Application of Data Mining in the 5G Network Architecture

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Abstract— **Data mining is considered to be one of the key enablers for the next generation of mobile networks. The building of knowledge models is expected to tackle the complexity of these networks and enable their dynamic management and operation. Recently, this research area has attracted a lot of interest and several models have been proposed by the research community. This paper provides a brief survey of these efforts and captures the latest status in 3GPP. It also provides a detailed description of which information needs to be collected by network components, so as to be analyzed by a data mining scheme. Finally, it quantifies the amount of information that is required to be reported to the data mining engine.**

Keywords- 5G cellular networks; data mining; control functions optimizations.

I. Introduction

During the past years, a tremendous effort has been made for the design of the 5th Generation of mobile networks (5G). Research and standardization activities worldwide are in the process of finalizing the first release, while all major vendors are preparing for the first commercial showcases and large-scale deployments. 5G mobile networks target the provision of tailor-cut solutions not only for the telecommunications sector but also for the so called “vertical industries” (e.g., intelligent transportation systems, smart factories, the health sector, etc.). This will be achieved by deploying multiple logical networks (a.k.a. network slices) over the same network infrastructure. Thus, 5G networks will be considerably more complex than the previous generations [1].

At the same time, the scientific community has identified that big data solutions can significantly improve the operation and management of existing and future mobile networks [2]. Data mining is used to discover patterns and relationships between variables in large data sets. Towards this end, several mechanisms that include statistical analysis, artificial intelligence and machine learning are applied in the data set to extract essentially knowledge from the examined data.

Figure 1 illustrates how data mining can be integrated as a process with the mobile networks and where the extracted knowledge can be used. More specifically, data are collected from a number of network components. These data may include a variety of information fields such as the quality of the wireless channel, the network load, accounting information, configuration and fault indications, the profile of the subscribers, etc. These data are stored and updated regularly. When collected, they are passed through a pre-processing phase. During this phase transformation, discretization, normalization, outlier detection and dimensionality reduction is executed. The outcome of this phase is then passed to a data analysis phase where a model is built to extract knowledge from the processed data. For example, the result of this process will be the identification of situations where the occurrence of some specific events (e.g., a significant increase of the number of high moving users) causes some specific result (e.g., increase of the handover blocking probability). The knowledge model may also include some solutions for specific situations (e.g., force the network components to place high moving users to macro cells). The list of the knowledge discovery results can then be communicated to either policy, management or control modules. These modules can use this information in order to optimize the operation of the network and improve the performance. Note that for selecting the best configuration or optimization action from the list of the knowledge results, the abovementioned communication modules may require also real-time information related to the current performance indicators of a network.

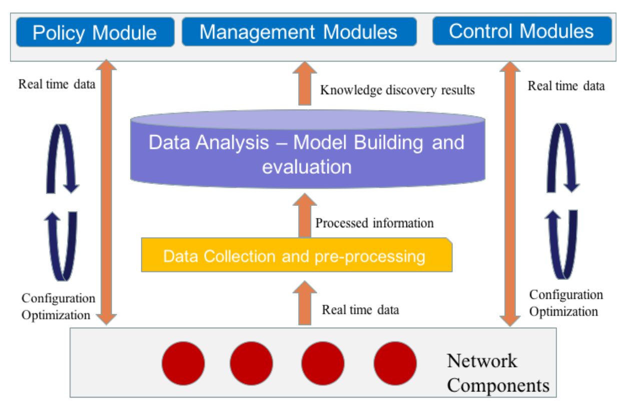

Figure 1. Big data analysis for cellular networks

As it will be presented in the next section, it is currently widely accepted that data mining will be an integral part of 5G networks. Currently, proposals focus on how data mining can feed knowledge on management and control modules. Although this work is quite valuable, the researchers focus on the data mining algorithms to be used and they do not always provide detailed examples of which exactly information needs to be collected, how often this collection has to take place and how one can minimize the data that has to be exchanged among network components and functions.

 ISBN: 978-1-61208-623-1

At the same time, 3GPP has included a dedicated function, called NWDAF (NetWork Data Analytics Function), in the latest specifications [3]. This function has currently limited functionality. It is used to provide information to influence, in real time, the policies that an operator is using.

