Unlocking the Path Towards Intelligent Telecom Marketplaces for Beyond 5G and 6G Networks

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***Abstract*—6G systems are perceived to be heavily softwarised, and therefore, the collaboration among all stakeholders, such as network and cloud providers, operators, application developers, service providers and device and equipment vendors, shall occur via software in a secured, distributed, and automated manner. This could be envisioned with a brokerless and immutable Marketplace anchored in Distributed Ledger Technologies, removing the need for a trusted party as Marketplace operator while avoiding this single point of failure, increasing transparency and flexibility of operational rules, and featuring automated contract negotiation and fulfillment supporting governance, delivery, and billing operations. This work goes a step forward and introduces a Smart Resource and Service Discovery application, based on intent recognition and Machine Learning assisted techniques, to enable the automated discovery of resources and services exposed over the Marketplace. Evaluation results demonstrate the accuracy of our approach and its suitability to provide decentralized Telecom Marketplaces with intelligent and data-driven discovery capabilities.**

***Index Terms*—Marketplace, Intent-based, Machine Learning, Artificial Intelligence, B5G, 6G.**

I. Introduction

Softwarization and cloudification of network resources and services have played a dominant role in the evolution of Telecom networks, with network slicing, i.e., logical partitioning of the physical compute, storage, and network infrastructure, providing great flexibility and unified network management via an abstracted and technology-agnostic view over available underlying resources. In this respect, the convergence between computing and networking ecosystems has been a key ingredient in realizing the "as-a-Service" paradigm, where different network resources and services can be provisioned, configured and combined dynamically and on-demand, to satisfy versatile and stringent latency, bandwidth, reliability, and security requirements of next-generation network systems.

At the same time, 6G systems [1] are expected to continue the trend of leveraging heavy resource softwarization, while pushing for significant improvements by orders of magnitude on Quality of Service (QoS) capabilities. The latter, combined with the objective of user-centricity and improved user experience, call for granular sophisticated services and for the densification of physical network (access) resources to satisfy ubiquitous network coverage with advanced services' availability. Nevertheless, the huge CAPEX and OPEX investment of such systems can only be shared in a viable and sustainable way by introducing multi-party schemata, i.e., "Marketplaces" whereby resources and services can be contributed by different administrative entities and consumed in such an integrated way to continuously respond to dynamically evolving networking and application needs.

For future networks to be application- and user requirements-aware, the transition towards such Telecom Marketplaces shall not be restricted to horizontal paradigm shifts among traditional stakeholders. Instead, it shall involve diverse communication service providers to cover the complete stack, from vendors' equipment to network operators, cloud and service providers, and application developers. However, the inclusion of such heterogeneous stakeholders and the management of multi-layer and multipurpose services into a common environment, introduce extreme complexity as well as privacy and trust challenges.

To respond to the requirements posed by modern smart applications for timely and efficient network optimization, while treating the ever-increasing amount of produced data as an opportunity instead of a performance bottleneck, data-driven Machine Learning (ML) techniques are expected to play an important role. At the same time, another key enabler towards coherent multi-stakeholder environments and alleviation of privacy and trust concerns, is the formulation of robust distributed Marketplaces for sharing network resources and services. In this context, automation techniques can significantly aid in the effective discovery of available offers, while trustless computing paradigms such as permissioned Distributed Ledgers Technologies (DLT) [2] can ensure the integrity and security of involved processes.

This paper proposes novel forms of dynamic resource and service discovery for 6G systems to enable the automated identification and selection of distributed and multi-party resources. The goal of this work is to provide an analytical tool that takes customization and flexibility as the main guiding principles to facilitate the identification of available offers. In this sense, the contribution of this work is three-fold:

- A novel architectural element is presented, named *Smart Resource and Service Discovery*, able to provide decentralized Telecom Marketplaces with intelligent and data-driven discovery capabilities, to enhance coordination and delivery across stakeholders on B5G/6G networks;
- Clustering and classification ML models are designed to draw patterns across offers types and determine the most

similar categories for a new offer to speed up the search in the requests of the Marketplace;
- Domain Specific Languages (DSL) are proposed to capture users' high-level intents and enable the matching with pre-trained offer clusters.

The rest of the article is organized as follows. Section II provides the related work. Section III presents the architectural view of our approach. Section IV describes the components and operation of the proposed framework. Then, the evaluation results are discussed in Section V. Concluding remarks are presented in Section VI.

