Transfer Learning Promotes 6G Wireless Communications: Recent Advances and Future Challenges

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***Abstract*—In the coming 6G communications, network densification, high throughput, positioning accuracy, energy efficiency, and many other key performance indicator requirements are becoming increasingly strict. In the future, how to improve work efficiency while saving costs is one of the foremost research directions in wireless communications. Being able to learn from experience is an important way to approach this vision. Transfer learning (TL) encourages new tasks/domains to learn from experienced tasks/domains for helping new tasks become faster and more efficient. TL can help save energy and improve efficiency with the correlation and similarity information between different tasks in many fields of wireless communications. Therefore, applying TL to future 6G communications is a very valuable topic. TL has achieved some good results in wireless communications. In order to improve the development of TL applied in 6G communications, this article performs a comprehensive review of the TL algorithms used in different wireless communication fields, such as base stations/access points switching, indoor wireless localization and intrusion detection in wireless networks, etc. Moreover, the future research directions of mutual relationship between TL and 6G communications are discussed in detail. Challenges and future issues about integrate TL into 6G are proposed at the end. This article is intended to help readers understand the past, present, and future between TL and wireless communications.**

***Index Terms*—Sixth generation (6G), transfer learning (TL), wireless communications.**

I. Introduction

WIRELESS communication technologies have been continuously developed to meet more advanced needs, from the first generation of wireless communications supporting basic coverage to the large and complex fifth generation (5G) wireless communications that will be commercially available on a large scale [1]. With the outbreak of 5G, it will stimulate the demand for the sixth generation (6G) wireless communications in the future [2], [3]. 6G wireless communications are a new communication mode that are expected to be deployed in ten years (2027–2030) and are expected to exceed 100 times the speed of 5G [4].

To overcome the limitations of 5G for facing new challenges, it will be necessary to develop 6G wireless systems with new attractive features. The key driving force of 6G will be the integration of all the past features, such as network densification, high throughput, positioning accuracy, energy efficiency, and massive connectivity. The 6G system will also continue the trends of the previous generations [5]. The research community is currently discussing the vision of implementing 6G communications under different technology needs and service requirements. The development of 6G requires many key enabling technologies, which have been comprehensively discussed and prospected in much research, such as artificial intelligence (AI) [6]– [8], multi-input multioutput (MIMO) [9], [10], quantum communication (QC) [3], random access [11], machine-type communications [12], terahertz communications [13], massive multiple access [14], [15], use of bands beyond 100 GHz [16], automated vehicles [17], and unmanned aerial vehicles (UAVs) [18]– [21]. The ability to handle large amounts of data and extremely high-data-rate connectivity per device is the most important requirement for 6G wireless networks [22].

The research on 6G is still in infancy. Most of the researchers focus on the future vision [23], [24], the potential technologies [25]– [27], and the diverse service requirements [28] in 6G. The main features of each generation of cellular networks from the first generation to the 5G have been reviewed in the literature [1], including supervision, services, innovations relative to the previous generation, and some auxiliary information, and further summarize some possible facts of 6G. The main successes and challenges of the first generation through 5G are also discussed in [23], which identified key requirements that cannot be addressed by previous generations from a user perspective in 6G. Saad *et al.* in [24] defined the main driver technologies and a specific future research agenda for 6G communications, further suggesting a development path for the technology, service types, and requirements in 6G. Zhang *et al.* [25] implied a large autonomous network architecture that contemplates the integration of space–air–ground–underwater networks, which provides complete coverage and unlimited wireless connectivity in 6G. In addition, the authors further discussed the impact of AI

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on autonomous networks. The article [26] discussed the development of 6G from different layers. At the physical layer, they believe that the subterahertz and visible light communication (VLC) methods will become powerful enablers for 6G development. At a higher level, they believe that the new architectures based on AI are needed. Recently, Yang *et al.* [27] sketched potential techniques associated with 6G, including transmission techniques, network security, and test hardware developments. Tariq *et al.* [28], highlighted that compared to 5G, 6G needs to make some orders of magnitude improvement in both technical updates and use cases. There are still a lot of comprehensive visions about 6G that can be found in [2].

The previous work on 6G have imposed stringent requirements on large-scale links, complex structures, and energy efficiency, a number of potential technologies have also been proposed. This article argues that learning from past experiences to apply them to the present and future will be very vital to 6G, and the key technology to achieve this capability is transfer learning (TL). Much research on 6G only regards TL as a branch of AI method without a detailed analysis on the potential application of TL in 6G, which is a defect to be made up in this article.

Through the aforementioned analysis, combined with 6G application and the advantages of TL, this article aims to study two important scientific problems.

1) Why does 6G wireless communications need TL?
2) How to use TL in 6G wireless communications?

To the author's best knowledge, this article is the first to explicitly review the application of TL in wireless communications and study the deployment of TL in future 6G communication networks. Specifically, the main contributions of this article are summarized as follows.

1) The requirements and expected technologies of the future 6G development are summarized, and five important research issues for the future development of 6G are summarized: high efficiency, seamless integration, innovation technologies, and secure green communication.
2) Popular TL techniques applied in wireless communications are comprehensively reviewed, including their basic logic and general classification, which are divided into two major categories: data knowledge TL (including instance-based TL, feature-based TL, and transfer kernel learning) and tool model TL (including classifier TL, deep networks TL, adversarial TL, and reinforcement learning (RL) based TL).
3) A comprehensive review of the research applying TL to wireless communications is presented, which is the important basis and reference of TL service for 6G in the future. We review from the following perspectives: TL for base stations/access points (BSs/APs) switching energy efficiency, TL for spectrum allocation in cognitive radio networks, TL for content popularity prediction, TL for wireless location, TL for intrusion detection, and some other applications.
4) Technology development and era demand are mutually reinforcing, so are TL technology and 6G era. This article describes the problem as a tree, where technology is the root and demand is the leaf. As technology takes root, demand will sprout. Some possible technical aspects of TL promoted by 6G are studied, and these advanced TL techniques have not yet been applied to the field of wireless communications, so the interpretation in this article will give future research opportunities. At the same time, it is also explained that TL may facilitate the resolution of some difficult challenges of 6G.
5) The future challenges and the problem that is eager to be solved related to the applications of TL in 6G wireless communications are proposed with collection and open access of rich real-word datasets, complex similarity analysis, and privacy protection during TL process.

The structure of this article is shown in Fig. 1. This article is organized as follows. Section I is the introduction. Section II discusses the possible scenarios of TL in 6G wireless communications. Section III presents the requirements and possible key technologies in 6G. The TL preliminaries are presented in Section IV. Section V is the review of the research activities on the application of TL in wireless communications. Mutual relationship between TL and 6G communications is described in Section VI. The current challenges and open issues of TL for 6G communications are presented in Section VII. Finally, Section VIII concludes this article.

II. Vision of TL Applied to 6G

TL as a significant enabling role in AI [29] can be utilized to manage 6G wireless communications with multiple different perspectives. Embedding TL into 6G wireless communications is promising. According to the discovery and theoretical verification, there is a certain temporal and spatial correlation in the wireless systems, such as the service request of the same user and the resource allocation of the neighboring cell [30]– [32]. Failure to take advantage of these correlations will result in the reuse and waste of resources, which is an important basis for the use of TL. TL can combine domains of relevance and use the experience of problem solving in old tasks to help solve new problems.

The possible scenarios of TL in 6G wireless communications are shown in Fig. 2. It is believed that these scenarios are only a few of the future TL applications in 6G. In fact, there has been a lot of infant research exploring these scenarios.

A. TL in Wireless Indoor Localization

Indoor localization is an important application in future 6G. TL algorithm is applied to verify the good transfer value of received signal strength (RSS) data collected by the Wi-Fi-based indoor localization [33], [34]. The experience transfer between different locations, or the experience transfer of localization tasks at different times in the same area, will make indoor wireless localization more efficient in the future.

B. TL in Smart Societies

The excellent features of 6G will accelerate the evolution of smart societies leading to intelligent medical, intelligent

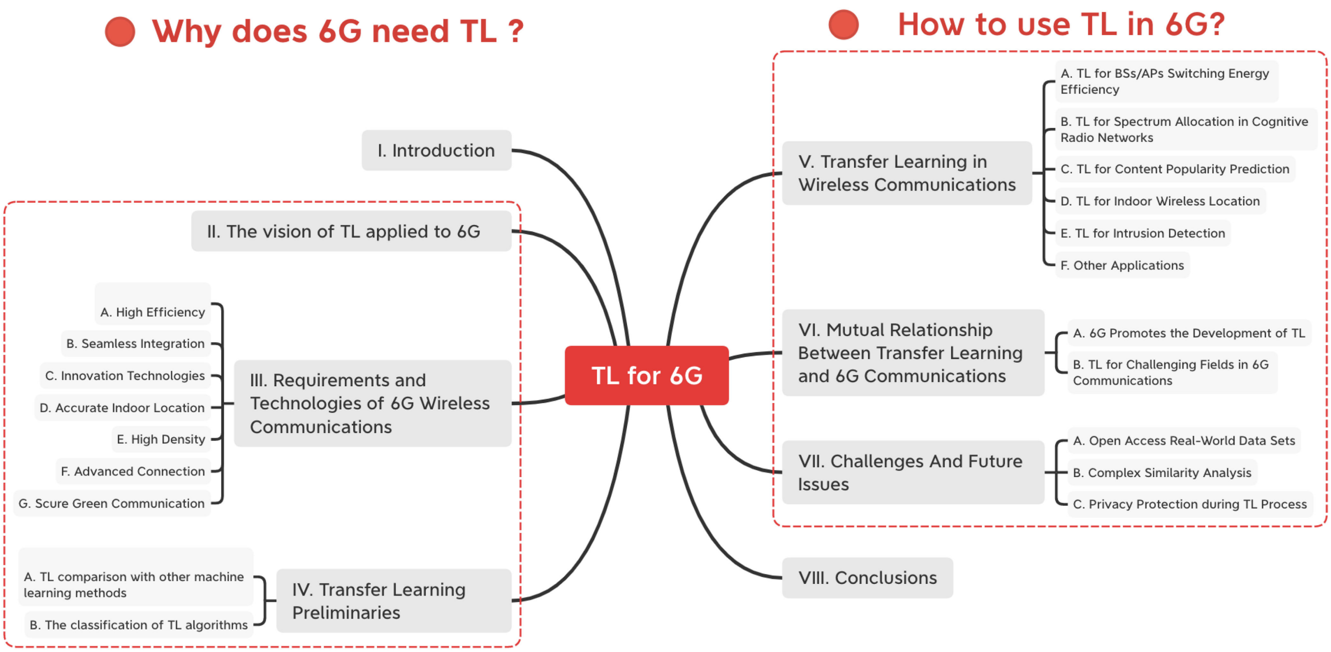

Fig. 1. Structure of this article.

