CrowdHMT: Crowd Intelligence with the Deep Fusion of Human, Machine, and IoT

Bin Guo*, Yan Liu, Sicong Liu, Zhiwen Yu, Xingshe Zhou

***Abstract*—Mobile crowd sensing and computing (MCSC) has become a hot research area in recent years. This article presents our vision of the next generation of MCSC, Crowd Intelligence with the Deep Fusion of Human, Machine, and IoT, namely CrowdHMT. It aims to build a self-organizing, self-learning, self-adaptive, and continuous-evolving smart space with the deep fusion of Crowdsourced Human, Machine, and IoT intelligence. This paper firstly characterizes the concept of CrowdHMT. We further investigate its challenges and techniques, and present its main application areas. Finally, we make discussions about the open issues and future research directions of CrowdHMT.**

***Index Terms*—AIoT; crowd intelligence; crowd sensing and computing; edge intelligence; urban computing.**

I. INTRODUCTION

UBIQUITOUS sensing and computing is one of the key topics in computer science [1]. In recent years, a wide range of mobile and embedded devices (e.g., smartphones and wearables) with rich sensing and computing capabilities have stimulated the emergence and development of a novel sensing and computing paradigm, i.e., **Mobile Crowd Sensing and Computing (MCSC)** [2]. MCSC empowers and inspires massive ordinary users to contribute their sensing data, e.g., the ambient environment and social data. With the help of heterogeneous data aggregating and analyzing techniques, such a paradigm has benefited various complex and large-scale sensing and computing tasks [3]. Different from traditional stationary wireless sensor networks, MCSC takes advantage of the inherent mobility nature of mobile users and the rich sensing capabilities of sensor-enhanced devices to gain a wealth of knowledge at the urban/community scale. The human-centric and collective participating nature of MCSC also raises numerous challenging issues, such as participant profiling and task allocation [4], [5], crowdsourced data selection and aggregation [6], [7], data privacy and incentive mechanisms [8], [9]. To address those issues, many research efforts have been devoted to MCSC during the last decade, where numerous successful applications (Google Waze[1], SeeClickFix[2]) and support platforms (e.g., CrowdOS[3]) are developed. Though stepping into a relatively mature stage, quite recently, several emerging technologies are driving the formation and evolution of the next generation of MCSC, as clarified below.

***(1) The emergence of Artificial Intelligence of Things (AIoT)* [10].** With the rapid development and cross-field fusion of Internet of Things (IoT), big data, and Artificial Intelligence (AI) techniques, AIoT has become a new frontier field with fascinating prospects. AIoT enables the collection of multi-modal data at real-time, and then utilizes data mining and machine learning algorithms on the end devices, edge clusters or cloud servers for intelligent processing. AIoT will empower several important domains such as smart city, intelligent manufacturing, and public safety. Specifically, AIoT builds the comprehensive interconnection of Human, Machine, and IoT to boost the quality of intelligent industrial manufacturing and service management.

***(2) The development of crowd intelligence in AI 2.0*.** As envisioned in Li *et al.* [11], AI is moving towards the 2.0 era, where crowd intelligence becomes one of the promising research directions. Crowd intelligence emerges in massive autonomic agents. It is motivated to carry out challenging computational tasks under a certain Internet-based environment. Particularly, the Internet-based crowd intelligence aims to integrate and interweave the crowd and machine capabilities seamlessly to deal with complex and large-scale problems. AIoT plays a key role in the fusion of Human and IoT devices, thus, how to utilize and combine group collaboration and crowd intelligence to further enhance its sensing and computing capabilities has become an important research issue.

(3) Interdisciplinary research on human-machine systems. In recent years, some cutting-edge research has explored the collaboration between human and machine. For example, the term "*Human Computation*" was coined in 2005 by Michelle of Cornell University [12], which emphasizes that the combination and collaboration of human and machine intelligence can be used to solve complex problems. Furthermore, the concept of "*Machine Behavior*" is put forward in 2019 by the Nature magazine [13], which emphasizes the cooperation and coevolution theory of human-machine behavior across spaces. In the same year, researchers from the MIT AI-Lab [14] present a swarm robotic system based on statistical mechanics, which is capable of simulating collaborative behavior of biological organisms, such as object delivery or obstacle avoidance. Meanwhile, the Gartner

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[1] https://www.waze.com
[2] https://seeclickfix.com
[3] https://www.crowdos.cn

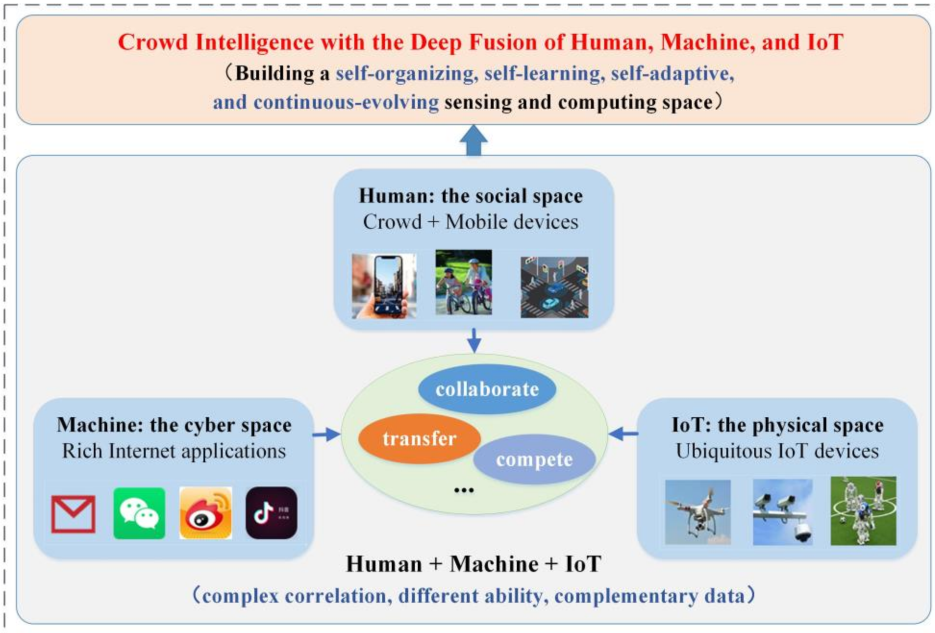

Fig. 1. The concept graph of CrowdHMT.

Company develops the concept of "Smart Space" [4], which is ranked as one of the Top 10 Strategic Technology Trends for 2020. Specifically, it points out that the rapid development and deep fusion of some advanced technologies, such as AI, IoT, edge computing, digital twins, and so on, will provide a highly-integrated smart-space for smart city, smart community, intelligent manufacturing, and other fields.

In summary, the collaborative fusion of human, machine and IoT has become an emerging trend, and will promote the development of a new generation of crowd sensing and computing. This paper extends traditional "people-centric" MCSC that merely focuses on collecting sensing data, and further presents the next-generation of MCSC, **CrowdHMT** (Crowd intelligence with the deep fusion of heterogeneous "Human-Machine-IoT" agents). CrowdHMT *investigates the basic principles and mechanisms of heterogeneous crowd intelligence collaboration, and further promote the organic connection, collaboration and enhancement of human, machine and IoT. It aims to build a smart sensing and computing space with promising capabilities such as self-organization, self-learning, self-adaptation, and continuous evolution*. Particularly, the key contributions of this paper can be summarized as follows:

- Investigating the next generation of MCSC, namely CrowdHMT, and characterizing the key features and concepts of CrowdHMT.
- Presenting the major challenges and key techniques of CrowdHMT, including the human-machine-IoT collaboration mechanism, self-organization and self-adaptation, crowd-agent-oriented distributed learning, and crowd transfer learning.
- Reviewing two major application scenarios of CrowdHMT, including urban computing and intelligent manufacturing.
- Discussing open issues and future directions of CrowdHMT, including community ecology, community learning and evolution, and human-machine intelligence.

The remainder of the paper is organized as follows. In Section II, we characterize the unique features and concept of CrowdHMT. Section III presents the research challenges and key techniques of CrowdHMT. In Section IV, we review two applications of CrowdHMT. The open issues and future trends are discussed in Section V. Finally, we conclude the paper in Section VI.

II. Characterizing CrowdHMT

Before introducing the definition of CrowdHMT, we first present the key elements in CrowdHMT, including human, machine, and IoT, as shown in Fig. 1.

- ***Human*** refers to a crowd of ordinary people and their associated smartphones or other mobile/wearable devices in the **social space**. Human is specialized in human intelligence (e.g., individual or crowd intelligence) in CrowdHMT, and they also participate in crowd sensing and computing using their mobile devices [2].
- ***Machine*** is in the form of rich Internet applications and cloud devices in the **cyber space**. With the prevalence of traditional Internet and mobile Internet, plenty of multi-model data and a variety of computing resources are aggregated in the cyber space [15].
- ***Internet of Things (IoT)*** includes IoT devices and edge devices that are ubiquitously distributed in the **physical**

[4] https://www.gartner.com/en/newsroom/press-releases/2019-10-21-gartner-identifies-the-top-10-strategic-technology-trends-for-2020

space. With the rapid development of IoT, a wide range of smart IoT devices plays an underlying role in sensing and understanding temporal and spatial variation in the dynamic physical space [16].

In general, the organic fusion of human, machine and IoT plays a fundamental role in sensing and computing in the same situation/application. In view of their complementary nature, they further need to interact and collaborate with each other to enhance the ability for executing complex sensing and computing tasks. Below we give a general definition of CrowdHMT.

Definition of CrowdHMT. Based on the deep fusion of Crowdsourced Human, Machine, and IoT intelligence, CrowdHMT aims to build a self-organizing, self-learning, self-adaptive, and continuous-evolving smart sensing and computing space, which is achieved by harnessing the complementary crowdsourced sensing/computing resources, as well as the interaction, collaboration, and competition of heterogeneous "agents", to promote the individual/crowd performance on sensing, cognition, and decision making.

In recent years, "people-centric" crowd sensing and computing has been studied extensively [2], including the research on data collection and data processing. Furthermore, traditional swarm intelligence [17], has successfully explored how to complete complex tasks (e.g., decision making, collective movement) by enhancing the collaboration and interaction among homogeneous agents. Different from the research fields mentioned above, CrowdHMT extends the definition of crowd intelligence, and expands the breadth and depth of research problems on sensing and computing with heterogeneous agents. Specifically, it focuses on studying the theory, model and approach in view of the deep fusion of human, machine, and IoT. Therefore, there are numerous novel challenges to be solved, as discussed in the next section.

III. Key Challenges And Techniques

CrowdHMT brings lots of opportunities for the development of crowd computing systems. However, it is also faced with numerous challenges. In this section, we focus on the key challenges and techniques to be addressed.

A. *The human-machine-IoT collaboration mechanism*

Most existing research on crowd intelligence focuses on the collaboration among homogeneous agents, but CrowdHMT pays more attention to the collaboration and interaction among heterogeneous agents to enable 'augmented' crowd intelligence, which needs to be further explored in theory and practice.