The purpose of this paper is to provide a short survey for data mining solutions in 5G networks and extend the work presented in [4], where a data mining framework, called Context Extraction and Profiling Engine (CEPE), was introduced to improve the performance of control functions in a mobile network. The CEPE extensions include the identification of the 5G network components, as specified by 3GPP, that can be used to collect the necessary information. Also, the paper identifies which 5G functions can use the outcome of CEPE. The paper quantifies the amount of data that must be exchanged between network components for the operation of CEPE.

The rest of the paper is organized as follows. Section II provides an analysis of the state of the art for data mining in 5G networks and the latest status of 3GPP for the specification of NWDAF. Section III briefly presents the CEPE framework and maps its functionality CEPE in the latest 5G architecture. Section IV quantifies the amount of data that needs to be exchanged and suggest an approach on how this can be further reduced. Finally, Section V concludes the paper.

II. State of the Art Analysis

This section discusses the existing state of the art proposals presented by the research community and the current status of 3GPP activities.

A. *Research literature survey*

As mentioned previously, many academic researchers have focused on the use of data analytics mechanisms in 5G communications. The authors in [5] explain how random matrix theory and machine learning can be used to enable the adoption of big data schemes for mobile cellular networks. Moreover, they provide a survey of solutions on how big data can be used to analyze signaling information in cellular networks as well as the traffic of user plane data. This analysis is able to reveal certain traffic and user behavior characteristics and even waveform related data to estimate the mobility of users. The work in [6] presents a generic extraction and correlation framework that targets to reduce the vast data set through randomization and a coarse preservation of statistical relationship among data records. This scheme is quite valuable but is generic and the authors do not provide detailed examples on the information be used and how the outcome can be used by 5G networks. Unfortunately, the removal of unrelated and non-useful data remains an open question. This is significant, because collection and transmission of useless information is burdensome on the network.

[7] presents the findings of the SELFNET H2020 project. Its target is to provide an autonomic network management framework for 5G mobile network infrastructures. The paper focuses on the analyzer module that infers data from a set of collected metrics. It describes in detail the operation of the analyzer module but it does not provide a detailed discussion on the information that needs to be collected to support specific 5G use cases. The authors of [8] provide a new framework, named Big Data SON (BSON) that takes into consideration subscribers' level data (i.e., network related performance on a per user basis such as throughput, delay, blocking and drop rates, etc.), cell level data (received signal strength of serving and neighboring cells, number of active users, etc.), core level data (alarms, configuration, security data, Call data records, etc.). By applying data mining schemes the authors suggest that these data can be used to improve SON mechanisms and essentially transform SON to be proactive instead of reactive. The paper provides an exhaustive list of information that can potentially be used but it does not analyze the traffic volume that needs to be collected in order for the scheme to perform the desired results. Although this is a holistic solution that can be used for all SON cases the authors only demonstrate its application for a simple scenario. Following the main principles presented in Section I, the authors of [9] present the key features of user and mobile network data that can be potentially collected and processed by a data mining scheme. They also discuss how resource management, planning, interference coordination and cache server deployment is done nowadays. They suggest that these can be greatly improved if data analytics is adopted by network operators. Although the paper discusses extensively main operation principles, there are no detailed examples.

In relation to the optimization of radio resources using data analytics, the authors of [10] present a scheme that analyzes historical information gathered from an operational wireless network. Their model uses a weighted k-Nearest Neighbors model and can predict future network load levels and optimize the network accordingly. An interesting idea is presented in [11] where it is proposed that big data can be used to optimize the performance of the protocol stack in RAN (e.g., reduce the overhead in Radio Header Compression in PDCP, or the minimization of signaling during the execution of a handover, etc.).

In [12], a system that can handle 4.2 Tbytes of traffic data from 123 Gbs links in the core network of a 2G/3G operator. By analyzing application layer information, they are able to identify the exact model of an end device as well characteristics of users' behavior. The authors of [13] discuss how the call detail records collected from a legacy mobile wireless network can be used to identify how a large fraction of people are moving inside a city. Using an end-to-end Hadoop system, they are able to identify the hangouts and trajectories of users with different interests. The goal of this work is for the operators to be able to deliver such data and insights to other enterprises.

The work presented in [4], provides a framework where data mining on user related information can provide to a number of control functions the needed extra context information to improve their performance.