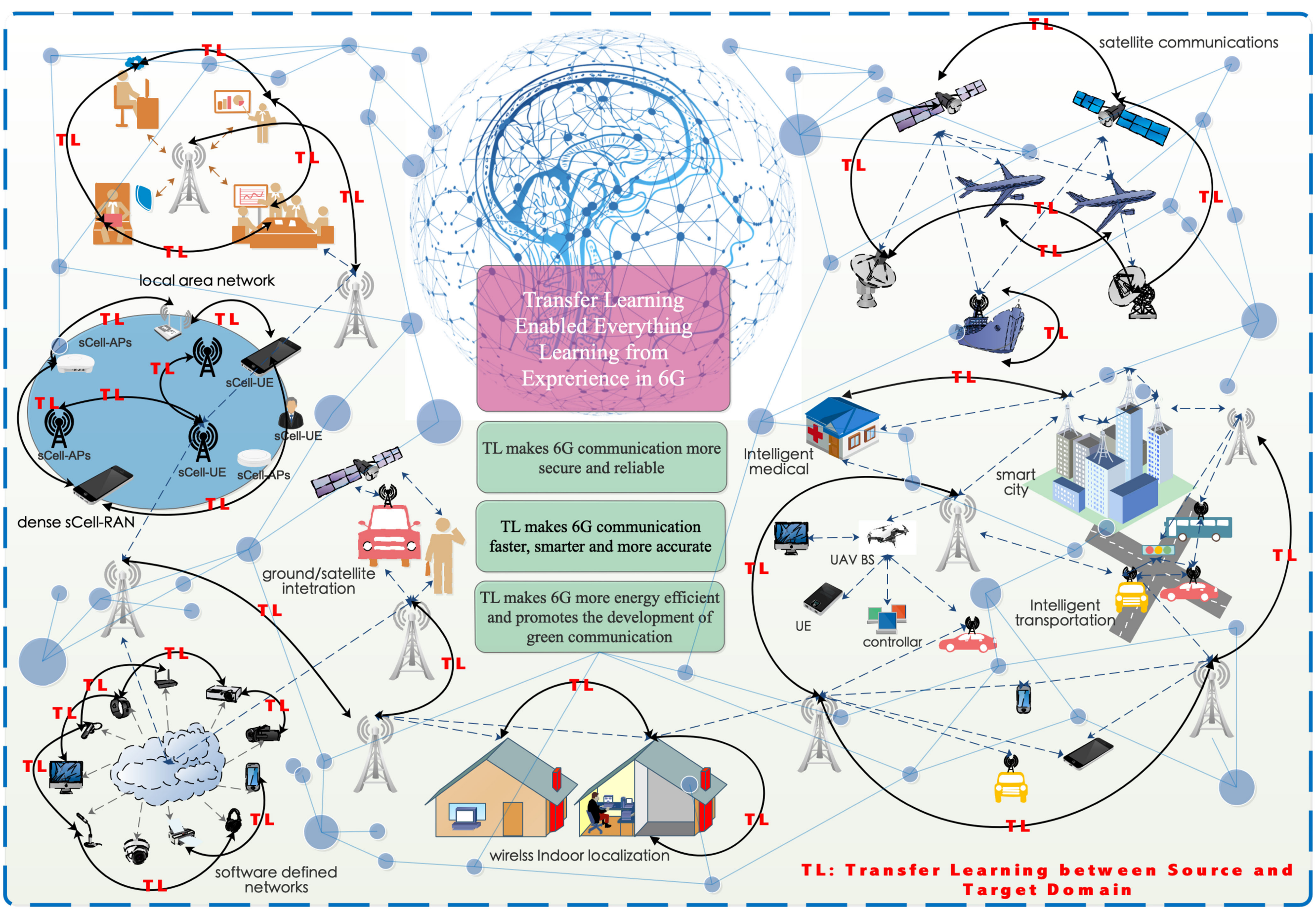

Fig. 2. Possible scenarios of TL in 6G wireless communications.

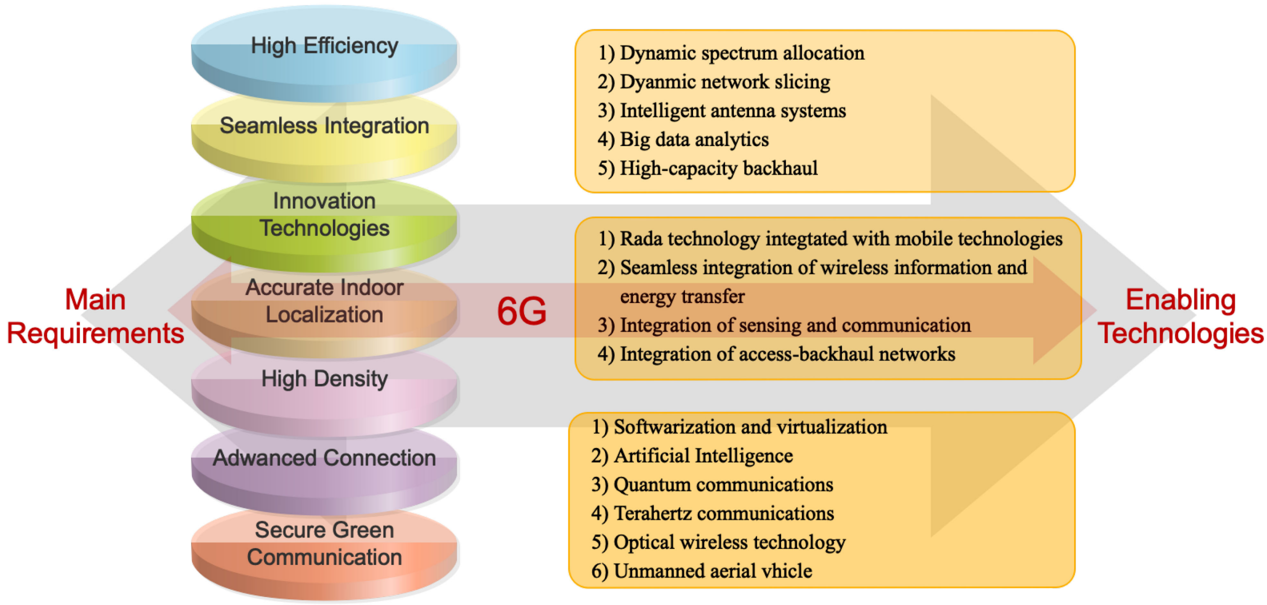

Fig. 3. Requirements and technologies of 6G.

transportation, and smart city and UAV relay BS improvements. The extensive wireless connections in 6G will make our society smarter through the use of smart mobile devices, remote control, autonomous driving technologies, etc.

Therefore, there will be super massive data for processing and analysis. Smart societies of 6G require the transfer of the already trained model. Even on the same task, a model is often difficult to meet various needs of different users, which requires the adaptation of models between different users.

C. TL in Satellite-Ground Integrated Communications

Due to the remote distance of the space nodes and the poor channel quality, the link usually has the characteristics of large transmission delay, high outage probability, and asymmetry. TL has made some research progress in helping BSs/APs conversion [35]– [38] and cache system/recommendation system cold start [39]– [42], etc. These works have provided the basis for the future development of TL to promote the integration of satellite-ground integrated communications.

D. TL in 6G Wireless Communication Networks

Wireless communication networks that are more powerful are a basic requirement for 6G in the future. Whether it is in software-defined networks, dense sCell-RAN, or local area networks, resource allocation and mutual coordination and experience transfer between high-density and diverse types of smart devices and users are very important. TL-based dynamic spectrum requires distributed cognitive agents to share their experience with each other, which can help the new subjects join in the networks and more quickly adapt to the radio environment [43]. For radio resource management applied to a multihop backhaul network, the key issues of knowledge transfer include where, what, and when to transfer [44].

TL would make 6G more secure, reliable, faster, smarter, accurate, energy efficient, and promote the development of green communication.

III. Requirements and Technologies of 6G Wireless Communications

The 6G system will be driven by many requirements and technologies. Fully understanding of these requirements and technologies is a necessary guarantee to improve the quality of 6G communications by using TL. There will be many new technologies that have never been seen before in 6G communications. This research introduces these technologies from the perspective of demands. As shown in Fig. 3, the main demands for the 6G systems are: high efficiency, seamless integration, innovation technologies, accurate indoor location, high density, advanced connection, and healthy communication. These more advanced demands naturally require more innovative technical support.