- ***Bio-inspired crowd intelligence emergence***. The widely-existing interaction, cooperation and competition behaviors within biological communities provide an essential basis for the building of a self-organizing, self-learning, self-adaptive, and continuous-evolving CrowdHMT system. It is necessary to explore and mine the emergence and fusion of human, machine and IoT intelligence, by means of gaining an insight into the implicit correlation and mapping mechanism between biological communities and heterogeneous CrowdHMT agents. There are several representative examples that can be leveraged from natural systems: *the formation and evolution of flocks of animals* [18], [19], [20] (e.g., ants, bees, birds, fishes), *collective animal motion* [21], self-organizing and self-adaptive patterns [22], *group decision making*[23], and so on.
- ***Efficient collaboration mechanism among CrowdHMT agents***. A CrowdHMT eco-system consists of various elements, including human, machine, IoT, environment, etc. To facilitate the collaboration among these heterogeneous agents, it is important to draw on the knowledge and principles about organic collaboration and organization in biological systems [21].
- ***Unified model representation for heterogeneous CrowdHMT agents***. CrowdHMT takes advantage of human, machine and IoT to enhance the system performance. Nevertheless, the usage of heterogeneous agents also introduces several issues, such as the heterogeneity of data representation, the diversity of individual skills, the fragmentation of information, etc. Hence, it is fundamental to build a unified representation model to characterize heterogeneous agents, from the aspects such as organization pattern, decision making, knowledge representation, and so on.

There have been quite a few studies that leverage bio-inspired mechanisms to build artificial crowd intelligence systems. Though the interactions among nearby individuals in the group can be simple and straightforward, they could complete complex tasks by means of distributed collaboration [21]. Swarm robotics [24] is a typical artificial crowd intelligence system that mimics the diverse collective behaviors of animal groups. For example, researchers at Harvard University present a multi-agent construction system by analogizing the collective behavior of mound-building termites, which could construct complex structures by automatically generating low-level rules for autonomous climbing robots [25]. Li *et al.* [14] from MIT propose a robotic system whose behavior could simulate the collective cell migration. Specifically, particle robotics in the proposed system could achieve some complex behaviors (e.g., robust locomotion, object transport and phototaxis) by exploiting the phenomena of biological cytology, such as statistical mechanics, information exchange, etc. This study provides a new idea and approach to develop large-scale swarm robotic systems. Furthermore, researchers from the University of California study the deep correlation between biological and artificial systems based on reinforcement learning [26]. On the one hand, the success of reinforcement learning algorithms derives from the simulation of learning behaviors in biology. On the other hand, the exploration and development of reinforcement learning contributes to the understanding of biological learning behavior. Recently, some new learning models have been proposed inspired by the fusion of biological and artificial systems, such as Meta-Reinforcement Learning [27], Feudal Reinforcement Learning [28], etc.

B. Self-organization and self-adaptation

Compared to traditional computing systems, CrowdHMT is faced with some new problems, such as the variability of the environment, the diversity of human-machine-IoT agents, and the dynamics of crowd-agent connection topology. Therefore, CrowdHMT should be able to organize each element adaptively to meet the dynamic environments and application scenarios, to improve the efficiency and quality of collaboration among heterogeneous crowd-agents. Specifically, the following key challenges need to be solved.

- ***Multi-dimensional context recognition***. To enable and facilitate the effective organization and collaboration of heterogeneous crowd-agents, it is necessary to first accurately recognize and predict the multi-dimensional contexts of CrowdHMT agents, such as energy state, computing power, communication bandwidth, network topology, trustworthiness, and so on.
- ***Crowd-agent self-organizing computing***. It becomes a necessity to form a dynamic collaboration group with multiple mobiles, wearable or edge devices coexisting in the surrounding area, to solve the problem of insufficient computing resource of a single agent (e.g., the so-called edge intelligence [29]). The self-organization of CrowdHMT agents (e.g., dynamically forming groups and collaboration) to meet diverse performance requirements (e.g., computing delay, accuracy) and runtime environments (e.g., network connection, energy consumption, etc.), however, becomes a crucial issue to be addressed.
- ***Cross-space collaborative sensing and computing***. According to specific sensing tasks (such as public safety event monitoring), we need to study how to quickly discover highly correlated groups in different spaces (e.g., crowd sensing participants, mobile Internet applications, urban IoT sensing devices) and investigate the collaborative strategies among them to enable efficient and effective sensing and computing.

There have been some prospective studies on the problem of context-adaptive organization and collaboration. In terms of collaborative computing among agents, Edge Intelligence [29] could connect resource-constrained edge and end devices to enhance data sensing and computing by some effective collaboration techniques, such as multi-device collaboration and end-edge collaboration, thus large-scale deep models can be deployed on end-devices by effective segmentation and distributed learning, such as the NeuroSurgeon model proposed by the University of Michigan [30]. In addition, the self-adaptive and self-organizing mechanism of biological systems provide an important basis for the study of artificial swarm intelligence systems. For example, Cully [31] proposes an intelligent trial-and-error algorithm inspired by animal adaptive mechanisms, which allows robots to find an adaptive solution in a short time under abnormal conditions. Researchers from Harvard University [32] are inspired by multicellular organisms and complex animal structures (e.g., flocks of birds and fishes), and design an effective distributed interaction mechanism based on Kilobots (robots with limited capabilities), which enables robust self-organization and collaboration behavior in the case of large-scale robots, including aggregation, formation, dynamic transformation, etc.

C. Crowd-agent-oriented distributed learning

An individual agent is often limited in its richness of data and experience, and thus the trained learning model is more or less weak to address different application scenarios and dynamic contexts. How to enable the collaborative and augmented learning of human-machine-IoT agents in a crowd-oriented distributed environment is a new challenge of CrowdHMT.

- ***Crowd distributed learning model***. It is necessary to explore a crowd distributed learning model based on the interactive learning mechanism of the biotic community [23], which integrates the characteristics such as collaboration, competition, and confrontation. In addition, a trusted crowd intelligence learning method should also be developed when the individual agent has limited data and high privacy requirements [33].
- ***Human-machine-IoT collaborative learning.*** It is all known that the learning and computing capabilities of humans and machines are complementary and different. Thus, it is necessary to study the learning models and paradigms such as human-in-the-loop machine learning [34] and human-machine hybrid intelligence [35]. The challenges include the design of effective collaboration modes, the determination of the right collaboration time, and the way to minimize human effort in collaborative learning.
- ***Edge-enhanced Crowd Intelligence.*** The processing of large-scale data from plenty of terminal devices by traditional cloud computing will consume too much network resources and increase response times, especially for a large number of heterogeneous agents in CrowdHMT. Therefore, we need to explore edge-enhanced crowd intelligence in CrowdHMT by leveraging edge computing to achieve real-time data processing, and build a distributed platform that integrates communication, computing, storage, and application taking into account of different characteristics of heterogeneous human-machine-IoT agents.
- ***Federated Crowd Intelligence.*** For collaborative machine learning without centralized training data in the distributed system, it is necessary to consider the privacy problem when sharing data, model and knowledge. To achieve crowd intelligence in the distributed environment taking privacy into consideration, some challenges should be tackled, such as developing communication-efficient methods that reduce the total number of communication rounds, tolerating low levels of device participation, etc.

Recently, there has been some research progress on the problem of distributed reinforcement learning, such as federated learning, swarm learning, and multi-agent deep reinforcement learning. Federated learning [36] , first proposed by Google, aims to build a machine learning model based on datasets distributed on multiple devices. Specifically, it implements efficient learning through multi-device collaboration to enhance the ability of crowd agents, under the premise of guaranteeing the privacy and security of data exchange. Swarm learning [37] is a fully-decentralized machine learning approach, which leverages blockchain-based peer-to-peer networking and coordination for maintaining data privacy. However, different from federated learning, it does not need a centralized coordinator in the learning process. The success of swarm intelligence has been proved on training classifiers for diseases such as COVID-19 using distributed data in different clinics. Multi-agent deep reinforcement learning (MADRL) [38] takes advantage of the collaboration and competition among agents to motivate new forms of intelligence. For example, in [39], DeepMind shows its latest progress of MADRL, where the agents are capable of mastering strategies, understanding tactics, and making team collaboration in a multi-player video game-StarCraft II.

D. Crowd Transfer Learning

Generally speaking, the superior performance of most existing deep learning models is conditioned on large-scale training data, and most of them cannot work well when there are few or no labeled data. Therefore, it is necessary to enable crowd transfer learning in CrowdHMT, which aims to transfer prior knowledge learned from the tasks/domains with abundant data to improve the performance in the data-scarce tasks/domains.

- ***Inter- and inner-agent knowledge transfer.*** In many real-world scenarios, agents may suffer from limited data or heterogeneous data distribution, such as the cold-start problem or the few-shot problem when facing new individuals, new tasks, and new scenarios. Therefore, it is necessary to explore the inter-agent and cross-task (inner-agent) knowledge transfer methods, which could transfer the knowledge of multiple experienced agents (or data-rich tasks) to inexperienced agents (or new tasks), and realize the continuous learning and evolution of agents.
- ***Multi-agent meta-learning.*** As is well known, a good machine learning model often requires training with a large number of samples. Humans, in contrast, learn new concepts and skills much faster and more efficiently. Therefore, how to design a learning model capable of well adapting or generalizing to new tasks and new environments is an important research problem for CrowdHMT, since the agents in a complex environment are often facing the problem of data sparsity. Specifically, the model should learn the prior knowledge and skills from other agents/tasks, and then quickly adapt to new agents/tasks with a few training examples.
- ***Federated transfer learning.*** The transferring and sharing of knowledge in different tasks or domains can raise significant privacy concerns, with information being sensitive and vulnerable to privacy attacks. Therefore, it is necessary to enable knowledge transfer in consideration of user's privacy and data security, and to achieve collective learning of multiple agents based on their own data to solve the problem data island.

Some recent works have leveraged transfer learning methods to solve the few-shot problem in many practical applications. Christianos *et al.* [40] propose a Shared Experience Actor-Critic (SEAC) algorithm, which applies experience sharing in an actor-critic framework by combining the gradients of different agents. Yang *et al.* [41] propose a Multiagent Option-based Policy Transfer (MAOPT) framework. Specifically, MAOPT learns what advice to provide and when to terminate it for each agent by modeling multiagent policy transfer as the option learning problem. Omidshafiei *et al.* [42] present a Learning to Coordinate and Teach Reinforcement (LeCTR) algorithm for intelligent agents to learn to teach in a multi-agent environment. Particularly, it addresses peer-to-peer teaching in cooperative multi-agent reinforcement learning. Liang *et al.* [43] present Federated Transfer Reinforcement Learning (FTRL) framework, which could enable real-time knowledge extraction and knowledge transfer among different RL agents in different environments. Peng *et al.* [44] present a federated domain adaptation method, which aims to align the representations learned from different nodes with the data distribution of the target node by adversarial learning. In addition, a dynamic attention mechanism is designed to enhance knowledge transfer by leveraging feature disentanglement.