Finally, the work in [14] aims to improve the personalized QoE for end users by following a two-step modelling approach, combined with big-data analysis, to identify the relationship between users and services. More specifically, this approach requires to obtain real-time information about the application the users are using (online part) and adopt a

 ISBN: 978-1-61208-623-1

data mining (offline training part) scheme to predict the users' preferences and expectations. Then, the network resources are managed accordingly to support a satisfactory QoE.

Some of the abovementioned solutions require user data traffic analysis (e.g., [5] [10] [12]). This however requires the transfer and processing of a huge amount of data some of which (e.g., video streams) may be encrypted. Some of the solutions try to address a holistic approach covering from network management process (e.g., healing, optimization, fault detection) to the support of personalized QoS for the users. These solutions identify a plethora of parameters that have to be taken into consideration (from radio measurements, preambles, link utilization, subscriber data, customer retention management data, as well as application data, etc.). Such solutions have of course a huge complexity and the current literature does not provide detailed examples, in terms of which data have to be collected and from which entities. Equally importantly, none of the abovementioned solutions elaborates on how to minimize the required information to be collected. Finally, some of the solutions like [10] and [11] are addressing the management of the resources in a coarse level for all users. Only [14] provides a personalized solution for end users, but since the paper focuses on QoE it requires that the User Equipment (UE) should collect a lot of information and transfer it regularly to the network for further processing. This requires a lot of processing power in the UE as well it may affect the battery level consumption. Moreover, the exchange of a significant amount of data over the wireless link, by a large number of UEs, may cause performance issues to the overall network. In the next section, we will describe how [4] can provide improved and personalized services to end users while at the same time eliminating the burden on the end devices and the exchange of data over the wireless link.

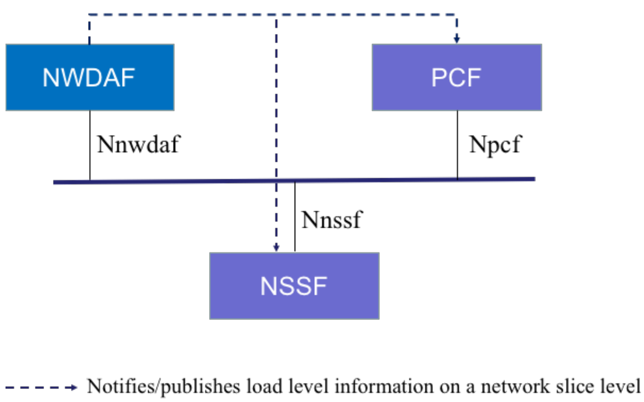

Figure 2. Data Analytics in 3GPP

B. 3GPP's NetWork Data Analytics Function (NWDAF)

Quite recently, 3GPP has identified the need to incorporate a dedicated data analytics function (NWDAF) in the latest specifications [3] [15] [16]. This entity represents an operator's managed network analytics logical function.

As shown in Figure 2, NWDAF provides slice specific network data analytics to the Policy Control Function (PCF) and the Network Slice Selection Function over their newly specified interfaces (i.e., Nnwdaf, Nnssf and Npcf). Interestingly enough the latest specifications describe that NWDAF will provide only load level information on a network slice level and that it is not required to be aware of the current subscribers using a slice. PCF uses the received information to select policy rules whereas NSSF may use the same information for selecting the most suitable slice for a UE. Note here that this type information can be collected from the network management system. Also, in Release 14, the RAN Congestion Awareness Function (RCAF) was used to inform the PCF about the congestion in RAN. Thus, 3GPP essentially is currently using NWDAF as a placeholder for future releases. In these, additional information will be provided to PCF and NSSF. This information will be related to the type of UEs or even for specific UEs, since PCF and NSSF are used to control the placement and treatment of UEs in the appropriate cell and radio access technology. Already, the output of NWDAF is considered to feed new network components related to access traffic steering, switching and splitting schemes (ATSSS) as reported in [17].