A. High Efficiency

High efficiency is a comprehensive issue, including high transmission rates, high capacity, large-scale data processing capability, accurate research, and results.

1) Dynamic Spectrum Allocation: High efficiency requires high flexibility in 6G networks. Dynamic spectrum allocation could need flexible use of perceptual context information, the allocation of spectrum resources in seconds, and the intensive use of valuable spectrum resources is the ultimate goal of dynamic spectrum allocation.

2) Dynamic Network Slicing: Network operators use dynamic network slicing technology to allow dedicated virtual networks to support optimized delivery of any service provided to a wide range of users, vehicles, machines, and industries.

3) Intelligent Antenna Systems: Massive use of multiple antenna systems is necessary because of the increasing frequency. MIMO is an abstract mathematical model used to describe multiantenna wireless communication systems [45]. It can transmit signals independently by multiple antennas at the transmitting end and multiple signals at the receiving end. The antenna receives and restores the original information. Holographic beamforming is another important antenna technology [46], which is quite different from MIMO systems because it uses software-defined antennas. Holographic beamforming will be a very effective method in 6G [25].

4) Big Data Analytics: Efficient collection and analysis of large-scale data require strong technology and strong experience. The amount of data in 6G will be very large, and there are many types of data [47]. Effective understanding of the hidden patterns and unknown correlations within the data are very important for big data processing.

5) High-Capacity Backhaul: High-capacity backhaul networks are very attractive for efficient communications. In the face of overtraffic backhaul information, high-speed optical fiber and free-space optical (FSO) systems are very promising solutions [48], [49].

B. Seamless Integration

Seamless integration between various fields will make the 6G communications smoother and faster.

1) Radar Technology Integrated With Mobile Technologies: The radar system will be integrated with the 6G wireless communications, which not only ensures high-accuracy localization in the communication field, but also brings convenience to radar communication.

2) Seamless Integration of Wireless Information and Energy Transfer: The 6G wireless networks will enable wireless charging of battery devices, so wireless information and energy transmission will be integrated. Wireless energy transfer requires that small devices, such as mobile phones, or large devices, such as cars, can be charged by wireless energy transfer, which not only guarantees battery life, but also freely charge anytime, anywhere [50], [51]. Wireless energy transfer will be one of the most innovative technologies in 6G.

3) Integration of Sensing and Communication: In 6G, continuously perceiving the wireless environment and exchanging information between different nodes according to dynamic changes will require close integration of sensing and communication [5], making cognitive wireless communication more adaptable to highly dynamic, complex electromagnetic environments.

4) Integration of Access Backhaul Networks: In the 6G communications, there will be huge dense access networks. The backhaul network has a one-to-one correspondence with the access network. In order to solve the problem that the access network transmits a large amount of information, the access network and the backhaul network will be tight integrated [5].

C. Innovation Technologies

The strong support of innovation technologies is a guarantee for the development of 6G, and there is unlimited possibilities behind each technology.

1) Softwarization and Virtualization: Softening and virtualization ensure flexibility, reconfigurability, and programmability. Moreover, they will allow billions of devices to be shared across a shared physical infrastructure.

2) Artificial Intelligence: The major breakthroughs in AI in various fields will also bring a revolution to wireless communications in the future. AI processes complex targets by using extensive analysis, which increases efficiency and reduces communication latency. AI will fully integrate automation and intelligence into the wireless communications and will play an important role in D2D, V2V communications [6]– [8]. It is also foreseeable that TL as a member of AI has great potential.

3) Quantum Communications: QCs have immense powerful computing ability through quantum superposition and quantum entanglement. Parallel processing of multidimensional big data can be realized by QC in a large tensor product space. QC will achieve extremely high data rate and link security in future 6G communications [3].

4) Terahertz Communications: Terahertz communications refer to high-rate transmission of short distances using a large frequency band exceeding 100 GHz, thereby handing over long-distance communications to the radio spectrum of the released lower frequency band [13], [52]. The advantage of terahertz is that the beam is narrower and has better directionality, which is suitable for MIMO. But also face large-scale fading, power consumption, and other issues.

5) Optical Wireless Technology: VLC, optical camera communication, light fidelity, and FSO communication based on optical frequency bands are already well-known optical wireless technologies. Whether in outdoor or indoor scenarios, communication based on optical wireless technology can provide high data rates, low latency, and ensure communication security, so that lower frequency band radio spectrum can be released for long-term use.

6) Unmanned Aerial Vehicle: The development of UAVs in various fields makes it destined to be an important element of 6G communications [53], [54]. The BSs could be equipped on the UAVs to build cellular networks, which are not only easy to deploy but also unaffected by obstacles. In emergency situations, such as natural disasters, UAV-based communications will play an important role.

D. Accurate Indoor Localization

Indoor location technology has been developed for many years, and RSS/fingerprint-based indoor location technology has been well used. In the future 6G communications, the dependence on indoor localization will be stronger, and some promising systems, such as distributed models, require very precise positioning systems to help model efficiency. The prerequisite for efficiency is accuracy. Due to the increase of mobile devices and mobile users, indoor communication environment will become more and more complex, and the impact of noise and obstacles will be more intense. High accuracy indoor localization is necessary, and high-precision wireless indoor localization will bring great help to virtual reality (VR), cache, context awareness, and recommendation systems.

E. High Density

Heterogeneous network is a multilayer network composed of heterogeneous networks that can improve QoS while reducing costs. While ultradense heterogeneous networks will be very popular in 6G, cell-free communication is also proposed to solve problems caused by frequent handovers when moving in dense cells, such as handover failures, handover delays, data loss, and ping-pong effects. The cell-free communications will automatically select the best network through advanced algorithms and provide better QoS.

F. Advanced Connection

Advanced connection includes intelligent connection, deep connection, holographic connection, and ubiquitous connection. 6G will update the development of wireless technology from “connected things” to “connected intelligence.” Driven by the development of three-dimensional (3-D) connectivity that integrates air, space, earth, and sea, there will be the function of accessing the network and core network through UAVs and low-orbit satellites in the future, which can be called super-3-D connection [55].

G. Secure Green Communication

Secure green communication requires both energy conservation and privacy and security, which is the subject of future wireless communications. In the 6G network, everything is interconnected and devices are interoperable. This poses new challenges for biometrics authentication, privacy protection, and intrusion detection. Furthermore, a security protection system capable of countering quantum attacks is needed. Blockchain technology does not require a central processing unit or data collection and operation in the form of structural blocks [56], [57]. It is an important technology to ensure the security, privacy, and reliability of future 6G massive data.

IV. TL Preliminaries

TL is hailed as the leading technology for the next generation machine learning (ML), which aims to extract the knowledge from one or more source tasks and applies the knowledge to a target task, so that the problem of ML dependence on data and labels can be solved. With the development of TL technology in recent years, a variety of TL methods have been developed to meet the transfer requirements in different scenarios. It is believed that these TL technologies will play a great role in the future 6G wireless communications.

A. TL Comparison With Other ML Methods

Supervised learning, unsupervised learning, and RL are three well-known ML branches [58]. The coming 6G era will also be the era of big data. ML and big data analytics have many potential applications in enhancing the performance of communication networks [59], [60]. For example, ML technology has significant advantages in addressing various issues, including network service/traffic congestion minimization, adaptive resource allocation, dynamic spectrum sharing, and personalized services in ultradense cellular networks [60]. However, the success of data-driven learning solutions relies heavily on the availability of a sufficiently large amount of data and powerful processing capabilities.

Traditional ML, especially supervised learning, has stringent requirements on the number of raw data, the uniformity of data distribution, and the integrity of labels. TL solves the problem of insufficient sample size and incomplete label in the ML task. This problem can be effectively learned by using other externally distributed data. As an unsupervised learning method, Generative Adversarial Network (GAN) learns through the game between two neural networks. The goal of GAN is to generate training samples. Since there is no need for premodeling, the model of GAN is too free and uncontrollable. In contrast, TL has the source domain as a reference and the model is more controllable. In addition, as the hottest ML technology in recent years, RL technology is considered to be simpler in calculation. RL learns the interaction between the learning agent and the underlying environment, and the learning agent uses future rewards to determine current actions to maximize its long-term rewards [61]. But, RL technology requires an understanding of the state transition function and has slow convergence. The model will waste a lot of time during the initial confusion stage in the tasks solved purely based on the RL model. Therefore, the research on RL is also gradually inclined to combine RL technology with TL technology. These combined technologies can be named as RL-based TL, which is a very promising technology.

B. Classification of TL Algorithms

According to different research objects (statistical distribution of raw data, characteristics of data, tool model used for data processing), TL methods can be divided into two broad categories: data knowledge transfer and tool model transfer. Data knowledge transfer takes data knowledge (instance, feature, kernel space features, etc.) as the transfer object, and uses the source domain data knowledge to enrich the target domain data knowledge. Tool model transfer refers to taking model knowledge (model parameters, network structure, etc.) as the transfer object and using the source domain model to assist the construction of the target domain model. Matching data samples can save time that is spent on building the target dataset. The right models make the task complete with good benefits.

The various TL algorithms are explained below and the classification of TL is shown in Fig. 4.

1) Data Knowledge TL: Data knowledge TL research includes instance-based TL, feature-based TL, and transfer kernel learning.