IV. Two Application Scenarios of CrowdHMT

CrowdHMT has important and potential application prospects in many fields, including smart cities, intelligent manufacturing, energy systems, etc. In this section, we will illustrate some main applications based on some preliminary exploratory research we are currently conducting.

A. Urban Computing

Urban computing studies aim at solving the complex and practical problems widely existed in cities, through continuously sensing, gathering and mining multi-source and heterogeneous data. The rapid development of the AIoT has boosted CrowdHMT and become an important development direction for urban computing to complete complex urban tasks.

Cities are characterized by temporal and spatial features. In the urban task platform, a large number of released tasks have temporal and spatial correlation in many cases, which in turn reflects similar regularities in the data distribution. However, many new crowd tasks suffer from the problem of missing data due to fewer participants or difficulty in data collection, which will lead to the ineffective provision of crowd services. To solve the problem of missing and insufficient data in new tasks, we conduct research on cross-task knowledge transfer for crowd intelligence in view of temporal and spatial correlation [45]. Particularly, we aim to enable cross-task knowledge transfer by mining and utilizing the crowd knowledge of existing task entities, to improve the service quality of crowd tasks in urban computing.

We propose a *cross-city* and *cross-entity* knowledge transfer model, namely CityTransfer, to solve the cold-start problem in the new city and new task [46]. The framework of CityTransfer is given in Fig. 2. More specifically, it first collects multi-source sensing data for multiple cities from crowd sensing (i.e., Human), mobile Internet (i.e., Machine) and IoT devices (i.e.,

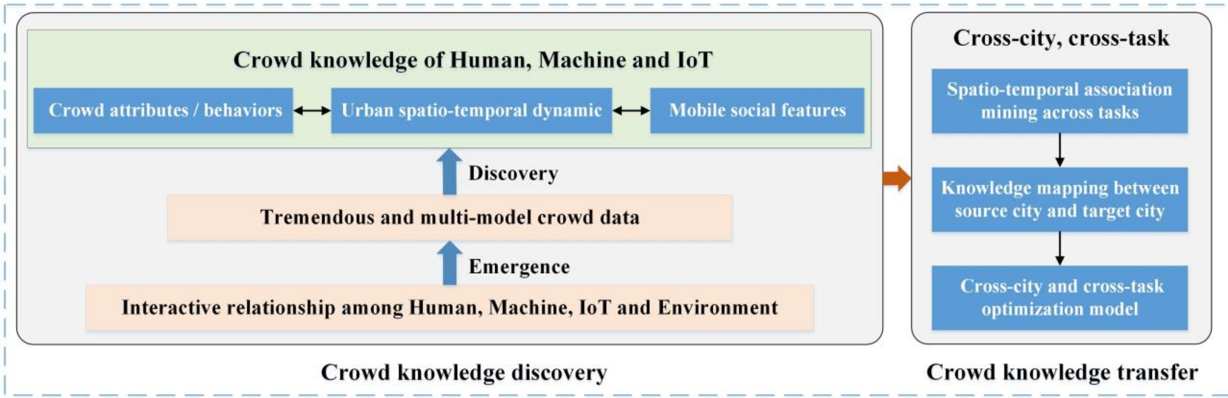

Fig. 2. Crowd knowledge transfer across cities and tasks [46].

IoT), including crowd flow data, POI distribution data, the trajectory data of taxis and bikes, etc. On the one hand, it extracts high-quality semantics by AutoEncoder to reconstruct original features, and then extends the SVD (Singular Value Decomposition)-based CF (Collaborative Filtering) model to make it possible to transfer the intra-city knowledge from similar tasks in the same city. On the other hand, we build correspondence between two cities by computing the Pearson correlation coefficient based on spatial-temporal features, and transferable features are further learned to enable inter-city knowledge transfer from other cities.

Our proposed model has shown superior performance on real-world urban datasets from four different cities. The results indicate that by leveraging two-fold knowledge transfer, our model is much better than other non-transfer methods. We also obtain some findings that can be used to steer better knowledge transfer among cities. For example, the transferring of both inter-city and intra-city knowledge performs better than single-fold knowledge transfer. In addition, for a target city, there could be several candidate source cities to be chosen for knowledge transfer, and carefully choosing source cities can to some extent improve the performance. Specifically, there are several common factors that could be useful for source city selection: First, the source city should have more instances of the target enterprise. Second, the source city should better be geographically close to the target city, which usually represents higher city similarity.

To solve the few-shot learning problem in urban computing and enhance the performance of knowledge transfer, we further explore *multi-city knowledge transfer*. We use the optimal store placement scenario as a practical application to illustrate our recent research on knowledge transfer.

Optimal store placement is one of the most fundamental services in urban computing for the development of brick-and-mortar chain enterprises (e.g., Starbucks, Walmart, etc.) [47], as it can provide insights for the future success of the chain enterprise when placing a new store at the given candidate location. Specifically, optimal store placement aims to identify the optimal location for a new brick-and-mortar store that can maximize its sale by analyzing and mining users' preferences from large-scale urban data (e.g., retail enterprise data, user data, POI data, etc.) from different sources (e.g., Human, Machine and IoT). In recent years, the expansion of chain enterprises in new cities brings some challenges because of two aspects: 1) data scarcity in new cities so that most existing models cannot work because the superior performance of these works is conditioned on large-scale training samples; 2) data distribution discrepancy among different cities so that knowledge learned from other cities cannot be utilized directly in new cities.

Previous studies have used transfer learning to solve the data scarcity problem by transferring available knowledge from those cities with abundant data (i.e., source city) to improve the performance in the data-scarce city (i.e., target/new city) [48]. However, the major downside of these transfer models is that they focus on transferring knowledge from only a single source city, which limits the performance of knowledge transfer because knowledge learned from multiple cities could be comprehensive and complementary. Furthermore, the knowledge transfer could hurt the performance due to the negative transfer if the data distribution between source city and target city is significantly different.

In view of the above reasons, we aim to make sufficient use of samples in data-rich cities and transfer knowledge from multiple source cities. We propose MetaStore [49], a task-adaptative model-agnostic meta-learning framework for optimal store placement in new cities with insufficient data, by transferring prior knowledge learned from multiple data-rich cities. The framework of MetaStore is shown in Fig. 3, consisting of two major components: the base network and the attention network. The main idea of MetaStore is to combine the base network and the attention network to quickly adapt to a new city in view of multi-modal data distribution. In order to acquire city-specific prior knowledge learned by the meta-learner, we first leverage the attention network to generate a set of city-specific parameters regarding the unique characteristic of the city, and then the output vector of the attention network is fed in the base network to modulate parameters of the base network through the attention-based modulation layer. Finally, the parameters of the modulated base network are further updated to adapt to the new city by the base-learner.

Our proposed model has shown superior performance on transfer project in cooperation with Alibaba. Compared with traditional supervised learning models (e.g., LR, GBDT) real-

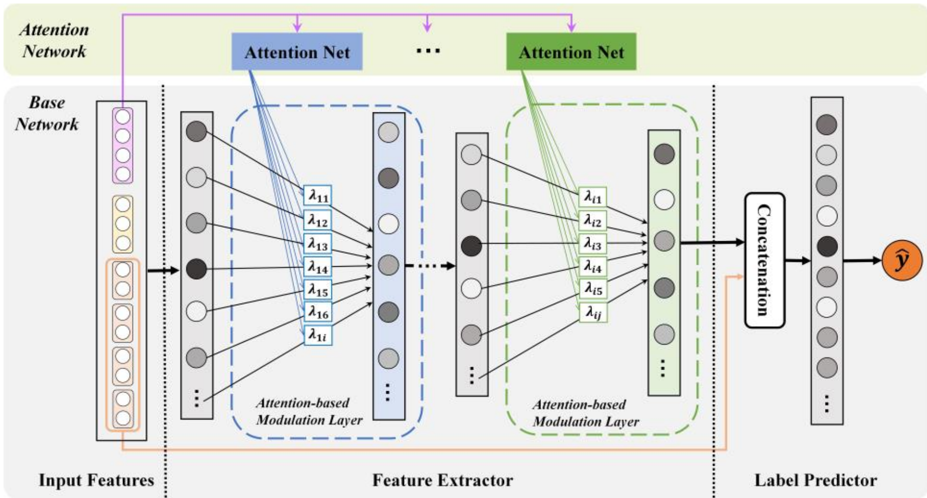

Fig. 3. The framework of MetaStore [49].

world urban services, and it is verified in the knowledge and deep learning models (e.g., DNN, CNN, etc.), MetaStore has a larger performance gain on commonly used metrics (e.g., the accuracy rate and error rate) in some spatio-temporal prediction tasks, such as site recommendation and flow prediction, and the empirical results demonstrate that our model has over 20% accuracy improvements compared with existing models in the business case.

B. *Intelligent Manufacturing*

The broad connection of multiple heterogeneous agents (e.g., human, machine, and IoT elements) is the key characteristic of the prospective intelligent manufacturing scenes, which not only provides the conditions but also derives the requests of crowd intelligence fusion and collaboration. As mentioned above, CrowdHMT is presented as a new paradigm that promotes efficient collaboration, self-motivated organization, and continuous learning over multiple heterogeneous agents of human, machine, and IoT. Therefore, CrowdHMT provides promising directions to optimize the full lifecycle of industrial product design, development, manufacturing, and service management.

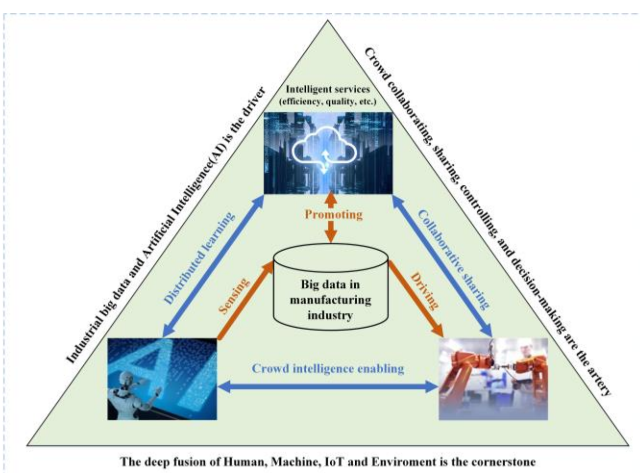

Fig. 4. Crowd smart-space model for manufacturing industry.

Recently, we are engaged in a project supported by the National Key R&D Program of China, which explores the building of high-level crowd intelligence space for intelligent manufacturing based on the deep fusion of human, machine and IoT (as shown in Fig. 4). It takes into account the underlying complex association among human, machine, IoT agents in manufacturing industry. Moreover, it explores the mechanism between the collaboration patterns of heterogeneous agents and the manufacturing quality and efficiency. We introduce some research practice we have carried out in the project as follows.

