 Food Classification Systems

| Name | Purpose | Reporting level |
|--|--|------------------|
| Food Balance Sheet (FBS) | Food and agricultural com- modities trade | Commodity level |
| Global Environment Monitoring System - Food Contamination Monitoring and Assess- ment Programme (GEMS/FOODS) | Exposure assessment (pollution) | Commodity level |
| DAta Food NEtworking (DAFNE) | Dietary surveys | Intake level |
| Global Product Classification (GPC) | Commodity Trade | Commodity level |
| Codex Classification of Foods and Animal Feeds | Exposure assessment (pesticide residues) | Commodity level |
| Codex General Standard for Contaminants and Toxins in Food and Feed (GSCTFF) categorization system | Exposure assessment (contaminants) | Commodity level |
| Harmonized Commodity Description and Coding System (HS Code) | Commodity trade | Commodity level |
| Eurocode-2 Food Coding System | Dietary surveys | Intake level |
| CIAA Food Category System | Exposure assessment (food additives) | Ingredient level |
| Codex General Standards for Food Additives (GSFA) | Exposure assessment (food additives) | Ingredient level |
| European Food Groups Classification System (EFG) | Dietary surveys | Intake level |
| PRODuction COMmunautaire (PRODCOM) | Commodity trade (manufactured goods) | Commodity level |
| What We Eat in America (WWEIA) Food Categories | Dietary and nutrition surveys | Intake level |
| EUROFIR FCDBs | Nutrition information reference | Intake level |
| Dutch National Food Consumption Survey (DNFCS) | Dietary and nutrition surveys | Intake level |
| Individuelle Nationale des Consomations Alimentaires 2 (INCA2) | Dietary surveys | Intake level |
| Indian Food Categorization System (IFCS) | Information and regulatory | Ingredient level |
| Version 2 of the EFSA Food Classification and Description System for Exposure Assessment (FoodEx2) | Exposure assessment | Ingredient level |
| Australia New Zealand Food Standards Code (ANZFSC) | Development of food standards | Commodity level |

Table 2
Summary on Existing Food Ontologies

| Name | Year | Domain | Language | Purpose |
|--|------|--|-----------|---|
| AGROVOC | 1980 | Agriculture, fisheries, forestry and food | SKOS, RDF | Agricultural field terminology reference |
| PIPS Food Ontology | 2005 | Food and nutrition | OWL | Providing food nutritional in- formation for PIPS users |
| Cooking Ontology | 2006 | Food and cooking | OWL | Ontology construction research |
| FOODS (Diabetes Edition) | 2008 | (Thailand) Food and nu- trition | RDF | Food or menu planning for people with diabetes |
| Edamam Food Ontology | 2012 | Food, recipes, nutrition and healthy | OWL | Building food-related applications |
| Open Food Facts Food Ontology | 2013 | Packaged food products | RDFS | Food product comparison and searching, nutrition database |
| BBC Food Ontology | 2014 | Food, recipes and diets | OWL | Recipe data publishment |
| Unified Traveler and Nu- trition ontology | 2015 | Food dishes and medicine | OWL | Healthy food recommendation |
| FOod in Open Data (FOOD) Ontology | 2015 | General food | OWL | Creating Linked Open Data (LOD) datasets |
| FoodWiki | 2015 | Packaged food | OWL | Building ontology-driven mo- bile safe food consumption system |
| Food Product Ontology | 2016 | Packaged food | OWL | National food products (Russia) food domain data publishment |
| OFPE | 2016 | Food processing | OWL | Research on Food Processing |
| DBpedia Food class | 2016 | Food products | RDFS | Building open-access database |
| RICHIFIELDS Ontology | 2017 | General food | - | Purposing a framework for food-related integration, re- trieval and updating |
| FoodOn Ontology | 2018 | Food product and materials | OBO, OWL | Semantics development for food-related process, practices and safety |
| AFEO | 2017 | Viticultural practices and winemaking products | OWL | Research about food traceability and quality |
| HeLiS | 2018 | Food and nutrition | OWL | Food and activity domains integration for users' actions and behaviors monitoring |
| ONS | 2019 | Food and nutrition | OWL | Nutritional studies |
| ISO-FOOD | 2019 | Food and isotopic | OWL | Describing isotopic data within Food Science |
| Food Safety Ontology | 2019 | Food safety | RDF | Building Food safety knowledge graph |
| FOBI Ontology | 2020 | Food nutrition and metabolite | OBO, OWL | Food nutrition and metabolite research |

Table 3
Summary on existing food knowledge graphs.

| Name | Year | Ontology | Usage | Size |
|--|------|--|--|--|
| FOODpedia | 2015 | Food Product Ontology | Russian food products in- formation publishment and retrieve | - |
| Knowledge graph for the Food, Energy, and Water (FEW) | 2017 | - | Data-driven research | - |
| Chinese Food Knowledge Graph | 2018 | - | Healthy diet knowledge retrieval | - |
| Foodbar Knowledge Graph | 2018 | - | Small miniature bites or dishes cognitive gastroevaluation | - |
| AgriKG | 2019 | - | Agriculture QA System | over 150k entities and 340k relations |
| FoodKG | 2019 | WhatToMake Ontology, Dietary Guideline Ontology, etc. | Integrated food suggestion service | over 1 billion recipes and 8k nutrition data |
| Food safety knowl- edge graph | 2019 | Food Safety Ontology | Food safety domain QA system | - |