1) Instance-based TL: The research of instance-based TL makes the distribution of the source domain and the target

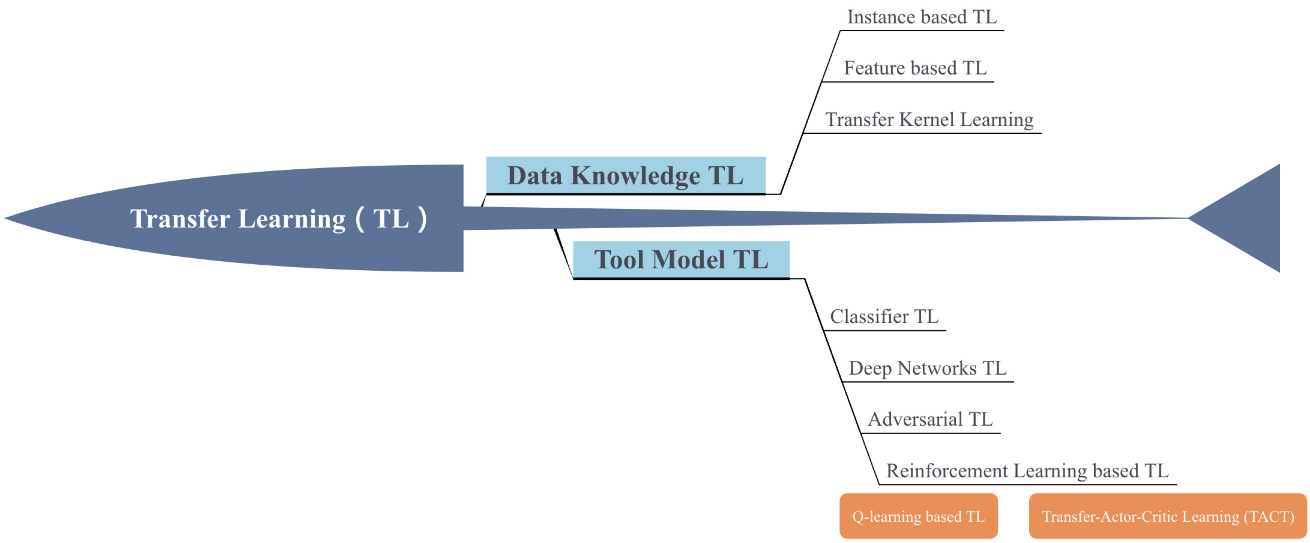

Fig. 4. Classification of TL.

domain as the same as possible. Attempting to better serve new learning tasks, instance-based TL assigns new weights to each sample in the source data. We pick out samples from the source data to participate in the training, which are more similar to the target data, and reject samples that are not similar to the target data.

2) Feature-based TL: The method transforming the characteristics of the source domain and the target domain into the same space is the feature-based TL. To reduce the gap between source domain and target domain, feature-based TL refers to mutual transfer through feature transformation. When ML implements a task, the learning effect may be poor due to the lack of sufficient labels in the target feature domain. By mining the cross-characteristics of source data and target data, the ML tasks can be accomplished. It realizes knowledge transfer between different feature spaces.

3) Transfer kernel learning: Transfer kernel learning aims to solve a projection matrix in the source and target domains by kernel mapping based weighting, so as to reduce the marginal distribution difference and conditional distribution difference between domains in a reproducing kernel Hilbert space (RKHS). Maximum mean discrepancy (MMD) [62], [63] and kernel mean matching [64] represent the difference in marginal distribution and in conditional distribution between the source domain and the target domain. The label of the target domain sample is usually not available in an unsupervised domain adaptation setting. So, the pseudolabel of the predicted target sample should be inherited to quantify the conditional MMD between the domains. An empirical estimate of MMD in the general RKHS can be given by [63]

$$d_{\mathcal{H}}^2\left(\mathcal{D}_s, \mathcal{D}_t\right) = \left\| \frac{1}{M} \sum_{i=1}^{M} \phi\left(x_i^s\right) - \frac{1}{N} \sum_{j=1}^{N} \phi\left(x_j^t\right) \right\|_{\mathcal{H}}^2 \quad (1)$$

where $\phi(\cdot)$ is the nonlinear mapping into RHKS $\mathcal{H}$. M and N denote the number of samples drawn from source and target domain, respectively.

2) Tool Layer TL: A good tool can get twice the result with half the effort. Tool layer TL is more straightforward and timesaving than data layer TL. The tool layer TL directly extracts the useful parts of the model completed on the source data and directly applies to the training model of the target data. These model parameters can be used as initial values for the target model or even as part of the target model.

1) Classifier TL: The classifier-based TL is designed to learn the general classifier when the samples extracted from the source domain are labeled and only a small number of samples taken from the target domain are labeled. Classifier TL is a method for quickly adapting a traditional classifier to the current task, which rely on a very small amount of labeled features from target domain. There is the kernel classifier, manifold regularizer, and Bayesian classifier in recent research. The target field completely unlabeled is prepseudomarked. It is then calculated and iteratively updated.

2) Deep network TL: Through the study of the deep learning model, it has been found that for similar learning tasks, although the final goals of the model may be different, the first few layers of the model often have similar functions. This similarity of functionality shows the versatility of the first few layers of the deep learning model, which can be moved across multiple target data. TL technique designed using the characteristics of deep learning is generally called deep TL.

3) Adversarial TL: After training robust DNNs, feature-level target samples can be generated by adversarial learning, which is a promising measure. GAN consists of two parts: the generative network and discriminative network. The generative network is responsible for generating as many samples as possible. The other is responsible for judging

whether the sample is real or generated by the generator. The game between generator and discriminator completes the antagonism training. The goal of GAN is to generate the training sample, which seems to be somewhat different from the goal of TL. However, a source domain and a target domain are naturally in TL, so it can avoid the process of generating samples, and directly treat the data of one domain (usually the target domain) as the generated sample. At this point, the function of the generator changes and no longer generates new samples, but plays the function of feature extraction. It constantly learns the characteristics of the domain data so as that the discriminator is unable to distinguish between the two domains.

3) RL-Based TL: The integration of TL and RL has been relatively mature, and relevant review articles can be found in [65]. We mainly introduce following two RL-based TL methods that have been successfully used in wireless communications: *Q*-learning-based TL and transfer-actor-critic learning (TACT).

1) *Q*-learning-based TL: *Q*-learning is an important method in RL. The update of the *Q* values is the necessary knowledge of *Q*-learning in completing the task, but the difficulty in selecting the initial *Q* values will affect the efficiency and energy consumption of the entire model system. TL can use the *Q* values obtained from the old tasks to solve similar new tasks, which can make the *Q*-learning-based model more intelligent in the initial stage of learning the *Q* tables. However, what needs to be avoided is that the differences between tasks or environments may lead to negative transfer, that is, TL has a negative impact on the target task.

   After the *Q* tables in the original task is transferred to the target task, the target domain adaptation training is performed to help the target task quickly adapt to the environment. The purpose of the *Q*-learning-based TL is to maximize the *Q* values of the positive impact and minimize the *Q* value of the negative impact. To achieve this, the *Q*-learning-based TL function is designed to enhance the target *Q* array by using those in the source domain, which also avoids information-bearing *Q* arrays in the source or target domain

$$\forall a_k \in a, Q_{a_k(TA)}(t) = Q_{a_k(TA)}(t-1) - \frac{\sum_{i \in N_{SA}} Q_{a_k(SA_i)}(t-1)}{|N_{SA}|} \tag{2}$$

   where $|N_{SA}|$ is the number of source agents. On the *Q* tables obtained from source domain, the TL function assigns negative reward R_{S_-} to the actions with positive *Q* value t_{S_+} and vice versa. This will prevent the target task from training the *Q* table from scratch

$$Q(t) = t_{S_+} R_{S_+} + t_{S_-} R_{S_-} \tag{3}$$

   where S_+ is a collection of all actions that produce positive rewards, and S_- is a collection of all actions that produce negative rewards. The *Q*-learning-based TL function can be expressed as follows:

$$N_{TA}(Q(t)) = N_{TA}\left(t_{S_+} R_{S_+}\right) + \frac{\sum N_{SA}\left(t_{S_-} R_{S_-}\right)}{|N_{SA}\left(t_{S_-}\right)|} + N_{TA}\left(t_{S_-} R_{S_-}\right) + \frac{\sum N_{SA}\left(t_{S_+} R_{S_+}\right)|}{\left|N_{TA}\left(t_{S_+}\right)\right|} \tag{4}$$

   where N_{TA} is target agent, N_{SA} is source agent, R_{S_-} is negative reward, R_{S_+} is positive reward, t_{S_+} is the actions with positive *Q* value, and t_{S_-} is the actions with negative *Q* value.

2) Transfer-actor-critic learning: TL is applied to a series of actor-critic learning processes, which is named TACT algorithm. TACT framework was first proposed to be applied to energy saving in cellular radio access networks [35]. In this scenario, TACT instructed the controller to optimize BS switching policy by learning the experience of historical period or neighboring regions. The most sensible choice made by the controller is to maximize overall system throughput and optimize energy savings.

   TACT adopts the policies transfer, which is different from *Q*-learning-based TL that uses static transfer knowledge for the initialization of new/target tasks training. The experience of the new tasks is divided into two sources: the "native policies" obtained through the actor-critic learning and the "exotic policies" transferred from the original/source tasks. As the local learning process progresses, the weight of the "exotic policies" in the overall policy is reduced. The actor-critic algorithm will criticize the actions taken in the past so that the next state s is biased toward the high-scoring action a, which will eventually form a policy $p(s, a)$ for the controller of the task. When the learning policy reaches convergence in the original tasks, the corresponding action a is selected with a high probability in a specific state s. Therefore, if the policy is transferred from the original tasks to the new tasks in the similar region, the controller in the new task can try to perform the same action a under the state s. Compared to learning from scratch, the controller may make the most sensible choice directly from the beginning. However, there may still have some differences between the source and target tasks. Instead of staying in the selected action a in the source task, TACT can perform more aggressive actions on the controller in the target task. Therefore, in this case, the transmission strategy is guided in a negative way. To avoid this potential problem, once the controller has developed a local learning strategy, the impact of the transferred policy on action selection should be gradually reduced.