II. Related work

Digitization has radically transformed Telecom industries, exposing a novel strategic perspective on demand and supply, as well as an "ecosystem" view that emerges from the transition to a service-based paradigm. In [3], a holistic resource configuration framework is introduced, emphasizing the promotion of customers to potential "value co-creators" in a digitally enabled, networked world and opening the door to multi-stakeholder services as synthesis of heterogeneous resources that correspond to heterogeneous needs. This framework is adopted in [4], together with the "coherent 4C typology" of commerce, context, content and connection, to evaluate the value-creation potential of decentralized Blockchain technologies in autonomous 5G network slice brokering and in energy-oriented smart grids. The authors conclude that the value-creation of such technologies is conditional to the concrete technological deployment decisions, such as Blockchain platform selection and configuration, as well as to the business frameworks that govern such deployment, having to do with regulatory aspects, use case-driven business rules, etc.

To bridge the business layer to technological primitives, Intent-based Networking (IBN) frameworks aim at capturing and automatically translating "sufficiently" networking-savvy users' high-level preferences, i.e., *intents*, to technical deployments and adaptations of network resources, usually in a closed-loop fashion.

Growing research interest has been recently devoted to the use of IBN systems to automate network slicing operations [5], [6]. In this context, IBN tools can take high-level configurations and generate a network slice template according to the network orchestrator's acceptable format, through a GUI or with Controlled Natural Languages (CNL), restricting the user input to pre-defined grammars.

Other than networking, intent-based systems have been proposed in various fields, particularly to tackle the complexity of multi-domain scenarios. In [7] a CNL was used to support Intent-based Blockchain selection. In [8] the Extended Backus-Naur Form (EBNF) helped define a simple grammar for supply chain assets access control. In these cases, restrictions on the user's natural language input are often imposed to guide the query, restricting it to a static grammar, which does not allow the reposition of the words in different places in the intent.

Once a user's request is translated, it is important to count on efficient algorithms that facilitate search and classification. In this sense, online and offline ML models allows identifying patterns and defining labels used to classify new requests. In particular, clustering mechanisms are generally employed to facilitate the intelligent categorization of requests from decision engines [6], and to enable a more consistent mapping between the users' intents and the resources provided. However, sometimes clustering algorithms may not be efficient if the input of a request does not have all the features of the training ones, their accuracy is harder to monitor, and online retraining is complex.

Prior research proposes for scenarios like Telecom Marketplaces, in which offers' requests are usually incomplete, the combination of offline clustering algorithms, to identify common features and assign clusters' labels, and online simple classification algorithms, e.g., decision trees, for more accurate classification and faster retraining [9]. Other works exploring the joint use of clustering and classification algorithms can be found in [10], [11]. The authors of [10] employ clustering and random forest models for improved management of 5G networks and service classification for Service Level Agreement (SLA) assurance, while the paper in [11] discusses the role of such algorithms in cognitive and zero-touch network management.

Based on the above, in this work, a mechanism building on the joint use of clustering and classification algorithms is proposed to facilitate the categorization and pattern identification of offers on a Telecom Marketplace based on multi-domain criteria. For the intent realization, a precompiled language model is used, showing the improved capabilities of a language model in contrast to a simple RegEx implementation.

III. Architecture

The system architecture taken as a reference in this work corresponds to a decentralized Marketplace [12], which is, at the same time, comprised of a mesh of distributed Offering Catalog instances and underpinned by the use of Smart Contracts and a DLT network. This Marketplace provides the tools for the onboarding of assets and the composition of offers, which are disseminated among multiple participants taking advantage of the underlying DLT network. Likewise, on-demand order capture and agreement settlement for offer purchase is automated via Smart Contracts, as programmable logic that rules the lifecycle operations of managed entities.

In this work, we introduce a new subsystem into this architecture, named *Smart Resource and Service Discovery*, aimed to complement the Marketplace functionalities with intelligent discovery capabilities. Fig. 1 illustrates the positioning and interaction of the proposed data-driven subsystem within such a decentralized Marketplace, able to foster collaboration for cross-domain and end-to-end service delivery among multiple stakeholders in the B5G/6G ecosystem.