III. INTEGRATING THE CEPE FRAMEWORK WITH THE 5G ARCHITECTURE

A. The Context Extraction and Profiling Engine (CEPE)

The work presented in [4], is able to automatically build a user profile that can be used to predict the future behavior of a subscriber. This information is used to improve the performance of network control operations. More specifically, static and dynamic information is collected about:

1. **User profile related information (static):** gender, device type characteristics (e.g., cpu, memory, os, device type)
2. **UE and device dynamic characteristics (dynamic):** location, transmission power, amount of transmitted and received data, experienced delay, loss of packets, associated cells identifiers
3. **Network related measurements (static and dynamic):** type of cell (e.g., macro, femto, etc.), power transmission level, available resource blocks, amount of transmitted and received, data, delay, packet loss, number of connected devices

Based on these measurements, the authors use data mining to build a knowledge model, the outcome of which is essentially a dynamic profile for end users. This profile predicts their future behavior based on their location, time and day, the battery level of their devices and their monetary charging status. This way the network can use this information to place users to the appropriate cells and radio access technologies during the execution of a handover or a new session establishment. Also, this information is used by the end devices to select the most suitable cell to camp on, when they are in an idle state. Extensive simulations demonstrate significant performance improvements both for the network operator as well the end users. Note here that this is exactly the information (i.e., the dynamic profile of users that captures their future behavior in terms of mobility and service consumption), that the newly introduced NWDAF can report to the PCF and other network components to improve the

 ISBN: 978-1-61208-623-1

performance of a 5G network. Thus, CEPE is essentially potential future evolution of NWDAF.

The next subsection presents in detail how the CEPE framework can be mapped in the latest 5G architecture by extending the interfaces connecting today NWDAF to multiple network functions. It also presents which information is collected from the network functions as well and the control functions that will receive the outcome from the data mining model.

B. Mapping the CEPE framework in the 5G Architecture

The introduction of NWDAF in the 5G architecture and its interfacing with the PCF clearly indicates that in the future, its output will be used to select the most appropriate policies for UEs or types of UEs (e.g., high/low moving terminals, terminals involved in high/low data rate exchange, etc.).

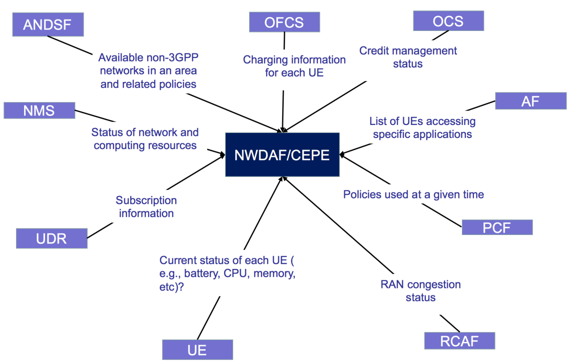

Figure 3 Provision of information to NWDAF

In the state of art research efforts (e.g., [4], [13]), it has been identified that users tend to have the same behavior that is dependent on the terminal they use, their monetary charging status and preferences, the status of their battery and obviously their location (e.g., home office, on the road, etc.) during specific dates and hours. Their behavior also depends on the status of network components (e.g., the load of the network, the received signal strength, the experienced delay or packets losses). All this information is required for a data mining function like NWDAF/CEPE to create a realistic model and enable the selection of appropriate policies or fine tune network control functions. In Figure 3, the network components that have to feed information to the NDWAF/CEPE as well as the type of this information are illustrated. These 5G network components are:

- **Unified Data Repository (UDR):** provides subscription information about a UE.
- **Network Management System (NMS):** reports performance indicators (e.g., bandwidth utilization, packet loss, latency, alerts, etc.).
- **Access Network Discovery and Selection Function (ANDSF):** reports the current policy rules shared with a UE to help it decide to which available WiFi it may connect to.
- **Offline Charging System (OFCS):** passes information contained in Charging Data Records (CDRs) that are related to the resource usage of a UE.
- **Online Charging System (OCS):** informs about the current credit management status of a UE.
- **Application Function:** is able to inform which services (even from those not being owned by the operator) are being used by a UE. As specified in [3], the communication of AF with the network operator's components takes place via the Network Exposure Function (NEF).
- **Policy Control Function (PCF):** provides information about the current session management policies being used in the network.
- **Radio Congestion Awareness Function (RCAF):** provides RAN user plane congestion information.
- **User Equipment (UE):** provides real time information about the current battery level of a UE.

Based on this information, the NWDAF/CEPE can collect information that is related to the current behavior of users and create their dynamic profile that essentially is a prediction of their future actions. Table I presents some examples of behavioral profiles that can characterize a single user or a set of users that have the same behavior. To create such a list the NWDAF/CEPE requires mainly information from the UE, the OFCS the OCS, the UDR and the AF (optionally). It also requires information from the NMS and the RCAF.