(1) Crowd knowledge transfer in manufacturing

In the manufacturing environment with open domain, the diverse target platforms, opportunistically connected entities, and continuously evolved manufacturing application scenarios usually challenge the performance of an existing intelligent model (e.g., deep learning model). To this end, we propose to comprehensively utilize meta-learning, multi-task learning, federated learning and other advanced learning techniques for enabling cross-agent or cross-scenario crowd knowledge transfer. The following is an example in the *surface defect detection* scenario.

Surface defect detection is very important in the manufacturing industry to guarantee the product quality. Automatic surface defect detection can timely find and eliminate the hazards of such defects on either aesthetics or functionality. Therefore, computer vision-based automatic detection methods are gradually replacing manual methods and benefiting a wide range of domains, such as machinery and aerospace manufacturing. Specifically, surface defect detection consists of two sub-tasks: *defect recognition* and *localization*. The prior is to recognize which types of defects exist, while the latter provides the exact location of the defects. Currently, the deep learning-based method (e.g., YoLov3 [50], Faster RCNN [51]) becomes a widely-used method to object detection tasks, which enables the selection of a candidate box for the target defect and then categorizes the target. However, such methods fail to work well in practice, especially in the cases of newly established product lines or new products. This is because the sample distribution of defect categories is always unbalanced and some categories even have extremely few samples in the collected training dataset. Subsequently, when these unbalanced samples are directly fed into the training phase, the features extracted by the regular training scheme may lose structural information of few-sample categories across several downsampling layers.

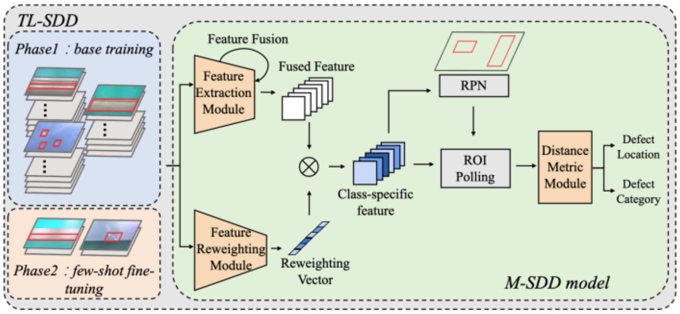

Fig. 5. The framework of TL-SDD [52].

To address the issues mentioned above, we propose a Transfer Learning-based method for Surface Defect Detection (TL-SDD) [52] which contains a two-phase transfer learning scheme and a novel Metric-based Surface Defect Detection (M-SDD) model (as shown in Fig. 5). In particular, the two-phase transfer learning scheme aims at transferring the positive knowledge from common defect categories to few-sample defect categories. In the first phase, we obtain a pre-trained defect detector with common defect samples and then fine-tune it with few-sample defect category data. In M-SDD model, feature fusion is adopted in the feature extraction module to prevent the loss of structural information. To leverage plenty of common defect categories and quickly adapt to the few-sample defect category, we design a distance metric module to categorize the defects instead of the fully connected network. Besides, we add a feature reweighting module trained in parallel with the feature extraction module. This module transforms examples to a reweighting vector that indicates the importance of features. Using Faster R-CNN as the base detector and choose ResNet-101 as the backbone, we compare our model with four baseline methods, i.e., Faster R-CNN [51] and three of its variants. The experimental results indicate that the detection performance of the proposed method outperforms other baselines by up to 11.9% in terms of accuracy.

(2) Context-adaptive collaborative device computing

In addition to the above surface defect detection application, a wider range of embedded facilities in the open domain manufacturing environment are integrated with intelligent functions to facilitate all aspects of manufacturing. For example, conveyor-based product sorting, mobile vehicle-based material delivery, camera-based anomaly detection. There is a growing trend to bring deep learning (e.g., DNN) powered intelligence into the local side of embedded devices, which benefits the reduction of response latency and the preservation of data privacy. However, it is non-trivial to deploy the computational-intensive DNN on mobile and embedded platforms with tightly limited resources (e.g., storage, battery).

Given those challenges, prior works have investigated different DNN specialization schemes to explore the desired trade-off between task performance (e.g., recognition accuracy, latency) and resource constraints (e.g., battery and storage budgets). The current studies either leverage hand-crafted DNN compression techniques, i.e., for optimizing DNN relative performance (e.g., parameter size), or on-demand DNN compression methods, i.e., for optimizing hardware-dependent metrics (e.g., latency), require offline retraining to ensure accuracy. Also, none of them has correlated their efforts with runtime adaptive compression to consider the dynamic nature of the deployment context of mobile applications. Actually, during the embedded device use, the device battery is dynamically consumed by the DNN execution and the memory access, and the storage unit is also dynamically occupied by other applications, resulting in various storage budgets for DNN parameters. Therefore, we face a common problem: *how to automatically and effectively re-compress DNN at runtime to meet dynamic demands in intelligent manufacturing scenes*? Technically, we face two challenges: (1) It is non-trivial to continually scale up/down the DNN compression configurations, including both architectures and weights, to meet the dynamic optimization objectives on DNN performance (e.g., accuracy, latency, energy consumption) on-the-fly. (2) It is intractable to provide an effective solution to the runtime DNN performance optimization problem. Moreover, it is difficult to systematically balance the compromising of multiple conflicting and interdependent performance metrics (e.g., latency, storage and energy efficiency) by merely tuning the DNN compression methods.

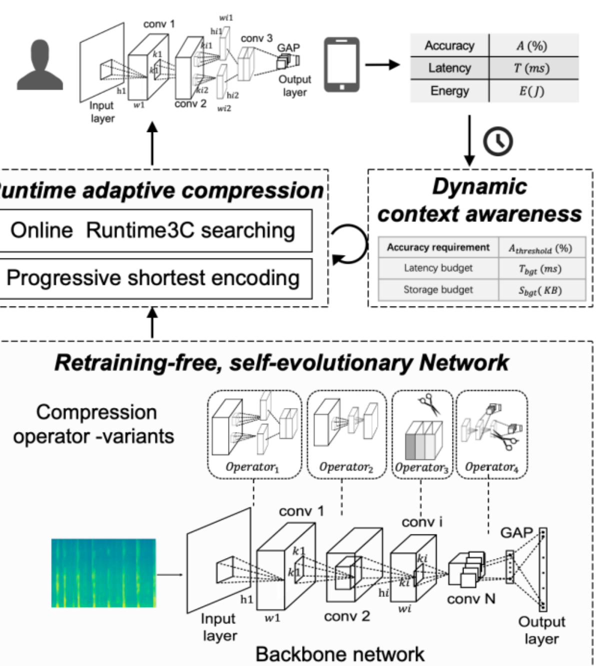

Fig. 6. The framework of AdaSpring [53].

Given those challenges and limitations, we present AdaSpring [53], a context-adaptive and runtime-evolutionary deep model compression framework, as shown in Fig. 6. It continually controls the compromising of multiple performance metrics by re-selecting the proper DNN compression techniques. We formulate the problem of runtime reselection of DNN compression techniques by a dynamic optimization problem. Furthermore, we model the dynamic context by a set of time-varying constraints, such as the accuracy loss threshold, latency and storage budgets, and the relative importance of objectives. To present a heuristic solution to this ticklish problem and eliminate the runtime retraining cost, we decouple offline training from online adaptation by putting weight tuning ahead in the training of a self-evolutionary network. The self-evolutionary network consists of a high-performance backbone network and multiple compression operator-variants. Furthermore, we present an efficient and effective search strategy. It involves an elite and flexible search space, the progressive shortest candidate encoding, and the Pareto decision-based runtime search algorithm to boost the locally online search efficiency and quality.

Using five mobile applications across three platforms and a real-world case study of DNN-powered sound recognition on NVIDIA Jetbot, extensive experiments validate the performance of AdaSpring on continually optimizing DNN configurations. It adaptively adjusts the compression configurations to tune energy cost by 1.6mJ~5.6mJ, latency by 1.3ms ~ 10.2ms, and storage by 201KB~1.9MB, with 2.1% accuracy loss. And the online evolution latency of compression configurations to meet dynamic contexts is 6.2ms.

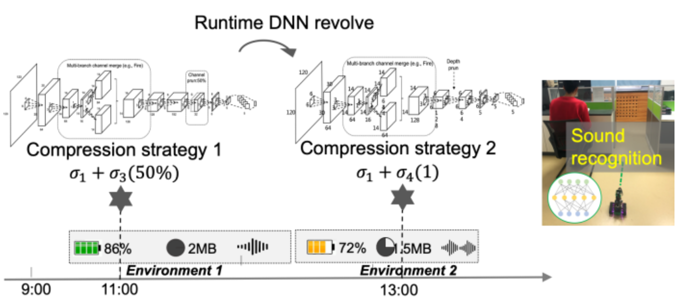

Fig. 7. A case study of AdaSpring on NVIDIA Jetbot.

We deploy AdaSpring on a commercial mobile robot platform (i.e., NVIDIA Jetbot) and conduct a one-day experiment (09:00 to 17:00) to continually optimize the DNN configurations for a sound assistant application (i.e., UbiEar [54]). Figure 7 illustrates the dynamic deployment context (i.e., energy, storage, event happening frequency) of the DNN for the continuous sound sensing application. In the experiments, the Jetbot's capacities of remaining battery and available L2-Cache dynamically change, which results in diverse performance and budget demands on DNN. At the same time, the sound emergency frequency will indirectly influence the battery's power. AdaSpring triggers the runtime DNN evolution block by a pre-defined frequency (e.g., every 2 hours) to shrink DNN configurations. It enables the adaptive selection of the best compression strategies to shrink DNN configurations.

Orthogonal to the above idea of compressing DNN for reducing the resource cost of DNN inference on a local device, *DNN partition* techniques [30] aim at uniting more computing resources by collaboratively deploying DNNs on multiple edge devices. Specifically, DNN model partition methods select the best partition point according to the overall performance requirements and the distributed resource budgets. Then different partition parts of the DNN model can be deployed on multiple devices for broadening the overall resource budgets. Despite the significant progress in existing efforts, such as Neurosurgeon[30], DDNN[55], and DADS[56]. All of them ignore the importance of the real-time adaption to the dynamic deployment context, and the majority of existing methods are costly to re-run to find the new partition solution when the deployment context changes. For instance, DADS takes about 18 seconds to find an optimal partition for the GoogleNet model deployed on Raspberry Pi 4B. However, it is necessary yet challenging to quickly adapt to the dynamically changing context, which mainly has the following challenges: *(i).* the deployment context of DNN models is constantly changing. How to realize the real-time perception of context change, and further map them into resource constraints understandable by the model is a challenge; *(ii).* the partition state of the model should be automatically adjusted according to the dynamic context to achieve efficient inference.