The Smart Resource and Service Discovery's main objectives are to intelligently define relationships in the offers and to translate high-level discovery intents from users' requests. To achieve these goals, it leverages ML-based models to perform intelligent discovery of resource and service offers published at the Marketplace.

Internally, the Smart Resource and Service Discovery application is the result of the following functional entities:

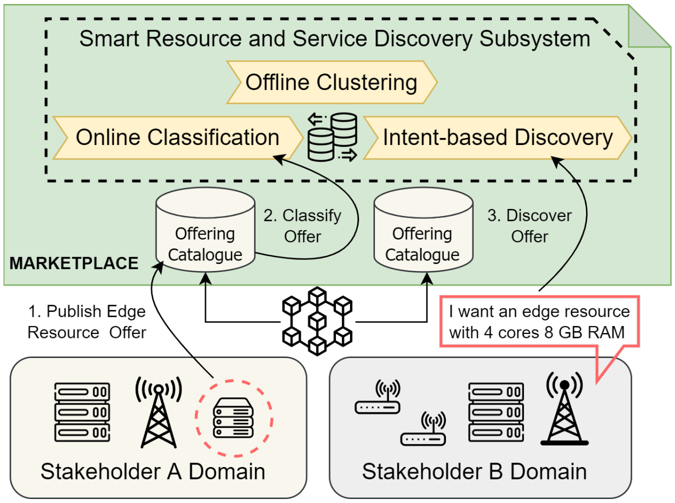

Fig. 1: Smart resource and service discovery architecture and sample workflow.

- *Offline Clustering Function* exploits clustering techniques for pattern identification across offers of a certain class. To do so, a clustering model is trained offline to learn the similarities between the resources and services' properties within each offer type and generate a set of artificial clusters. To ensure the model's accuracy over time, this procedure can be repeated periodically (e.g., after receiving a certain set of offers or during system maintenance) taking as training dataset incoming offers accumulated since the last performed training.
- *Online Classification Function* employs supervised learning, taking the resulting clustered offers as labeled dataset for training. The trained model can then determine at runtime, for every incoming offer, the cluster it belongs to. The selected cluster is added then to the stored offer information. Similarly, retraining can commence upon any update to the offer's clusters.
- *Intent-based Discovery Function* receives offers' retrieval requests in the form of high-level *intents* in a natural language. The intent for desired offers includes users' requirements and preferences, which correspond to the offer type (e.g., edge, spectrum) and to characteristics to be prioritized (e.g., memory capacity, operating band). Using intelligent Natural Language Processing (NLP) techniques, this intent is automatically translated into a ranked set of offers that best satisfy users' requirements.

IV. Smart Resource and Service Discovery

The workflow associated with the services offered by the Smart Resource and Service Discovery application is depicted in Fig. 1. This figure illustrates a sample scenario involving two Marketplace parties, i.e., Stakeholder A and Stakeholder B, which act as provider and consumer, respectively, of an edge offer. Coarsely, the main steps are 1) the submission of a new offer into the Marketplace; 2) the classification of the incoming offer; and 3) the translation of the received intent and the retrieval of corresponding offers. These steps are further described next. For the sake of illustration, the workflow assumes a sequential order of steps, however, the occurrence of the discovery request (step 3) can happen at any moment and the response will be following the existent offers in the Marketplace.

Step 1: To publish the offer, Stakeholder A, acting as the provider, encapsulates the technical specification of the considered edge resource, together with the corresponding business-related terms (e.g., SLAs and pricing). This information is submitted to the system using open standard interfaces [13]. To meet the requirements of the considered Telecom Marketplace context, multiple offer categories are supported representing the heterogeneous types of network assets to be traded.

Step 2: Upon the submission of a new offer, an online ML model (served at the Online Classification functional entity), is used to define the group (i.e., the cluster) to which it corresponds. The resulting classified offer (i.e., the received offer augmented with the identified cluster) is then stored and propagated cross-domain (via the DLT network). Notice that after the offer is published to the DLT, it becomes available for discovery and purchase from all the trading parties, which is facilitated by complementing the Blockchain recording operations with off-chain distributed storage provided by the Offering Catalogue instances.

Step 3: Stakeholder B provides an intent for the discovery of an edge offer. The information provided by the consumer requested via the intent-based interface (implemented at the Intent-based Discovery functional entity) is automatically translated into the cluster(s) that best reflect the customer expectations shown in the intent. The resulting offers from the identified clusters are then returned, ranked by their Squared Euclidean distance from the initial query.