   The architecture of TACT algorithm is shown in Fig. 5. The process of TACT in target tasks is summarized as follows.

Step 1: Initialize "native policies" function, "exotic policies" function, and overall policy $p(s, a)$.

Step 2: Choose an action a in state s according to the overall policy $p(s, a)$.

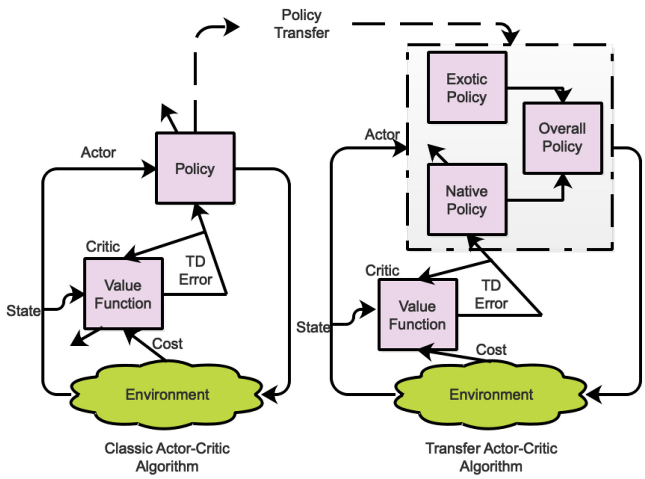

Fig. 5. Architecture of the TACT algorithm [35].

Step 3: The cost function is calculated.
Step 4: Update state and compute the TD error.
Step 5: Update the "native policy" function and the overall policy function $p(s, a)$.

V. TL IN WIRELESS COMMUNICATIONS

The successful research works of TL in wireless communications are the basis for future TL applied to 6G communications, and it also shows that TL is indispensable for 6G communications.

There will be an exponential upsurge in data intensive applications over the communication networks in 6G thanks to various data intensive services being envisioned to support paradigms, such as Internet of Things (IoT), smart grids, cloud computing, etc. As a result, huge deployment of new BSs of various sizes can be expected in the near future. In Wi-Fi networks, most of energy consumption occurs on the access network entities, which makes the energy efficient operation of Wi-Fi APs extremely crucial. So, the works about TL for BSs/APs switching energy efficiency will be helpful for this vision.

Efficient utilization of spectrum resources is also an important topic of 6G communications. In particular, dynamic spectrum allocation requires that the spectrum should be reallocated according to the context every second. Fortunately, some work has been done on TL for spectrum allocation in cognitive radio networks as well. In fact, the program can further improve performance, speed up the learning process, and further save energy.

Accurate location based service is one of the fundamental but crucial services in the era of IoT. TL has also achieved some success in indoor localization.

This section provides a comprehensive review of advanced work-based TL in wireless communications, such as BSs/APs switching, indoor wireless localization, and intrusion detection, etc. Combined with 6G requirements, we can see the potential value of these works.

A. TL for BSs/APs Switching Energy Efficiency

The switching of BSs in the cellular networks and APs in the Wi-Fi networks is the most energy consuming unit. The energy saving work of BSs/APs switching mainly relies on the dynamic ON/OFF actions based on traffic conditions, which can avoid the problem that significant operating cost and energy consumption is generated because the BSs are always in an active state with a peak load capacity. Table I summarizes the studies on TL for BSs/APs switching energy efficiency.

RL has been widely used in BSs switching because it does not require prior knowledge of the traffic load, but from the perspective of overall cost, the RL method usually takes some time to converge to the optimal solution. Therefore, the TACT method is proposed and applied to coordinate BSs ON/OFF in a cellular network [35]. TACT considers the temporal and spatial correlation in traffic loads, and applies the BSs switching operation strategy transferred in historical time or adjacent area (source task) to the target task in order to speed up the ongoing RL process. Compared with the homogeneous network, TACT used in the more complex situation of heterogeneous networks (HetNet) consisting of macro BSs and small cells is discussed in [36]. In [37], the TACT-based framework helps APs switching decisions at the current time by transfer data knowledge learned over the past appropriate time period in Wi-Fi networks. In [38], Sharma *et al.* believe that the BSs switching should have a third state, which is the omnidirectional state at medium traffic. This is more energy efficient than only two states: the active state and the sleep state under high traffic and low traffic, respectively. Fortunately, TACT is also used for further improvement in energy savings and speeding up the learning process in this model.

B. TL for Spectrum Allocation in Cognitive Radio Networks

Most of the TL solutions so far applied to spectrum allocation are based on RL, thanks to a lot of research has been done to apply RL in cognitive wireless networks [71]. *Q*-learning-based TL and TACT are two transfer methods currently successfully applied in CRN. Research work can be roughly divided into two categories: transfer between agents and transfer between users. Table II summarizes the studies on TL for spectrum allocation in cognitive radio networks.

1) Transfer Between Agents: In [44], the weight tables in the RL are used as the shared knowledge between the agents in the multihop backhaul network, thus optimizing the decision problem of the agent doing spectrum resource allocation. We think this is the prework of *Q*-learning-based TL applied to spectrum resource allocation, which specified and exploited the key issues of knowledge transfer, including where, what, and when to transfer. In [66], *Q*-learning-based TL is applied to the spectrum and topology management of the rapidly deployable opportunistic network in the postdisaster and temporary event scenarios. The earlier stage of the network topology learns the dynamic wireless environment and transfer knowledge to later network deployments to allow the network structure to change rapidly at different stages of the disaster and maintain a high degree of flexibility in temporary events. In [43], distributed

TABLE I
TL FOR BSS/APS SWITCHING ENERGY EFFICIENCY

Literature	Year	Scenario	Optimization Object	TL method
[35]	2014	RL based BSs switching in in cellular network.	Old task RL policy transfer to new task to speed up RL process.	TACT
[36]	2017	RL framework based BS switching operation in heterogeneous networks.	TL enables the newly joined BS to learn the previous experience of the environment from neighboring BS, so as to speed up the learning process of RL.	TACT
[37]	2017	RL based APs switching in Wi-Fi networks.	TL enables the current APs switching decision learn from the past period.	TACT
[38]	2019	RL based BSs switching that have a third state:omnidirectional-state.	Old task RL policy transfer to new task to speed up RL process.	TACT

TABLE II
TL FOR SPECTRUM ALLOCATION IN COGNITIVE RADIO NETWORKS

Literature	Year	Scenario	Optimization Object	TL Method
[44]	2013	RL based cognitive resource management in multi-hop backhaul networks.	Transfer the weight values calculated from RL between the BSs.	RL based TL
[66]	2013	Q-learning used for rapidly deployable networks in either disaster or temporary event scenarios.	The earlier stage transfer knowledge to later stage to guarantee network flexibility in a dynamic radio environment.	Q-learning based TL
[67]	2014	Q-learning based users association decision in 5G networks.	Neighboring BSs transfer Q-values learnt from spectrum assignment to establish a knowledgebase for user association.	Q-learning based TL
[43]	2015	Distributed Q-learning based cognitive agents in wireless networks.	TL help the agents share their experiences.	Q-learning based TL.
[68]	2016	Q-learning for SU conducts spectrum decision in wireless mesh networks.	Newly-joined SU learn from a experience SU to overcome the initial learning.	Q-learning based TL
[69]	2016	Q-learning for SUs conduct spectrum decision in wireless mesh networks.	Speed up the spectrum decision process by choosing multi expert SUs to new SU.	Q-learning based TL
[70]	2017	Actor-Critic for SU conducts spectrum decision in intelligent spectrum mobility management.	Speed up the ongoing learning process of the RL-based-model.	TACT

cognitive agents learn the wireless network environment by used Q-learning-based TL to share their experiences for dynamic spectrum management.

2) Transfer Between Users: Zhao and Grace [67] perform user association from the perspective of BS users. Users select neighboring BSs through reference signal received power and transfer their Q values accumulated in Q-learning-based spectrum allocation tasks so that users can select suitable cells more quickly. In [68], a second user (SU) conducts spectrum decision making through Q-learning. In order to prevent the newly joined SU from taking too long to make the correct spectrum decision in the initial stage, Q-learning-based TL is used for newly joined SU to learn from an adjacent experience SU and speed up the decision-making process. Wu *et al.* [69] further considered the newly joined SU to learn from multiple experience SUs, and multiple experience SUs transferred knowledge to an inexperienced SU to make a more mature adaptation strategy. TACT is also used in the new SUs to learn from the expert SUs [70]. Compared with the previous work, the advantage is that the new SUs will gradually update a new policy on themselves.

C. TL for Content Popularity Prediction

Content popularity prediction currently plays an important role in proactive caching networks and the recommendation systems. However, they all face a similar problem with data sparsity, which has a big impact on popularity prediction. In addition, it takes massive time to calculate large amounts of data for accurate predictions. TL can transfer knowledge from other domains to solve these problems and improve prediction accuracy. Table III summarizes the studies on TL for content popularity prediction.