In view of these challenges, we propose Context-aware Adaptive Surgery (CAS) [57], a framework to automatically partition DNNs for accelerating the inference process, and quickly adapt to the dynamic context. We formulate the optimal DNN partition as a runtime search problem under resource constraints and performance requirements, and propose a Graph-based Adaptive DNN Surgery (GADS) algorithm to realize efficient search. The CAS framework has three blocks, i.e., context perception, partition state graph construction, and graph-based adaptive DNN surgery, as shown in Fig. 8. Specifically, the context perception block first actively perceives the dynamic context of edge devices, including platform resource constraints, task performance requirements, etc. The partition state graph construction block takes the model structure and context as the input to construct the partition state graph and profile all partition states. Finally, the GADS algorithm quickly searches for the most suitable partition point under the current context.

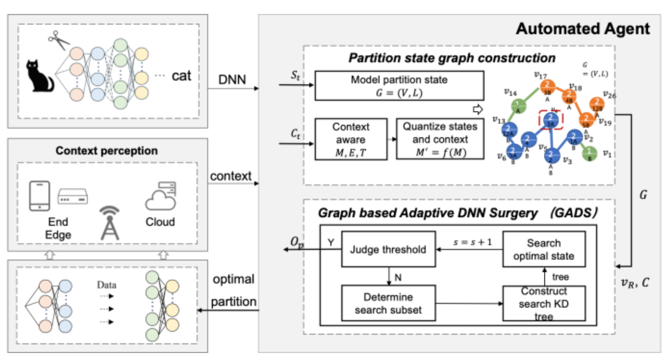

Fig. 8. The framework of CAS [57].

Notably, the efficiency of GADS is inspired by a novel rule, namely "*the neighbor effect*", which is discovered through empirically studies with comprehensive experiments. The neighbor effect implies that, if the state of available resources changes within a threshold, the re-searching of the optimal

DNN partition solutions can start from the optimal solution of the previous resource state to boost its search speed. That is, we can find a new optimal partition solution around the previous solution. It is because that the continuity of the resource state changes in the multi-dimensional performance space, and thus the dynamic search for the optimal partition solution can start from the optimal solution of the previous state. Inspired by the neighbor effect, searching along the direction of the suboptimal solutions of the previous resource state is helpful to find the most suitable solution for the dynamic context quickly. The performance of CAS is validated on multiple datasets and DNN models by comparing with state-of-the-art methods. Experimental results demonstrate that the proposed GADS method realizes adaptive tuning of the model partition points within 0.1ms on average, and the total inference latency decreases up to 56.65% without accuracy drop.

V. Open Issues and Future Directions

Despite the above research progress, there are still many open issues in CrowdHMT. For example, we observe that the majority of existing crowd intelligence studies only consider homogeneous agents (e.g., human community-based crowdsourcing [58], UAV cluster-based formation flight [59], and biological swarm-based dynamic models and optimization algorithms [60]). There are few studies about heterogeneous crowd collaboration, community co-evolution, and augmented human-machine intelligence. Therefore, more efforts and insights for these topics are crucial yet challenging, especially in the real-world scenarios, such as urban management, intelligent manufacturing, and military defense.

To this end, we turn to trace the source of swarm intelligence and seek more inspiration from a wider range of areas, such as community ecology [61] and evolutional learning [62]. This is a promising way to solve the above problems and obtain harmonious interation among heterogeneous CrowdHMT agents. We present the open issues and future directions of CrowdHMT as follows.

A. Community Ecology

As mentioned above, controlling the interactions, i.e., collaboration and competition, between multiple heterogeneous CrowdHMT agents is an emerging problem. We identify the heterogeneous CrowdHMT system as an artificial community ecology. The term of "*community ecology*" [61] was coined by the German zoologist Ernst Haeckel in 1866, which refers to the study of the interactions between diverse species and their environment in the real-world ecosystem. Different from the ecology of individuals that focuses on one type of organism (e.g., humen, cats, or palm trees), community ecology emphasizes the complex interplay of species and the biological (e.g., the relationship between organisms of the same or different species) as well as the non-biological environment (e.g., soil, water, air, humidity, temperature, etc.). Subsequently, the science of community ecology is well established and comprehensive to study the interaction theory between species at all temporal and spatial scales [63]. However, there is still a big gap in applying them into the CrowdHMT system.

Our key idea is to exploit the general interaction rules among the community ecology and effectively apply them to the interaction process between heterogeneous CrowdHMT agents. However, it is non-trivial to find the proper theory for harmonizing multiple human, machine and IoT agents in CrowdHMT system to obey the unified interaction rules. This is because different CrowdHMT agents always have highly heterogeneous characteristics and functionalities, and are only compatible with some specific communication protocols and decision policies. In particular, we face the following two tough challenges:

- *How does the entire CrowdHMT system obtain the stability state by controlling the competition and cooperation between multiple heterogenous agents?* It is non-trivial to formulate the cooperation and competition rules for each kind of CrowdHMT agent, in a computable manner, for achieving the overall objective.
- *How to effectively control the evolution of each CrowdHMT agent and the entire CrowdHMT system under the dynamically changing context?* The natural evolution of each agent or the environment will affect the whole system's characteristics. And, conversely, the system characteristics determine the evolution criterion of each agent to achieve the best fitness.

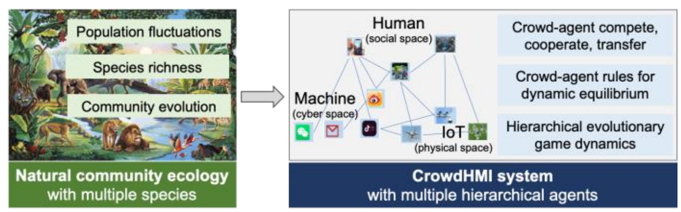

Fig. 9. From community ecology to a harmonious CrowdHMT system.

To solve the above challenges, we resort to the research on community ecology to seek more insights about managing the interaction and evolution of heterogenous CrowdHMT agents. As shown in Fig. 9, some studies have exploited the general rules of the community ecology in terms of population fluctuations [64], species richness [65], and community evolution [66]. We draw lessons from the following two directions.

(1) Theory foundation. In community ecology, species compete for natural resources and then reach an equilibrium state through population fluctuations [67], e.g., competition, cooperation, mutualism, and predation. Specifically, one species may have the predation relationships with multiple species simultaneously, and show diverse predation preferences in different scenes. To formulate these cooperation, competition, and predation relationships in the complex ecosystem, the subtle information cycles and energy flows among them hold deeply scientific and mathematical mechanisms. Specifically, Schoener *et al.* [68] present the *optimal foraging theory* (OFT) to formulate the energy gain of predators and the hunting cost. It explores the predation decisions in food choice and other behaviors (e.g., habitat migration) for maximizing the energy gain rate. Also, there are competition and coexistence relationships among populations. Mittelbach *et al.* [69]

conclude that the key factor to establishing a coexistence prediction model lies in understanding the differences and complexity of the niches of species in the community, as well as how to map them to species coexistence. Besides, the most famous theory for explaining the stability of species richness in fluctuating environments is Intermediate Disturbance Hypothesis (IDH) [70]. It presents that the highest species richness can be maintained when the community is under moderate disturbance. Generally speaking, the hierarchical niches (e.g., location, computing resources, and functionalities) and balance-guided response decisions of each agent are important factors for the CrowdHMT system to achieve "*dynamic equilibrium*". And the coexistence of multiple CrowdHMT agents, i.e., the result of niche division, is also affected by the external environment and dynamic interactions. That is, understanding the CrowdHMT agent niche and mapping it to the system are key issues.

(2) Community evolution. Previous efforts have formed a series of theories for community ecological evolution in both the micro and macro time-space granularities. In a nutshell, several factors, e.g., population characteristics, interaction rules, resource competition, and environmental changes affect the community evolution from different aspects. On the micro level, the community evolution of species traits exists within a few generations [71]. The species need to make rapid eco-evolutionary feedbacks to response ecological changes. Becks *et al.*[72] find that the rapid evolution of species can resist or slow down the negative impact of external environmental degradation on species, referred to as evolutionary rescue. Gomulkiewicz *et al.* [73] further clarify that the key factor for the evolutionary rescue is the species adaption speed. On the macro level, Darwin *et al.* [74] propose the evolutionary tree to show how the community structure and biodiversity are formed in the evolutionary history. Phylogenetic studies [75] further suggest that species with similar niches have similar requirements for resources, thereby are likely to evolve in the same direction. Based on the above evolutionary rules, some recent works have investigated the algorithms and systems. For example, Tembine *et al.* [76] extend the evolutionary dynamics to mobile wireless networks, exploring the interaction behavior between mobile devices and the influence of wireless transmission channels on dynamic evolution. Nowak *et al.* [77] leverage the evolutionary game dynamics, i.e., reciprocal strategy, in finite populations to allow a single cooperator to confront a population of defectors. Furthermore, Howard *et al.* [78] propose Multi-Level Evolution (MLE) to design robots across multiple levels of niches, tasks, and environmental conditions to evolve together.

In summary, inspired by the above thread of community ecology studies, CrowdHMT mainly focuses on the interaction and coevolution of heterogeneous human, machine, and IoT agents. First, the community ecology provides some general mechanisms and successful theories to the collaboration and competition between CrowdHMT agents. Second, the community ecology presents both micro and macro evolution perspectives for the inter-agents and intra-agents in CrowdHMT. Further efforts, however, are still needed to fill the gap between ecosystem and the CrowdHMT system in the social-cyber-physical space.

B. *Community Learning and Evolution*

From the systematic perspective, CrowdHMT aims to build a self-learning, self-adaptive, and continuous-evolving intelligent system with the deep fusion of heterogeneous human-machine-IoT agents. To achieve the aim, we present the following four promising research directions, i.e., *policy evolution*, *cognition evolution*, *embodied evolution*, and *hardware evolution* in CrowdHMT, as shown in Fig. 10.

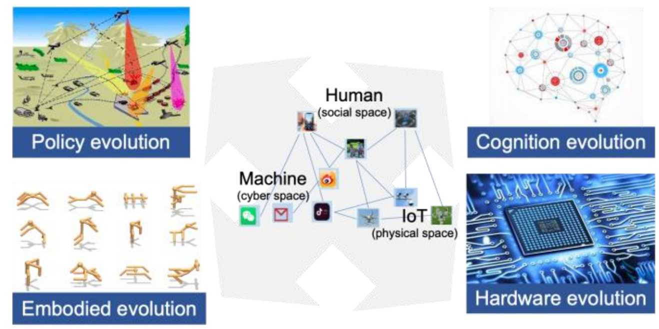

Fig. 10. Community learning and evolution from four aspects.

Policy evolution. The heterogeneous agent in the CrowdHMT system should continuously evolve their collaboration or competition policies to satisfy the dynamic contexts and application demands. The *evolutionary game* [79] is an effective way to study the evolution of cooperation and competition policy in multi-agent groups. Different from the static equilibrium in traditional game theory, the "evolutionary game dynamics" emphasize the dynamics of equilibrium via continuous trial and feedback. It is just about how individuals in the group evolve their policies via a continuous game process for better reward [80]. The "evolutionary stable strategy" [81] and "replicator dynamics" [82] are a pair of the most important basic concepts in the evolutionary game theory, and they exploit the stable policies adopted by most individuals and the dynamic convergence process, respectively. As a stepping stone to this goal, DeepMind [39] presents the multi-agent reinforcement learning based algorithm to reach the top league of human players in the StarCraft II real-time strategy game. The authors leverage the social division and cooperation scheme and put forward the concept of league agents. Hamidou *et al.* [76] extend the evolutionary game framework to study the wireless channels and pricing problem. We conclude that the evolutionary game dynamics can benefit the CrowdHMT to solve the complex cooperation and competition policy optimization problems.