A. Clustering and Classification

The clustering and classification components aim to classify an offer in the Marketplace according to its characteristics, which depend on the offer type. First, clustering methods are employed to identify patterns on a set of offers of the same type, hence, sharing the same characteristics. For instance, the features identifying a spectrum offer, such as frequency band, would differ from the ones characterizing cloud resources, such as RAM. This process is done initially offline on a training dataset comprising a variety of values for the features of several offer types. These clusters are used to build a classification ML model that is used online to label new offers in the Marketplace. The workflow to build these components is depicted in Fig. 2, where 5 stages are identified.

The initial stage (1) refers to the training datasets' generation with around 15K entries for several offer types (i.e., cloud, edge, spectrum, Radio Access Network (RAN), Network Service (NS) and slice), which are modeled following standard TM Forum specifications [13]. They all have a set of common features (e.g., location, price, SLA) and a group of distinct features according to the offer type. For instance, cloud and edge offers contain features related to CPU, RAM and storage, while RAN offers are given by the specific radio technology, coverage area, etc. The values used to generate the training dataset have been chosen taking as a reference

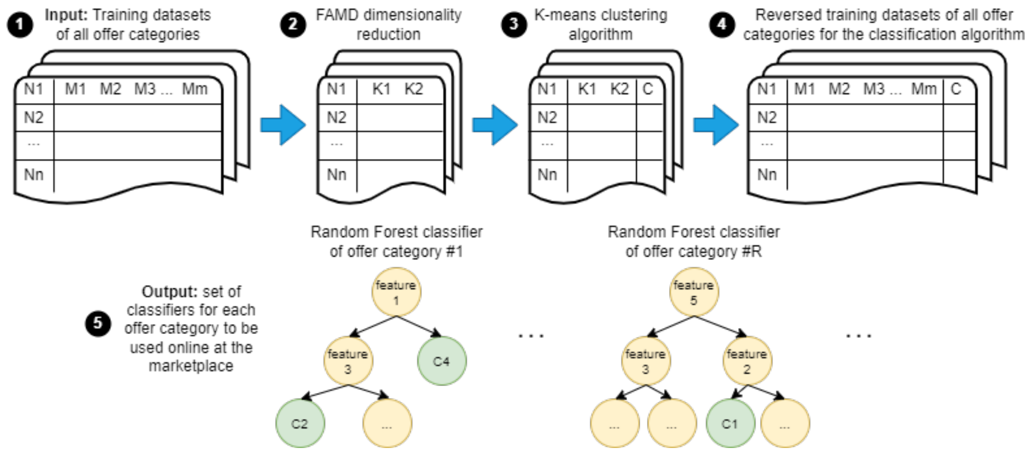

Fig. 2: Clustering and classification pipelines.

Infrastructure as a Service products on several providers and worldwide spectrum portfolios. The next stages to build the aforementioned ML models are described below.

1) Clustering Model: To facilitate human understanding and reduce its complexity, this model comprises two sub-models, namely Factorial Analysis of Mixed Data (FAMD) and K-means.

The FAMD algorithm (stage (2) in Fig. 2) aims to lower the number of dimensions of a dataset with m variables by reducing the information required to represent each point with k principal components. This prepares the field for the clustering model, reducing the number of clusters to group all the entries. As opposed to a combination of one-hot encoded categorical features and Principal Component Analysis (PCA), only suitable for numerical variables, FAMD can find the orthogonal components that maximize fairly the projected inertia of all variable types. This would not be true for PCA, since the weight of the categorical variables would depend on the new variables provided by the one-hot encoding process.

Once the dimensionality is reduced, a K-means algorithm is proposed to partition the entries of each training dataset (one per offer type) into c clusters characterized by the nearest mean and minimal inner variance. This allows identifying relationships among the offers of the same type and adding the corresponding cluster to each of them (stage (3) in Fig. 2), to obtain a labeled dataset. The number of clusters can differ for each offer type and is computed using the Silhouette method, a coefficient that measures the similarity of data points on a cluster compared to the neighbors.

2) Classification ML Model: This model seeks to serve as an online tool for offer classification in the Marketplace, i.e., the ML model must assign online a cluster to the incoming offers. However, such offers are represented by the original features of the training datasets. To make this classification human-readable, before training, the datasets' features are reversed from the principal components to the original features (stage (4) in Fig. 2) while preserving the cluster's label.