At the same time, the NWDAF/CEPE should have the information about the current policies being used by the operator as it receives the related information from the PCF and ANDSF. This way it is able to correlate the received input and identify a) the best policies to be used, b) the estimated bandwidth required for a future period of time in an area and c) what is the optimum placement of UEs in cells and radio access technologies. This is doable since the network is aware of the type of users in an area, their number (from those that are connected or those that have recently performed a location update process) and the available capacity of the network. Thus, NWDAF/CEPE can provide rules to PCF in the form of

- Profile (Home C) ^ # of users (high) ^ Network load (high) → place users in femto cells
- Profile (On the road) ^ # of users (any) ^ Network load (any) → place users in macro cells

 ISBN: 978-1-61208-623-1

TABLE I. EXAMPLES OF BEHAVIORAL PROFILES

Profile Type	Location	Day	Time	Battery Status	Charging Status	Service	Consumption level	Mobility	Network Status
Home A	Home	Mon-Fri	19:00-21:00	High	Credits available	Voice calls	Frequent and long duration	Static	Any status
Home B	Home	Mon-Fri	19:00-21:00	low	Low credits	Voice calls	Infrequent short calls	Static	Any Status
Home C	Home	Mon-Fri	21:00-24:00	High	Credits available	Video streamin g	High data consumption	Static	No load
Home D	Home	Mon-Fri	24:00-08:00	Any status	Any status	No activity	No activity	Static	Any Status
Office A	Office	Mon-Fri	09:00-18:00	High	Credits available	Voice calls	Frequent and medium duration	Low mobility	Low-Medium Load
Office B	Office	Mon-Fri	09:00-18:00	low	Credits available	Voice calls	Infrequent and short duration	Low mobility	Any Status
On the road	!Home && !Office	Mon-Fri	Any time	Any status	Any status	Voice calls	Infrequent and short duration	High Mobility	Low-Medium Load

The behavioral profiles of users can be communicated to any network functions that are responsible for managing the user mobility or the establishment and management of user sessions. Such entities are:

- **Access and Mobility Management Function (AMF):** supports mobility management, access authentication and authorization, security anchor functions and context management. The behavioral profile can be used to fine tune the location update procedure (e.g., its frequency, the tracking area list, etc.).
- **Session Management Function (SMF):** supports session management, selection and control of UP functions, downlink data notification and roaming. The behavioral profile can be used to select the most appropriate user plane path.
- **Traffic Steering Support Functions (TSSF):** receives traffic steering control information from the PCF, to steer traffic towards specific WiFis. The behavioral profile can affect these steering decisions.
- **5G Base Station (gNB):** provides user plane and control plane protocol terminations towards a UE. The behavioral profile can be used to fine tune the admission control and handover procedures as well as the information broadcasted to the UEs to assist them selecting the best cell to camp on.

The next section presents an approximation of the amount of data that is required to be exchanged and suggests how this can be minimized.

IV. QUANTITATIVE ANALYSIS

The analysis in Section III indicates that the sources providing data to the NWDAF can be distinguished in four categories. The first one consists of sources that provide static or rarely changed information. In this category belongs ANDSF and PCF that provide the list of active policies in a network and UDR that contains user related subscription information. Since this information does not change often limited actions can take place in order to minimize their communication to NWDAF/CEPE.

The second category contains information from the NMS and the RCAF that have to be reported to the NWDAF either at regular intervals or whenever there is a specific event (e.g., a threshold violation). This information is required for NWDAF to create a knowledge model that correlates the number of specific types of UEs in a specific area, the applied policies in this area and the performance of the network. Again, this information cannot be easily avoided or minimized.

The third group of information is related to the battery level of UEs (that influence the usage from the users) and the accessed services from the application servers. This information can be considered as optional since the behavior based on the remaining battery level can be inferred by information available in the fourth category, whereas the accessed services information is useful for the operator to fine tune the support of the services (e.g., video caching schemes). The final category contains information available at OFCS and OCS [18]. The CDRs contain essentially all the information needed to create the user behavioral profiles while avowing any extra communication of network components with the UEs. Table II contains the required parameters and their size. Note that this is a simplified version of the overall list since as specified in [19], several parameters are duplicated based on the network used (GSM, UMTS, LTE) as well as the specific services (circuit switched, packet switched, IP Multimedia Subsystem – IMS, etc.)