Cognition evolution. DNNs are inspired by the deep hierarchical structures of human perception system, which have been widely used to stimulate the cognition intelligence in various domain applications, including computer vision, speech recognition, and natural language processing [62]. The DNN architectures, weights, and training schemes play key roles to the DNN's cognition performance. Our key insight is that the DNN's cognition ability in CrowdHMT should go through an evolution process as the same with that in the human lives to accomplish challenging tasks in uncertain environments. That is, we should evolve the DNN architectures, weights, and training strategies to adapt to the new scenes at a low cost. "*Neuro-evolution*" is a closely related term, which is introduced by Ronald *et al.* in 1994 [83] to describe the automated network weight configuration using evolutionary algorithms. Stanley *et al*. [84] present the neuroevolution of DNNs to generate DNN weights, architectures with a simple, gradient-free, population-based genetic algorithm. Such *et al*. [85] present the evolution method to train DNNs for reinforcement learning problems. Moreover, with the success of neural architecture search (NAS) studies, Elsken *et al.* [86] present the population-based evolutionary algorithm for automated, multi-objective NAS. However, despite the above efforts on solely evolving a single agent DNN, more insights on the evolution of multi-agent DNNs in CrowdHMT are needed.

Embodied evolution. Different from the above policy or cognition algorithms, the notion of embodied intelligence places emphasis on the role of an agent's body in generating behaviors and interacting with the surrounding environments. It can help us control the behavior of CrowdHMT agents. Historically, embodied intelligence originates from the bio-inspired computational intelligence methods [87]. It is closely linked to the morphological computation and sensory-motor coordination in evolutionary robotics models [78]. A critical issue under this topic is embodied intelligence evolution, i.e., the agent must evolve its behavior for adapting to the dynamic environment. To address this issue, Auerbach *et al*. [88] place both the robot's body plan and behavior control under evolutionary control to allow them successfully move over ice or flat ground. Moreover, to evolve diverse agent morphologies in the complex locomotion and manipulation environments, Gupta *et al*. [89] present the novel Deep Evolutionary Reinforcement Learning (DERL) framework. Specifically, they present the double-loop evolutionary learning mechanism. The inner loop leverages the Policy Gradient algorithm to allow the individual agent to perform the proprioception and external observation for learning the performance, while the outer loop adopts the tournament selection algorithm to randomly select four individuals at a time to maximize adaptability. This study yields scientific insights into how embodied evolution benefits the generation of intelligent agent morphologies via the passive physics of body-environment interactions. However, we still encounter some technical challenges. For example, *how to reduce the evolution cost for obtaining a desired morphologies fitness to the dynamic environment situation? How to deal with the decentralized, parallel features of embodied evolution of the CorwdHMI system*?

Tackling these problems is necessary yet challenging. Specifically, in the decentralized CrowdHMT system, there is no central control, each agent should trigger and select evolution strategies based on the locally collected information. As mentioned in Section V.A, the key factor for the evolutionary rescue is the species adaption speed, therefore the agent needs to learn and evolve locally online in some latency-sensitive and performance-sensitive cases. Some existing efforts, such as online learning of the decision policy of agent [90] and on-device adaptation of deep model [91], are related but still suffer from the thorny problem of how to balance the behavior dependence, training consumption, and evolution performance.

Hardware evolution. The hardware evolution aims to leverage the evolutionary algorithms to evolve the hardware and electronic system design for obtaining physical hardware adaptation, programmable logic self-organization, or self-repair [92]. One advantage is that hardware design process for robustness, scalability is automated and self-evolving, without human labors. The evolutionary hardware of CorwdHMI involves diverse agent platforms (e.g., FPGA, Raspberry Pi, and MCU), they can adjust the computation logic or resource schedule autonomously along with the environmental dynamic changes. Existing works have explored the *evolving digital circuits*, *evolving derivation trees*, *evolving analogue circuits*, and *function level aspects*. For example, the FPGA platform requires 2,000~30,000 architecture bits to configure its circuit, and its logic functions are used as primitive functions in the evolution process to optimize the high-level hardware functions, e.g., addition and subtraction [93]. Furthermore, to achieve the fast online evolution of hardware, the agent must adapt its hardware architecture in the real environment. For example, Thompson *et al.* [94] design a robot hardware controller that is evolved for wall-avoidance behavior. They implement the evolution of architecture bits in FPGA platforms to manage the functional blocks of the FPGA and their interconnections. However, we identify a raising problem in online hardware evolution, i.e., the difference between simulated environment and real-world one, which has a major impact on the performance of evolved hardware in the physical environment. Therefore, the online evolution of hardware is much required yet an open issue.

C. Human-Machine Intelligence

The deep fusion of human and machine intelligence from multiple CrowdHMT heterogeneous agents is another open issue. The research on the combination of human and machine intelligence has a long history. The concept of "*Man-Computer Symbiosis*" was presented by Licklider in 1960, and he described a vision for a complementary (symbiotic) relationship between humans and computers at a potential time of the future [95]. In recent years, with the development of computer software and hardware technology, the hybrid intelligence of human-machine collaboration is becoming a typical characteristic of the new generation of AI [96]. Although AI has more advantages than human in the fields of large-scale search, intensive computing, mass storage and iterative optimization, its cognitive ability is far behind the human brain.

CrowdHMT aims to further promote the deep fusion of human intelligence and machine intelligence. On the one hand, human has shown the wisdom in the daily life, such as the ability of perception, comprehension and social interaction. However, they are limited in memory and computation. On the other hand, the machine is capable of performing a large amount of computation and storage effectively, and IoT agents can provide a wide range of sensing, distributed computing, and collaborative movement. A lot of advanced machine learning and deep learning algorithms are proposed to automate knowledge discovery and event understanding. Therefore, the combination and collaboration of human and machine will boost the emergence and development of crowd intelligence or human-machine intelligence.

Generally speaking, there are two ways to achieve human-machine intelligence, as shown in Fig. 11. One is *explicit human-machine intelligence fusion*, e.g., Human-in-the-loop Hybrid-augmented Intelligence (HITL hybrid intelligence), which introduces the role of humans into intelligent systems, and forms a human-in-the-loop hybrid intelligence paradigm to improve the confidence of intelligent systems. The other is *implicit human-machine intelligence fusion*, e.g., Cognitive Computing based hybrid-augmented intelligence (CC hybrid intelligence), which imitates the human to improve the ability of perception, comprehension and decision-making, to make the best use of human knowledge. At present, the development of human-machine hybrid intelligence is still in its infancy, and both of these two forms are facing many challenges to achieve efficient hybrid intelligence for CrowdHMT. For example, how to break through the barriers of human-machine interaction and design appropriate intervention methods so that human knowledge can be naturally incorporated into machine learning training. How to combine the intuitive decision-making of human with the logical decision-making of machine to achieve efficient human-machine collaboration. How to design a task-driven or concept-driven machine learning method, which could complete the target task based on the knowledge learned from a large number of training samples and human knowledge.

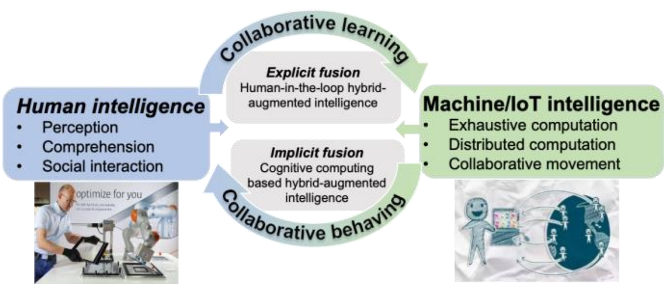

Fig. 11. Human-machine intelligence in CrowdHMT system.

There have recently been some studies that try to solve the above-mentioned challenges and combine the strengths of human and machine intelligence. Zhang *et al.* [97] propose a crowd-AI hybrid system for deep learning-based damage assessment (DDA) applications, named CrowdLearn. It leverages the crowdsourcing platform to troubleshoot, tune, and eventually improve the blackbox AI algorithms by welding crowd intelligence with machine intelligence, which could provide more reliable results taking into account domain experts. Cheng *et al.* [98] present hybrid crowd-machine learning classification models, and built an interactive machine learning platform, Flock. Specifically, classification models that start with a written description of a learning goal, use the crowd to suggest predictive features and label data, and then weigh these features using machine learning to produce models that are accurate and use human-understandable features. In addition to labeling samples in the training process of machine learning, human could provide the knowledge and guide the learning of agents at a more tactical level. Knox *et al.* [99] propose a framework of Training an Agent Manually via Evaluative Reinforcement (TAMER). Differing from previous approaches to interactive shaping, a tamer agent models the human's reinforcement and exploits its model by choosing actions expected to be most highly reinforced. Furthermore, Warnell *et al.* [100] propose Deep TAMER, an extension of the TAMER framework that leverages the representational power of deep neural networks in order to learn complex tasks in just a short amount of time with a human trainer. Wilson *et al.* [101] propose a Bayesian model to solve the problem of learning control policies via trajectory preference queries to an expert. Specifically, the agent presents an expert with short runs of a pair of policies originating from the same state and the expert indicates which trajectory is preferred. The agent's goal is to elicit a latent target policy from the expert with as few queries as possible. Zhao *et al.* [102] propose a convolutional neural network (CNN) model of visual attention for image classification inspired by the human vision system.

In general, CrowdHMT, based on human-machine intelligence, further emphasizes the deep fusion of the cognitive intelligence of human, the computing intelligence of machine, and the sensing intelligence of IoT across human-machine-IoT space. First, the fusion of human and machine intelligence can improve the cognitive ability of machine, so as to design effective algorithms and models. Second, the fusion of human and IoT intelligence can enhance the performance of AIoT to improve distributed sensing, computing and learning capabilities. Finally, the fusion of machine and physical intelligence can improve the efficiency of data processing and promote distributed learning to save communication resources.

VI. CONCLUSIONS

This paper introduces a new computing and learning paradigm, Crowd Intelligence with the Deep Fusion of Human, Machine, and IoT (CrowdHMT). First, we illustrate the definition of CrowdHMT. Second, we investigate the research challenges and key techniques, such as the human-machine-IoT collaboration mechanism, self-organization and self-adaptation, crowd-agent-oriented distributed learning, and crowd transfer learning. Third, we present two major applications of CrowdHMT, including urban computing and intelligent manufacturing. Finally, we discuss the open issues and future directions of CrowdHMT, including community ecology, community learning and evolution, and human-machine intelligence.