1) In Cache-Enabled Wireless Networks: The early contribution of TL in cache-enabled networks is Bennis and Debbah [39] that transfer available information from relevant source domains to help mitigate data sparsity and help CF more effectively in the target domain. The work in [40] proposes the uses of rich contextual information extracted in the D2D interaction process as the source domain to help the target domain learn similar potential features to optimize the content caching in the small cells. The specific solution is to use the classic collaborative filtering (CF) algorithm for training and predicting in the source domain, and then sharing the content popularity matrix with the target domain with similar tasks. However, the TL caching method based on classical CF learning technology was not superior enough, so the research in [42] replaces CF with the regular singular value decomposition (RSVD).

The research in [41] is interested in deriving the minimum training time of the content popularity prediction model to achieve a desired performance accuracy. The method is to use the knowledge acquired in the interaction between the users and the community as the source domain, and the request of users as the target domain. The calculation process of using TL to obtain the target domain popularity estimation is as follows.

1) At the BSs, using the target domain samples, calculate the following parameters:

$$\hat{S}_i^{(\mathrm{tar})} \triangleq \sum_{x\in\mathbb{B}(0,R)} \sum_{\Phi_u} \sum_{l=0}^{k_x} 1\left\{X_x^{(l)} = i\right\}, i = 1, \ldots, N \tag{5}$$

TABLE III
TL FOR CONTENT POPULARITY PREDICTION

Literature	Year	Scenario	Optimization Object	TL Method
[39]	2014	Due to the poor estimation of CF, the performance of small base stations with cache enabled is low.	Transfer available information from relevant source domains to help mitigate data sparsity and help CF more effectively in the target domain.	Feature-based TL
[40]	2015	Data sparsity and cold-start issues disrupt local caches at the edge of the network.	Transfer the rich contextual information extracted in the D2D interaction process to the target domain learn similar potential features to optimize the content caching.	Feature-based TL
[41]	2016	Knowledge acquired in the interaction between the users and the community as the source domain, and the request of users as the target domain.	Deriving the minimum training time to achieve a desired performance accuracy.	Feature-based TL
[42]	2017	RSVD-based CF is used to estimate the content popularity and TL is adopted to improve the estimation accuracy.	Transfer the prior information from social networks to the target networks.	Feature-based TL
[72]	2018	The scoring matrix is usually not comprehensive and sparse in application recommendation systems.	Features from Wikipedia and other different domains combine with the target feature vectors for the recommendation systems.	Feature-based TL

where k_x is the number of requests made by the user at the location $\mathcal{X}$. The corresponding lth request by the user at the location $\mathcal{X}$ in the time interval $[0, \tau]$ is denoted $X_x^{(l)}, l = 1, 2, \ldots, k_x$.

2) The source domain samples $\mathcal{X}^s \triangleq \{X_1^s, \ldots, X_m^s\}$ are drawn i.i.d. from a distribution, where $X_l^s = i(l = 1, 2, \ldots, \mathcal{N})$ indicates that the user corresponding to the lth sample has requested the file f_i. Using this, the BS computes

$$\hat{S}_i^s \triangleq \sum_{k=1}^{m} 1\left\{X_k^s = i\right\}, i = 1, 2, \ldots, N. \tag{6}$$

3) The BS uses (5) and (6) to compute an estimate of $\hat{p}_i^{(tl)}$ (the superscript tl indicates transfer learning) given by

$$\hat{p}_i^{(tl)} = \frac{\hat{S}_i^{(tar)} + \hat{S}_i^s}{\sum_{x \in \{\mathbb{B}(0,R) \cap \Phi_u\}} k_x + m}. \tag{7}$$

Using the estimate given by (7), the minimum training time is obtained.

In order to meet the needs of cache-enabled wireless networks, Hou *et al.* [73] propose a TL-based collaborative caching strategy. It also emphasizes that the proper use of TL may provide important improvements for content caching in mobile edge networks.

2) In Recommendation Systems: As multimedia applications become more diverse, application recommendation systems are attracting attention by inferring user preferences based on the scoring matrix of the user's past operations to avoid information overload problems. However, the scoring matrix is usually not comprehensive and sparse. The aforementioned problem is solved by the cross-domain recommendation algorithm of feature transfer and unbalanced classification [72]. First, the recommendation problem of the target domain is expressed as a rough unbalanced classification problem, and then it uses the extra user features acquired in the auxiliary domain, the item features obtained from Wikipedia, and the rough features of the target domain to construct a 2-D feature vectors. Finally, the new feature is used to classify and complete the recommendation.

D. TL for Indoor Wireless Localization

Most ML-based indoor Wi-Fi localization methods rely on collecting a large amount of labeled data to train a precise localization model offline for use online, and they assume that the distribution of RSS data over different time periods is static. However, calibrating localized models in large environments is expensive. In addition, RSS values are noisy and can change over time. As a result, even in the same environment, the RSS data collected in one period may be different from the RSS data collected in another period. How to build an indoor wireless location model that is robust to changes in the domain or environment? How to make full use of the training labels obtained in the older field to save manpower in localization tasks in the new environment? TL provides an effective tool for solving these problems.

TL aims to learn mature experiences from one or more source domains and apply knowledge to different but related target domains. Table IV summarizes the studies on TL for indoor wireless localization. In [74], in order to better perform feature-based TL, a new feature dimension reduction method is proposed, and the mapping relationship between the source domain and the target domain is found in the low-dimensional space to help the target domain learn the transfer knowledge and complete accurate positioning. The manifold alignment is also used in [75], the FP data in the source domain come from the historical radio map, and the target domain is the radio map collected in real time. In [76], the APs and calibration points in the wireless location environment are used as the source domain with labels, and the test points without labels are used as the target domain. The transfer kernel learning is used for adaptive localization. In [77], the source domain and the target domain are two different spatial indoor location systems, which are expressed in matrix form. The TL-based location method is divided into two steps: matrix learning and matrix transfer, which is to learn the similarity matrix from the source domain and decide which source domain selections are more appropriate for the target domain.

Since the RSS data collected by the Wi-Fi-based indoor localization research work have very good transfer value, a large

TABLE IV
TL FOR INDOOR WIRELESS LOCALIZATION

Literature	Year	Scenario	Optimization Objective	TL Method
[74]	2008	Make a Wi-Fi based indoor localization system have ability for adaptive localization, regardless of time or device factors.	The mapping relationship between the source domain and the target domain is found in the low-dimensional space to transfer knowledge and complete accurate positioning.	Feature-based TL
[75]	2015	The target indoor environment looks for an environment with the same spatial correlation of RSS as the source domain.	Multi-space cooperative positioning based on TL achieve better results.	Feature-based TL
[76]	2016	Adapt the data distribution changes constantly as devices change and over different time periods.	Access points and calibration points with labels are used as the source domain, and the test points without labels are used as the target domain.	Transfer Kernel Learning
[77]	2017	Enhance system scalability of fingerprint-based indoor localization by reducing offline training overhead without compromising localization accuracy.	Learn the similarity matrix from source domain to reshape logical distributions of distances among points in the target domain.	Transfer Kernel Learning

TABLE V
WI-FI DATASETS VERIFY TL METHODS

Literature	Year	Transfer Learning Method
[33]	2010	Semi-supervised TCA
[34]	2011	Feature Selection for TL-Feature Separation with MMD
[78]	2015	Kernel-based Random K-samplesets Method for TL
[79]	2017	Feature Subspace Adaptation-Matric Based

number of research work on the TL algorithm [33], [34], [78], [79] uses the RSS dataset to verify the effectiveness of the proposed algorithm. These advanced TL algorithms have great potential for future research on indoor wireless positioning. The specific summary can be seen in Table V.

E. TL for Intrusion Detection

A huge threat to the signature-based detection systems is posed by new and unseen cyber attacks. To detect attacks, ML approaches that extract features form cyber data are applied. Because the distribution of features in the training and testing datasets is different, the performance of the learned models is affected. Moreover, it is time-consuming and expensive to generate labeled datasets. Due to standardized network protocols, features extracted from network data are common. With the help of the common latent model, TL techniques can be applied, in which source domain data are used to distinguish new attacks from the target domain. Table VI summarizes the studies on TL for intrusion detection.

The application of TL to intrusion detection can be divided based on judging whether the features of the source domain and the target domain are isomorphic. In the TL-based intrusion detection model studied in [81], it is assumed that the source domain and the target domain have homogenous features. But, this is not the common case for cyber intrusion detection, which usually exhibits heterogeneous features. In general, we need to do the TL of the original domain and the target domain is heterogeneous [82]. The source domain is an old network, but the target domain comes from a new network [83]. Existing studies can also be divided into four categories based on the type of TL used: model-based TL [80], instance-based TL [81], feature-based heterogeneous TL [82], and domain adaptation manifold alignment [85].

F. Other Applications

1) TL for UAVs: UAVs are used in a variety of fields, such as communication, vision, transportation, etc., due to their high maneuverability and low consumption. Reliable communication is a prerequisite for ensuring connectivity between UAV nodes [18]. ML-based air-to-ground millimeter-wave channel path loss and delay spread prediction methods can be used to accurately predict the radio channel parameters to provide a reasonable reference for the comprehensive overall design of the UAV communication systems. The TL is applied to predict the limited path loss of the data when the scene or frequency changes, which can reduce the time-consuming and expensive consumption.

2) TL for Large-Scale Radio Signal Classification: The authors conducted the training in two kinds of thinking: without TL and with TL in order to explain that transfer large-scale dataset knowledge to small-scale datasets to help train their new tasks is better than the small datasets train by themselves. This result emphasized the importance of large-scale datasets [86].

3) TL for IoT: With the development of IoT technology, research about the environmental impact on fingerprints of IoT objects cannot be ignored. In [87], among the various objects under the same environmental influence, there were objects with the same feature space as the source domain and objects with different feature spaces as the target domain. Evaluate the IoT network environment by transferring knowledge between different types of objects with different feature spaces to grasp the practical network deployment method and improve the performance of the framework.