TABLE II. CDR PARAMETERS

Parameter	Size
1. International Mobile Subscriber Identity (IMSI)	64 bits
2. International Mobile Equipment Identity (IMEI)–*Which device a user is using*	64 bits
3. Timestamp	32 bits
4. Call duration (CS)	16 bits
5. Cell Identifier	20 bits
6. RAT Type-*which Radio access technology was used*	8 bits
6. Duration (PS)	16 bits
7. Data Volume Downlink	16 bits
8. Data Volume Uplink	16 bits
9. Record Opening time	32 bits
9. Change Condition – *e.g., user location change*	5 bits
10. QoS Profile – *requested/negotiated*	128 bits
11. Service Identifie	32 bits
13. Traffic Steering Policy Uplink	8 bits
14. Traffic Steering Policy Downlink	8bits
15. User location information	8 bits
16. User location information time	32 bits
Total	505 bits

Note that to identify the level of mobility of a user NWDAF/CEPE can simply process the information about cell identifiers, and user location that is contained in the parameters of Table II. This way neither the UE has to monitor and report its mobility level, nor the network components perform any complex functions to estimate it.

The analysis above indicates that based on this small amount of data per UE, the behavioral profile of end users can be created and improve the control performance of a mobile network [4]. Also, this process is transparent to the UEs and is based on information already available to the operators. Overall, the data that has to be collected from all network components is captured the following equation:

$$\text{Total} = \sum_{k=1}^{n} \text{CDR}_{\text{k}} * \text{T}_{\text{k}} + \sum_{l=1}^{\mu} NMS_{\text{NCl}} * \text{T}_{\text{l}} + RCAF_{\text{data}} * T_{\text{r}}$$

Where CDR_k and T_k are the information of Table I for every UE and their transmission rate, NMS_{NCl} and T_l are the network related information for the different network components and its correspondent transmission rate and $\text{RCAF}_{\text{data}}$ and T_r indicates the information transmitted by RCAF. From the above discussion only the first part of the equation can be minimized. This can be achieved only if the behavioral profiles of the UEs are communicated to the OFCS. When the received profile of the users is consistent with their current recorded behavior, no additional information needs to be transmitted back to NWDAF/CEPE. The gain in efficiency of such a scheme can be deduced from an example with basic parameters, as presented in Figure 4. In the figure, the performance gain is compared in a network of 1-10 million users using scenarios where data is sent every 30' to the NWDAF/CEPE without optimization versus optimization via several assumptions on "profile consistency". The assumptions on "profile consistency" include scenarios where data is transmitted only when user behavior is inconsistent with the received profile 30%, 60%, and 90% of the time.

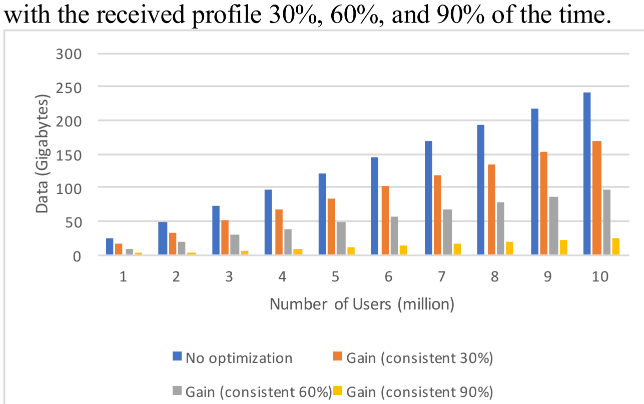

Figure 4. Comparison of data transfer schemes

V. CONCLUSIONS

This paper discusses why data mining is going to be a key enabler for 5G networks by providing a short survey of existing proposals. Also, based on the latest progress of 3GPP it analyses why the newly introduced NWDAF is not adequate, in the current version, to support data mining.

Moreover, it presents in detail which information is required to be collected and reported to NWDAF/CEPE and quantifies the amount of information that is required. It also, reports which entities of the 5G architecture could exploit of the knowledge created by a data mining framework.

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 ISBN: 978-1-61208-623-1