In the future, it is necessary to explore the relation between natural ecosystems and artificial swarm intelligence systems, and learn the mapping relationships to build a heterogeneous multi-agent group based on the collaboration and evolution of different species of the community. In addition, it is necessary to explore the distributed learning model in a multi-agent environment, and comprehensively utilize the interactions between species to enhance learning and evolving of heterogeneous multi-agent.

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REFERENCES

[1] M. Weiser, "The computer for the 21st century," *ACM SIGMOBILE mobile computing and communications review*, vol. 3, no. 3, pp. 3–11, 1999.

[2] B. Guo, Z. Wang, Z. Yu, Y. Wang, N. Y. Yen, R. Huang, and X. Zhou, "Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm," *ACM computing surveys (CSUR)*, vol. 48, no. 1, pp. 1–31, 2015.

[3] B. Guo, C. Chen, D. Zhang, Z. Yu, and A. Chin, "Mobile crowd sensing and computing: when participatory sensing meets participatory social media," *IEEE Communications Magazine*, vol. 54, no. 2, pp. 131–137, 2016.

[4] Y. Liu, B. Guo, Y. Wang, W. Wu, Z. Yu, and D. Zhang, "Taskme: Multi-task allocation in mobile crowd sensing," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2016, pp. 403–414.

[5] J. Wang, F. Wang, Y. Wang, D. Zhang, L. Wang, and Z. Qiu, "Socialnetwork-assisted worker recruitment in mobile crowd sensing," *IEEE Transactions on Mobile Computing*, vol. 18, no. 7, pp. 1661–1673, 2018.

[6] B. Guo, H. Chen, Q. Han, Z. Yu, D. Zhang, and Y. Wang, "Workercontributed data utility measurement for visual crowdsensing systems," *IEEE Transactions on Mobile Computing*, vol. 16, no. 8, pp. 2379–2391, 2016.

[7] B. Guo, H. Chen, Z. Yu, X. Xie, S. Huangfu, and D. Zhang, "Fliermeet: a mobile crowdsensing system for cross-space public information reposting, tagging, and sharing," *IEEE Transactions on Mobile Computing*, vol. 14, no. 10, pp. 2020–2033, 2014.

[8] T. Zhou, Z. Cai, B. Xiao, L. Wang, M. Xu, and Y. Chen, "Location privacy-preserving data recovery for mobile crowdsensing," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 2, no. 3, pp. 1–23, 2018.

[9] B. Guo, H. Chen, Z. Yu, W. Nan, X. Xie, D. Zhang, and X. Zhou, "Taskme: Toward a dynamic and quality-enhanced incentive mechanism for mobile crowd sensing," *International Journal of Human-Computer Studies*, vol. 102, pp. 14–26, 2017.

[10] J. Zhang and D. Tao, "Empowering things with intelligence: a survey of the progress, challenges, and opportunities in artificial intelligence of things," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 7789–7817, 2020.

[11] W. Li, W.-j. Wu, H.-m. Wang, X.-q. Cheng, H.-j. Chen, Z.-h. Zhou, and R. Ding, "Crowd intelligence in ai 2.0 era," *Frontiers of Information Technology & Electronic Engineering*, vol. 18, no. 1, pp. 15–43, 2017.

[12] P. Michelucci and J. L. Dickinson, "The power of crowds," *Science*, vol. 351, no. 6268, pp. 32–33, 2016.

[13] I. Rahwan, M. Cebrian, N. Obradovich, J. Bongard, J.-F. Bonnefon, C. Breazeal, J. W. Crandall, N. A. Christakis, I. D. Couzin, M. O. Jackson et al., "Machine behaviour," *Nature*, vol. 568, no. 7753, pp. 477–486, 2019.

[14] S. Li, R. Batra, D. Brown, H.-D. Chang, N. Ranganathan, C. Hoberman, D. Rus, and H. Lipson, "Particle robotics based on statistical mechanics of loosely coupled components," *Nature*, vol. 567, no. 7748, pp. 361–365, 2019.

[15] R. Rajkumar, I. Lee, L. Sha, and J. Stankovic, "Cyber-physical systems: the next computing revolution," in *Design automation conference*. IEEE, 2010, pp. 731–736.

[16] J. Pan and J. McElhannon, "Future edge cloud and edge computing for internet of things applications," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 439–449, 2017.

[17] J. Kennedy, "Swarm intelligence," in Handbook of nature-inspired and innovative computing. *Springer*, 2006, pp. 187–219.

[18] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," in *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, 1987, pp. 25–34.

[19] S. Kondo and T. Miura, "Reaction-diffusion model as a framework for understanding biological pattern formation," *science*, vol. 329, no. 5999, pp. 1616–1620, 2010.

[20] M. Nagy, Z. Akos, D. Biro, and T. Vicsek, "Hierarchical group dynamicsin pigeon flocks," *Nature*, vol. 464, no. 7290, pp. 890–893, 2010.

[21] D. J. Sumpter, Collective animal behavior. *Princeton University Press*, 2010.

[22] M. Dorigo, V. Trianni, E. S¸ ahin, R. Groß, T. H. Labella, G. Baldassarre, S. Nolfi, J.-L. Deneubourg, F. Mondada, D. Floreano et al., "Evolving self-organizing behaviors for a swarm-bot," *Autonomous Robots*, vol. 17, no. 2, pp. 223–245, 2004.

[23] L. Conradt and T. J. Roper, "Group decision-making in animals," *Nature*, vol. 421, no. 6919, pp. 155–158, 2003.

[24] M. Brambilla, E. Ferrante, M. Birattari, and M. Dorigo, "Swarm robotics: a review from the swarm engineering perspective," *Swarm Intelligence*, vol. 7, no. 1, pp. 1–41, 2013.

[25] J. Werfel, K. Petersen, and R. Nagpal, "Designing collective behavior in a termite-inspired robot construction team," *Science*, vol. 343, no. 6172, pp. 754–758, 2014.

[26] E. O. Neftci and B. B. Averbeck, "Reinforcement learning in artificial and biological systems," *Nature Machine Intelligence*, vol. 1, no. 3, pp. 133–143, 2019.

[27] J. X. Wang, Z. Kurth-Nelson, D. Kumaran, D. Tirumala, H. Soyer, J. Z. Leibo, D. Hassabis, and M. Botvinick, "Prefrontal cortex as a metareinforcement learning system," *Nature neuroscience*, vol. 21, no. 6, pp. 860–868, 2018.

[28] A. S. Vezhnevets, S. Osindero, T. Schaul, N. Heess, M. Jaderberg, D. Silver, and K. Kavukcuoglu, "Feudal networks for hierarchical reinforcement learning," in International Conference on Machine Learning. *PMLR*, 2017, pp. 3540–3549.

[29] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1738–1762, 2019.

[30] Y. Kang, J. Hauswald, C. Gao, A. Rovinski, T. Mudge, J. Mars, and L. Tang, "Neurosurgeon: Collaborative intelligence between the cloud and mobile edge," *ACM SIGARCH Computer Architecture News*, vol. 45, no. 1, pp. 615–629, 2017.

[31] A. Cully, J. Clune, D. Tarapore, and J.-B. Mouret, "Robots that can adapt like animals," *Nature*, vol. 521, no. 7553, pp. 503–507, 2015.

[32] M. Rubenstein, A. Cornejo, and R. Nagpal, "Programmable selfassembly in a thousand-robot swarm," *Science*, vol. 345, no. 6198, pp. 795–799, 2014.

[33] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings et al., "Advances and open problems in federated learning," *arXiv preprint* arXiv:1912.04977, 2019.

[34] F. M. Zanzotto, "Human-in-the-loop artificial intelligence," *Journal of Artificial Intelligence Research*, vol. 64, pp. 243–252, 2019.

[35] N.-n. Zheng, Z.-y. Liu, P.-j. Ren, Y.-q. Ma, S.-t. Chen, S.-y. Yu, J.-r. Xue, B.-d. Chen, and F.-y. Wang, "Hybrid-augmented intelligence: collaboration and cognition," *Frontiers of Information Technology & Electronic Engineering*, vol. 18, no. 2, pp. 153–179, 2017.

[36] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 10, no. 2, pp. 1–19, 2019.

[37] S. Warnat-Herresthal, H. Schultze, K. L. Shastry, S. Manamohan, S. Mukherjee, V. Garg, R. Sarveswara, K. Handler, P. Pickkers, N. A. ¨ Aziz et al., "Swarm learning for decentralized and confidential clinical machine learning," *Nature*, vol. 594, no. 7862, pp. 265–270, 2021.

[38] T. Chu, J. Wang, L. Codecà, and Z. Li, "Multi-agent deep reinforcement learning for large-scale traffic signal control," I*EEE Transactions on Intelligent Transportation Systems*, 21(3), pp.1086-1095, 2019.

[39] O. Vinyals, I. Babuschkin, W. M. Czarnecki, M. Mathieu, A. Dudzik, J. Chung, D. H. Choi, R. Powell, T. Ewalds, P. Georgiev et al., "Grandmaster level in starcraft ii using multi-agent reinforcement learning," *Nature*, vol. 575, no. 7782, pp. 350–354, 2019.

[40] F. Christianos, L. Schafer, and S. V. Albrecht, "Shared experience ¨ actor-critic for multi-agent reinforcement learning," *arXiv preprint* arXiv:2006.07169, 2020.

[41] T. Yang, W. Wang, H. Tang, J. Hao, Z. Meng, H. Mao, D. Li, W. Liu, C. Zhang, Y. Hu et al., "Transfer among agents: An efficient multiagent transfer learning framework," *arXiv preprint* arXiv:2002.08030, 2020.

[42] S. Omidshafiei, D.-K. Kim, M. Liu, G. Tesauro, M. Riemer, C. Amato, M. Campbell, and J. P. How, "Learning to teach in cooperative multiagent

reinforcement learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, no. 01, 2019, pp. 6128–6136.

[43] X. Liang, Y. Liu, T. Chen, M. Liu, and Q. Yang, "Federated transfer reinforcement learning for autonomous driving," *arXiv preprint* arXiv:1910.06001, 2019.

[44] X. Peng, Z. Huang, Y. Zhu, and K. Saenko, "Federated adversarial domain adaptation," *arXiv preprint* arXiv:1911.02054, 2019.

[45] L. Wang, B. Guo, and Q. Yang, "Smart city development with urban transfer learning," *Computer*, vol. 51, no. 12, pp. 32–41, 2018.

[46] B. Guo, J. Li, V. W. Zheng, Z. Wang, and Z. Yu, "Citytransfer: Transferring inter-and intra-city knowledge for chain store site recommendation based on multi-source urban data," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 1, no. 4, pp. 1–23, 2018.

[47] D. Karamshuk, A. Noulas, S. Scellato, V. Nicosia, and C. Mascolo, "Geo-spotting: mining online location-based services for optimal retail store placement," in *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2013, pp. 793–801.