4) TL for VR Resource Management: In the cloud-enabled cellular networks, providing seamless connectivity to VR users in the future is a daunting problem [88] since the VR users request or transmit data is relevant, which is due to the users engaging in the same immersive virtual environment in different locations or directions. The TL-based model can transfer the already learned resource allocation strategy to a new resource allocation task, which can improve the convergence speed faster when the users request allocation and data correlation change.

TABLE VI
TL FOR INTRUSION DETECTION

Literature	Year	Transfer Learning Method	Cross Domain	Attack in Source and Target (Dos,R2L,Probe)
[80]	2008	Model-based TL	Datasets Verify	Seldom two training, one test
[81]	2009	Instance-based TL	Datasets Verify	R2L training to R2L test
[82]	2017	Feature-based heterogeneous transfer learning (HeTL)	Cross Time	Dos training to R2L test
[83]	2018	Domain Adaptation Manifold Alignment (DAMA)	Cross Network	KDD99 training to Kyoto2006 test
[84]	2019	Clustering hierarchical transfer learning (CeHTL)	Cross Time	Dos training to R2L test

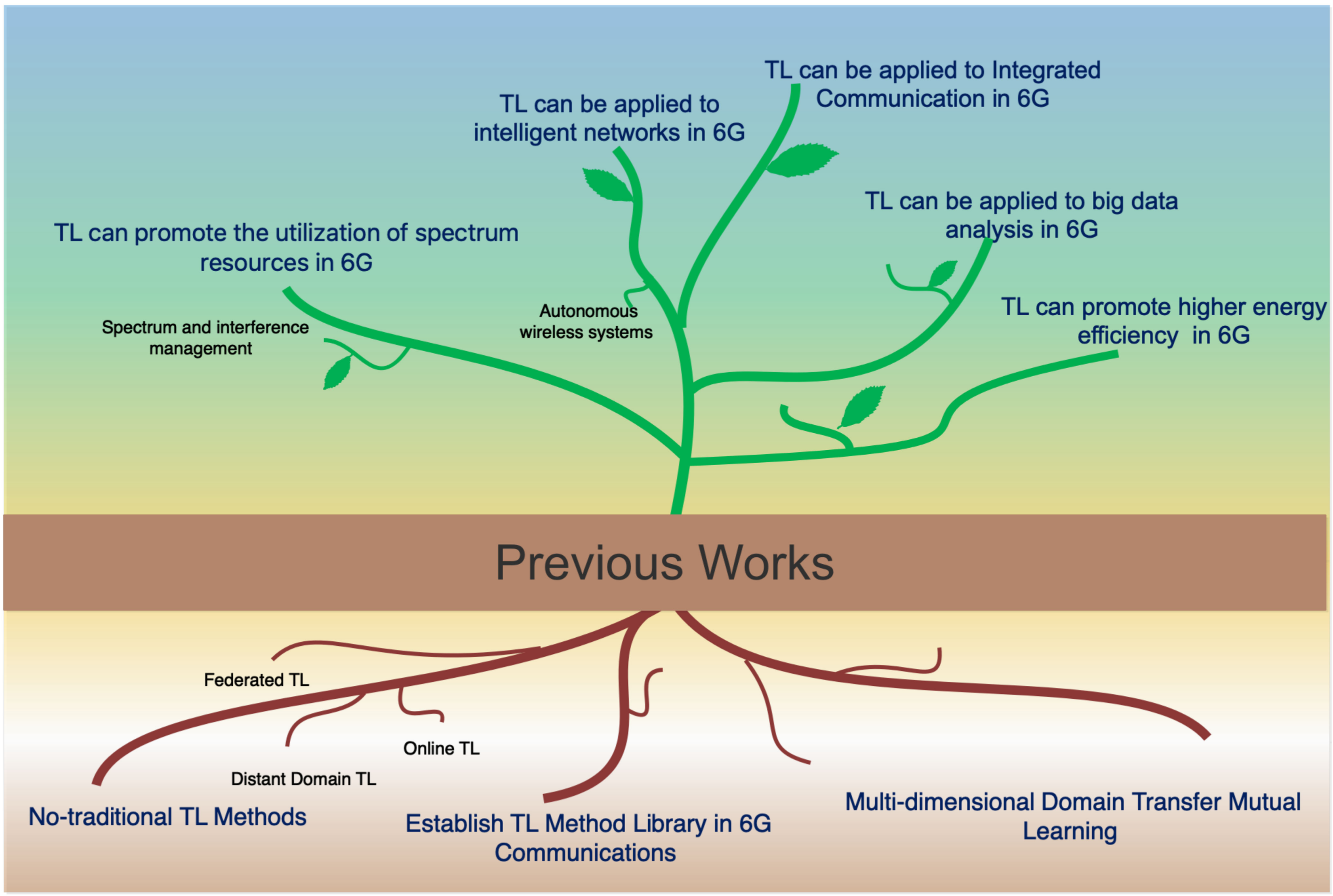

Fig. 6. Tree illustration of mutual aid between TL and 6G.

VI. MUTUAL RELATIONSHIP BETWEEN TL AND 6G COMMUNICATIONS

6G wireless communications has entered the planning stage, so it is necessary to make a reasonable effort to outline the future view of next generation wireless communications. The increasing quantity, complexity, and performance demands of communication systems require thinking to envision new technologies to balance the relationship between growing demand and consumption. In recent years, TL is also believed to enable system further efficiency, which means learning time and energy consumption can both be reduced. The successful application of TL in wireless communications described earlier has a clear motivation to view it as a potential technology for 6G wireless communications. This section presents some possible directions for the application of advanced TL techniques in 6G communications, and some of the challenges in 6G communications may be addressed through the aid of TL. Furthermore, the potential mutual relationship between them is similar, as shown in Fig. 6.

A. 6G Promotes the Development of TL

With the development of 6G communication and TL, advanced TL methods will be more capable of solving complex problems. Here are some possible development directions.

1) Distant Domain TL (DDTL): DDTL [89] relaxes the close relationship between the source domain and the target domain, which is very different from traditional TL, and it even allows the source domain and the target domain to be completely different. 6G will involve a large variety of heterogeneous communication systems, such as frequency bands, communication topologies, and service delivery. Moreover, the hardware settings of the AP and the mobile terminal will be very different. Therefore, integrating all communication systems into one platform will be challenging. If DDTL can be applied to this large heterogeneous platform, it can not only closely connect heterogeneous devices to learn from each other, but also avoid the loss caused by repeated training.

2) Online TL: It is generally assumed that the source and target domain data are given and the transfer can be done directly. However, the real application is often not like this: at the beginning, perhaps only the source domain data and the target domain data are continuously sent from a little bit. This is called "online transfer learning" [90]. Online real-time processing is very important for many applications in 6G, such as cell-free communication, dynamic network slicing, and integration sensing and communication.

3) Federated TL (FTL): FTL is a part of federated learning (FL). FL is a distributed ML algorithm that allows users to collaboratively learn shared models while preserving their private data not being shared and retaining the collected data on the device. Privacy is one of the essential properties of FL [91]. The ever-increasing computing and storage capabilities of wireless mobile devices will provide opportunities for 6G local processing data to achieve distributed training on the device. However, volatile wireless channels cannot guarantee data privacy and security, which has become an important bottleneck for distributed training on mobile devices. In order to enhance data privacy and security, FL technology allows training data to be stored on each device and to learn a shared global model from distributed mobile devices. However, the local update model and global model aggregation calculated on each mobile device are limited by bandwidth and computing resources. The FTL will provide a very important way for interconnected learning and privacy protection for large-scale close-knit and independent network structures. Suppose the shared resources between source and target domains are very few, in this case, the TL-based approach can be used to provide a shared approach to the entire sample and feature space under federated conditions. In particular, a shared representation among the feature spaces is learned using a finite set of overlapping samples and then applied to the prediction of the samples that obtain the features of the target domain. It is an important development direction of existing FL, and even exceeds the scope of existing TL algorithms in the future. Some researchers have studied the problem of training FL algorithms over a realistic wireless network, and in the future communication networks, FTL would be the main security/privacy solutions for cooperative communication system.

4) Multidimensional Domain Transfer Mutual Learning: The 6G system will integrate ground and air networks, such as 3-D BSs, which will be provided through low-orbit satellites and drones to support the communication of users in vertical expansion. The 3-D network expands in the vertical direction. Therefore, a new dimension has been added. Cross-dimensional TL can promote dimensional communication and greatly enhance overall system performance.

5) Establish TL Method Library in 6G Communications: The application of TL in 6G wireless communications has great potential value, and there will be all kinds of TL algorithms applied to different fields of wireless communications. Under the same source domains and target domains, different TL methods transfer different knowledge, so the final improvement effect on the target domain is different. Manual selection of TL algorithms by researchers is not only time consuming but sometimes not accurate enough. In order to enhance the TL effectiveness from a source to a target domain by leveraging previous TL experiences to optimize what and how to transfer between them, a learning to transfer (L2T) algorithm is proposed [92]. Based on the above, our idea is to establish a TL method library under the demand of wireless communication in the future and apply L2T algorithm to automatically match the optimal TL method in the library according to different environmental requirements to achieve adaptive TL in a complex wireless communication environment.

B. TL for Challenging Fields in 6G Communications

Successful deployment of 6G communication systems requires solving many technical problems. The application of TL will greatly help solve the problem. Several future research directions are introduced below.