[48] L. Wang, X. Geng, X. Ma, F. Liu, and Q. Yang, "Cross-city transfer learning for deep spatio-temporal prediction," *arXiv preprint* arXiv:1802.00386, 2018.

[49] Y. Liu, B. Guo, D. Zhang, D. Zeghlache, J. Chen, S. Zhang, D. Zhou, X. Shi, and Z. Yu, "Metastore: A task-adaptative meta-learning model for optimal store placement with multi-city knowledge transfer," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 12, no. 3, pp. 1–23, 2021.

[50] J. Redmon and A. Farhadi, "Yolov3: An incremental improvement," *arXiv preprint* arXiv:1804.02767, 2018.

[51] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," *Advances in neural information processing systems*, vol. 28, pp. 91–99, 2015.

[52] J. Cheng, B. Guo, J. Liu, S. Liu, G. Wu, Y. Sun, and Z. Yu. "TL-SDD: A Transfer Learning-Based Method for Surface Defect Detection with Few Samples", *The 7th International Conference on Big Data Computing and Communications (BigCom'21)*, Deqing, China, 2021.

[53] S. Liu, B. Guo, K. Ma, Z. Yu, and J. Du, "Adaspring: Contextadaptive and runtime-evolutionary deep model compression for mobile applications," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 5, no. 1, pp. 1–22, 2021.

[54] S., Liu, Z. Zimu, D. Junzhao, S. Longfei, J. Han, and X. Wang. "Ubiear: Bringing location-independent sound awareness to the hard-of-hearing people with smartphones." *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, no. 2, pp. 1-21, 2017.

[55] S. Teerapittayanon, B. McDanel, and H.-T. Kung, "Distributed deep neural networks over the cloud, the edge and end devices," in *2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 2017, pp. 328–339.

[56] C. Hu, W. Bao, D. Wang, and F. Liu, "Dynamic adaptive dnn surgery for inference acceleration on the edge," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*. IEEE, 2019, pp. 1423–1431.

[57] H., B. Guo, J. Liu, S. Liu, Y. Wu, and Z. Yu. "Context-aware Adaptive Surgery: A fast and effective framework for adaptative model partition", *The 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing (ACM UbiComp'21)*, 2021.

[58] B. Guo, Z. Yu, X. Zhou, and D. Zhang, "From participatory sensing to mobile crowd sensing," in *2014 IEEE International Conference on Pervasive Computing and Communication Workshops (PERCOM WORKSHOPS)*. IEEE, 2014, pp. 593–598.

[59] C. Hao, W. Xiangke, S. Lincheng, and C. Yirui, "Formation flight of fixed-wing uav swarms: A group-based hierarchical approach," *Chinese Journal of Aeronautics*, vol. 34, no. 2, pp. 504–515, 2021.

[60] S. Binitha, S. S. Sathya et al., "A survey of bio inspired optimization algorithms," *International journal of soft computing and engineering*, vol. 2, no. 2, pp. 137–151, 2012.

[61] P. J. Morin, Community ecology. John Wiley & Sons, 2009.

[62] E. Galvan and P. Mooney, "Neuroevolution in deep neural networks: Current trends and future challenges," *IEEE Transactions on Artificial Intelligence*, 2021.

[63] S. Sahney and M. J. Benton, "Recovery from the most profound mass extinction of all time," *Proceedings of the Royal Society B: Biological Sciences*, vol. 275, no. 1636, pp. 759–765, 2008.

[64] D. M. Green, "The ecology of extinction: population fluctuation and decline in amphibians," *Biological conservation*, vol. 111, no. 3, pp. 331–343, 2003.

[65] J. M. Scott, B. Csuti, J. D. Jacobi, and J. E. Estes, "Species richness," *BioScience*, vol. 37, no. 11, pp. 782–788, 1987.

[66] L. Tang, H. Liu, J. Zhang, and Z. Nazeri, "Community evolution in dynamic multi-mode networks," in *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2008, pp. 677–685.

[67] E. Ranta, V. Kaitala, and P. Lundberg, "The spatial dimension in population fluctuations," *Science*, vol. 278, no. 5343, pp. 1621–1623, 1997.

[68] T. W. Schoener, "Theory of feeding strategies," *Annual review of ecology and systematics*, vol. 2, no. 1, pp. 369–404, 1971.

[69] G. G. Mittelbach and D. W. Schemske, "Ecological and evolutionary perspectives on community assembly," *Trends in ecology & evolution*, vol. 30, no. 5, pp. 241–247, 2015.

[70] J. A. Catford, C. C. Daehler, H. T. Murphy, A. W. Sheppard, B. D. Hardesty, D. A. Westcott, M. Rejmanek, P. J. Bellingham, J. Pergl, C. C. Horvitz et al., "The intermediate disturbance hypothesis and plant invasions: Implications for species richness and management," *Perspectives in Plant Ecology, Evolution and Systematics*, vol. 14, no. 3, pp. 231–241, 2012.

[71] D. M. Post and E. P. Palkovacs, "Eco-evolutionary feedbacks in community and ecosystem ecology: interactions between the ecological theatre and the evolutionary play," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 364, no. 1523, pp. 1629–1640, 2009.

[72] L. Becks, S. P. Ellner, L. E. Jones, and N. G. Hairston Jr, "Reduction of adaptive genetic diversity radically alters eco-evolutionary community dynamics," *Ecology letters*, vol. 13, no. 8, pp. 989–997, 2010.

[73] R. Gomulkiewicz and R. G. Shaw, "Evolutionary rescue beyond the models," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 368, no. 1610, p. 20120093, 2013.

[74] C. Darwin, On the origin of species: A facsimile of the first edition. *Harvard University Press*, 1964.

[75] J. B. Losos, "Seeing the forest for the trees: The limitations of phylogenies in comparative biology: (american society of naturalists address)," *The American Naturalist*, vol. 177, no. 6, pp. 709–727, 2011.

[76] H.Tembine, E. Altman, R. El-Azouzi, and Y. Hayel. "Evolutionary games in wireless networks," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 40(3), pp.634-646, 2009.

[77] M. A. Nowak, A. Sasaki, C. Taylor, and D. Fudenberg, "Emergence of cooperation and evolutionary stability in finite populations," *Nature*, vol. 428, no. 6983, pp. 646–650, 2004.

[78] D. Howard, A. E. Eiben, D. F. Kennedy, J.-B. Mouret, P. Valencia, and D. Winkler, "Evolving embodied intelligence from materials to machines," *Nature Machine Intelligence*, vol. 1, no. 1, pp. 12–19, 2019.

[79] J. W Weibull, "Evolutionary game theory," *MIT press*, 1997.

[80] J. M. Smith and G. R. Price, "The logic of animal conflict," *Nature*, vol. 246, no. 5427, pp. 15–18, 1973.

[81] W. Hines, "Evolutionary stable strategies: a review of basic theory," *Theoretical Population Biology*, vol. 31, no. 2, pp. 195–272, 1987.

[82] P. Schuster and K. Sigmund, "Replicator dynamics," *Journal of theoretical biology*, vol. 100, no. 3, pp. 533–538, 1983.

[83] E. Ronald and M. Schoenauer, "Genetic lander: An experiment in accurate neuro-genetic control," in *International Conference on Parallel Problem Solving from Nature*. Springer, 1994, pp. 452–461.

[84] K.O. Stanley, J .Clune, J. Lehman, and R. Miikkulainen. "Designing neural networks through neuroevolution," *Nature Machine Intelligence*, 1(1), pp.24-35, 2019.

[85] F. P. Such, V. Madhavan, E. Conti, J. Lehman, K. O. Stanley, and J. Clune, "Deep neuroevolution: Genetic algorithms are a competitive alternative for training deep neural networks for reinforcement learning," *arXiv preprint* arXiv:1712.06567, 2017.

[86] T. Elsken, J. H. Metzen, and F. Hutter, "Efficient multi-objective neural architecture search via lamarckian evolution," *arXiv preprint* arXiv:1804.09081, 2018.

[87] R. D. Beer, "A dynamical systems perspective on agent-environment interaction," *Artificial intelligence*, vol. 72, no. 1-2, pp. 173–215, 1995.

[88] J. E. Auerbach and J. C. Bongard, "On the relationship between environmental and mechanical complexity in evolved robots," in *ALIFE 2012: The Thirteenth International Conference on the Synthesis and Simulation of Living Systems*. MIT Press, 2012, pp. 309–316.

[89] A. Gupta, S. Savarese, S. Ganguli, and L. Fei-Fei, "Embodied Intelligence via Learning and Evolution," *arXiv preprint* arXiv:2102.02202, 2021

[90] N. Bredeche, E. Haasdijk, and A. Prieto, "Embodied evolution in collective robotics: A review," *Frontiers in Robotics and AI*, vol. 5, p. 12, 2018.

[91] D. Sahoo, Q. Pham, J. Lu, and S. C. Hoi, "Online deep learning: Learning deep neural networks on the fly," *arXiv preprint* arXiv:1711.03705, 2017.

[92] A. Thompson, "Hardware Evolution: Automatic design of electronic circuits in reconfigurable hardware by artificial evolution," *Springer Science & Business Media*, 2012.

[93] W. Liu, M. Murakawa, and T. Higuchi, "Atm cell scheduling by function level evolvable hardware," in *International Conference on Evolvable Systems*. Springer, 1996, pp. 180–192.

[94] A. Thompson, "Evolving electronic robot controllers that exploit hardware resources," in *European Conference on Artificial Life. Springer*, 1995, pp. 640–656.

[95] J. C. Licklider, "Man-computer symbiosis," *IRE transactions on human factors in electronics*, no. 1, pp. 4–11, 1960.

[96] E. Kamar, S. Hacker, and E. Horvitz, "Combining human and machine intelligence in large-scale crowdsourcing." in *AAMAS*, vol. 12, 2012, pp. 467–474.

[97] D. Zhang, Y. Zhang, Q. Li, T. Plummer, and D. Wang, "Crowdlearn: A crowd-ai hybrid system for deep learning-based damage assessment applications," in *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 2019, pp. 1221–1232.

[98] J. Cheng and M. S. Bernstein, "Flock: Hybrid crowd-machine learning classifiers," in *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*, 2015, pp. 600–611.

[99] W. B. Knox and P. Stone, "Tamer: Training an agent manually via evaluative reinforcement," in *2008 7th IEEE International Conference on Development and Learning*. IEEE, 2008, pp. 292–297.

[100] G. Warnell, N. Waytowich, V. Lawhern, and P. Stone, "Deep tamer: Interactive agent shaping in high-dimensional state spaces," in *ThirtySecond AAAI Conference on Artificial Intelligence*, 2018.

[101] A. Wilson, A. Fern, and P. Tadepalli, "A bayesian approach for policy learning from trajectory preference queries," *Advances in neural information processing systems*, vol. 25, pp. 1133–1141, 2012.

[102] D. Zhao, Y. Chen, and L. Lv, "Deep reinforcement learning with visual attention for vehicle classification," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 9, no. 4, pp. 356–367, 2016.