1) Spectrum and Interference Management: In the face of scarcity of spectrum resources and spectrum interference, effective management of 6G spectrum (including spectrum sharing strategies and innovative spectrum management technologies) is very important. Efficient spectrum management is essential for maximizing QoS while achieving maximum resource utilization. As mentioned earlier, TL has been applied to help BSs/SUs share spectrum allocation experience and reduce the decision time of spectrum allocation and spectrum selection time of new SUs. Currently, TL used in the spectrum management is based on the application of RL, with a relatively single application approach. In the future, the 6G communication environment will change rapidly, with a large number and density of BSs and SUs. Therefore, it is of great value to further develop similar fast matching between BSs/SUs and agents, as well as rich TL methods in the study of spectrum resource management. In addition, researchers need to study how to eliminate interference using standard interference elimination methods, such as parallel interference elimination and continuous interference elimination. There may be similarities in the interference modes in different environments. TL can help the target environment to quickly identify the interference and actively eliminate the interference.

2) Autonomous Wireless Systems: The 6G system will provide full support for automated systems, such as autonomous vehicles, UAVs, and AI-based Industry 4.0. In order to create autonomous wireless systems, we need to mix different software subsystems (such as autonomous computing, interoperable processes, ML, autonomous clouds) and different heterogeneous hardware systems. Therefore, the development of the entire system becomes very complex and challenging, and the cooperation between the systems is very important. A complication caused by hardware heterogeneity is the excessive effort to redesign the system for different hardware settings. For example, different transceiver architectures have been proposed for mmWave systems, including analog beamforming, hybrid beamforming, and 1-b digital beamforming. The traditional method relies on manual design, which is very inefficient. These different

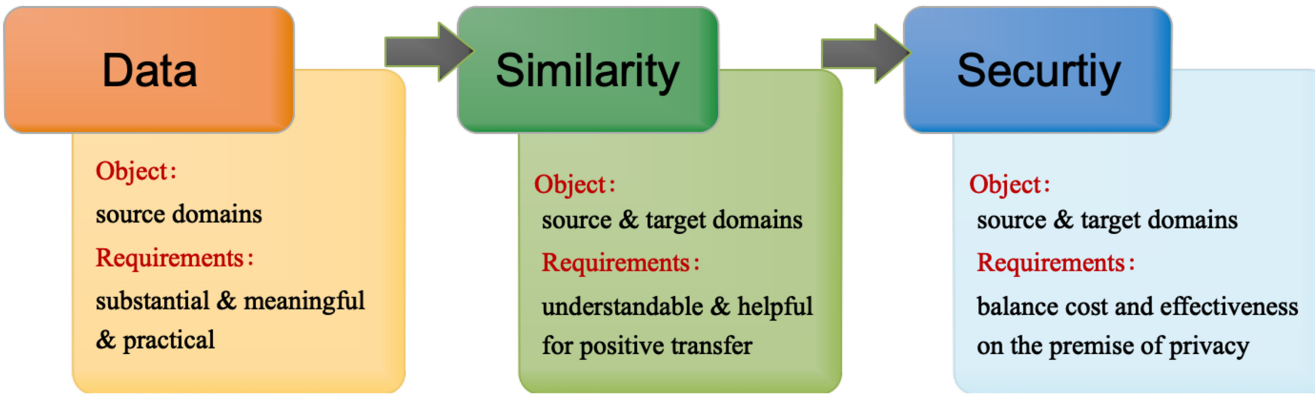

Fig. 7. Challenges and future issues.

types of transceivers will face the same problems in mmWave channels, so a well-designed algorithm for one transceiver may also help solve the design problems of another. TL is a promising technology that can help transfer the design of one architecture to others [6], [93]. TL can help share experiences between systems in similar tasks, thereby increasing autonomous wireless systems efficiency. In addition, TL can transform human experience into automation systems, such as a driver's driving experience, worker's operating experience, etc., reducing the difficulty and challenge of learning from scratch.

3) Big Data Analysis: The widespread application of intelligentization (big data) requires massive data transmission requirements. Intelligent application based on big data may be one of the important driving forces for the development of 6G communication system. Fully mining the relevance of big data system is the key to realize the efficient use of big data, and the relevance is just the premise of positive transfer. Therefore, using the relevance of big data for TL can further improve the use efficiency of big data in the future.

4) Integrated Communication: The goal of air, space, ground, and sea integrated communication is to expand the breadth and depth of communication coverage, that is, on the basis of traditional cellular networks, it is deeply integrated with satellite communications and deep-sea and ocean-going communications, respectively. The integrated communication is based on the ground network and extended with the space network, covering natural spaces, such as space, air, land, and ocean. Because satellite communication networks are affected by factors, such as the space propagation environment and network settings, they are significantly different from land mobile communication networks. No matter in the cooperation of different satellite systems or the cooperation of satellite systems and ground-based systems, the application of TL can reduce the delay and improve the system efficiency.

5) Higher Energy Efficiency: TL can help the system improve energy efficiency and save cost, which is an important reason for its popularity and will be the focus of the next 6G. The ultralarge-scale mobile communication network has become an indispensable part of the world's energy consumption. Not only does it generate huge carbon emissions, but it also accounts for a considerable portion of operating costs. In the future, 6G networks will have ultrahigh throughput, ultralarge bandwidth, and ultramassive ubiquitous wireless nodes, which will bring unprecedented huge challenges to energy consumption. Preventing the system from repeating the same work and facilitating the accumulation of experience between similar tasks are the advantages of TL and the key to reducing energy consumption.

VII. Challenges and Future Issues

We have demonstrated the great potential of TL in 6G wireless communications. In spite of the apparent opportunities, there are also challenges to apply TL to future 6G communications. This section summarizes the future challenges, including data, similarity, and security, as shown in Fig. 7. First, although TL can solve the problem of sparse data and greatly reduce the computational burden of network entities and BSs for the target domain, it cannot avoid the need for the amount of data and rich model training experience in the source domain. Second, the matching degree of the source domains and the target domains will directly affect the effect of the transfer model, but as the network scale expands and the node tasks increase, the similarity measurement of the source domains and the target domains will become more and more complicated. In addition, in the process of transfer of the source domain information to the target domain, how to balance the relationship between privacy information protection and the effectiveness of transfer model and cost consumption is also a big problem.

A. Collection and Open Access of Rich Real-World Datasets

From previous research, it was found that most applications of TL in wireless communications are based on ML research in this field, especially relying on RL. The ML model in the source domain requires a lot of data during the training process. It has to be admitted that accessible measured datasets in various application contexts are important sources of the rise of learning technology, such as the most famous "ImageNet" in the field of computer vision. These open access datasets provide support for the comparison of different learning algorithms in the same field. However, such accessible datasets for wireless communication are still under development. The difficulty of open access to real communication data lies in data protection and privacy regulations. TL can reduce the demand for data volume because it can avoid repetitive work, rather than create data unfounded. This is a fact that we need to recognize when applying TL.

B. Complex Similarity Analysis

As we know, looking for similar source domains is a prerequisite for positive TL, otherwise, it will cause negative transfer and other bad effects. So far, when TL is applied to wireless communications, the collocation of source domains and target domains is only through simple similarity analysis or artificial selection. However, the 6G network structure will be bigger and more heterogeneous, and the business types and application scenarios will also be more complex and changeable, resulting in more types of terminals and network equipment. The more complex the communication environment is, the more difficult the similarity analysis will be. In the future, more attention should be paid to the similarity analysis, namely the matching of the source domains and the target domains.

C. Privacy Protection During TL

Privacy and security are the prerequisites for effective technology. In recent years, a number of security and privacy protection solutions have emerged, such as quantum cryptography and physical layer security. In the application of TL in wireless communications, the issue of privacy protection has not received enough attention. The reason may be that the current transfer process is relatively simple and there is no conflict between domains. FTL is the most famous TL method for privacy protection, which requires data to be kept at the mobile devices instead of being uploaded to the cloud during the model training process, and frequent communications among the computing devices are needed for model updates. Privacy protection in the process of transfer is a very difficult issue because it involves multiple aspects, such as source domain knowledge selection, model definition, transfer knowledge acquisition, etc., and these factors need to coordinate with each other to ensure the effectiveness and control the cost.

VIII. Conclusion

Wireless communications need to be more flexible, more energy efficient, faster, and larger in scale, and TL is playing an increasingly indispensable role in wireless communications and will bring tremendous value to future 6G research. The conclusion of this article is described around two scientific problems, which are as follows.

1) The first part of the work highlighted why TL was needed for 6G communications.
   The requirements and technologies of 6G wireless communications were first outlined, where many of the requirements were contradictory, such as high efficiency and high density, just as high density and large amount of data inevitably led to loss of energy efficiency. TL can not only mitigated this contradiction but also affected almost every aspect of 6G requirements. Next, the basic concepts and classification of TL methods were introduced.
2) The second part of the work emphasized how to apply TL in 6G communication.
   We gave a detailed review of the advanced work based on TL in the wireless communications, focusing on the TL's outstanding contributions in six different application backgrounds, such as BSs/APs switching energy, spectrum allocation, content popularity prediction, indoor wireless localization, and intrusion detection. These studies are the cornerstone of future TL promoting adaptive wireless communications for 6G.

TL and 6G must promote each other and develop together. We sorted out the possible development directions between them like a tree: the technology was the roots and the demand was the leaves.

Finally, the future application trends and challenges of TL in 6G were discussed: data, similarity, and security. These three issues will be very critical for TL to apply to 6G.

Hopefully, this work will provide some ideas and inspiration for the application of TL in the future of 6G communications.

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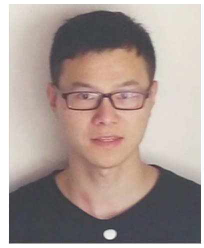

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