Random Forest (RF) is employed as a supervised ML model to perform the classification process, which is an ensemble learning algorithm, providing high accuracy and precision by leveraging a set of decision trees (whose depth is in this work limited to avoid overfitting) that are trained with part of the observations. In this case, the leaf node of each tree provides a specific cluster C (belonging to that offer type) as output, and the final selection of the forest follows a majority-voting approach. Notice that, as shown in stage (5) in Fig. 2, an RF model is trained for each offer type. These ML models are validated with additional datasets containing 1.5K entries.

In this work, the clustering and the classification models are trained offline. However, only the RF model is used online to classify the incoming offers. The reason for this is two-fold. On the one hand, the clustering model is built to set a label in the training offers according to their distinctive features. These labels are used as the *class feature* to build the RF models. On the other hand, only the random forest models are run online because of their accuracy in performing accurate classifications even if the input data is incomplete and not all the features in the training dataset are provided. This is a common case in Telecom Marketplaces, in which users do not always fill in all the characteristics of the offers they search, but rather a subset of them. For those reasons, and given that random forests are one of the lightest supervised learning algorithms (e.g., compared to neural networks), they have been selected as the ones better suiting the requirements of this work.

B. Intent-based Discovery

For the automated translation of user intents into best matching service offers, we followed an intelligent NLP approach, combined with a concrete DSL syntax to optimally balance expressiveness with service discovery performance. DSL frameworks can be utilized for building language models, which focus on the specifics of the language used by the application, rather than generating a more generic natural language. For this research, the RITA NLP framework was used, which is loosely based on Apache UIMA RUTA, a language for writing manual definitions or rules that are application specific. Two pattern recognition techniques were used. The spaCy [14] ML technique, an open-source software library for advanced NLP, which compiles the intents into spaCy compatible patterns, and the RegEx compilation technique.

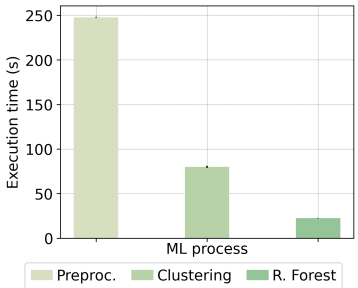

Fig. 3: Execution time consumed by the ML models' training.

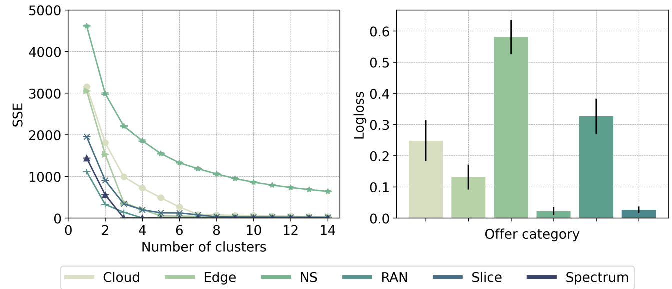

Fig. 4: Accuracy results of the ML models.

For simple language patterns identification, if the description is rich enough, RegEx can provide a sufficient degree of understanding to a user intent. Nevertheless, using an NLP framework, real pre-trained language models can offer further capabilities, such as synonyms, lemmas, named-entity recognition, and more importantly, physical grammar comprehension. In this work, an increase in the physical language understanding of the user queries was observed using a pre-trained spaCy model, as will be shown below. That is despite the built-in grammar comprehension of the model not being so important in this particular use case, since it was mainly defined by the specified rules.

A two-level intent recognition technique was implemented, first performing the general intent format and then extracting the users requested amounts and types of resources. These requirements defined the Euclidean distance-based cluster selection criteria, resulting in matching ranked offers. For the intent realization, general attributes were defined as in the following example.

Let's consider the definition of two lists: a "RAM names" list and a "Quantity types" list, with the possible values of "RAM", "Memory" as well as "MB", "GB" respectively. Those lists serve as the first-level recognition rules. Afterward, second-level recognition rules can be applied using the RITA syntax, as showcased in [15], describing the intent grammar. In this case, the second-level rule could be: *"if a word combination is provided, consisting of a numerical value, a "Quantity types" item, a random word, and a possible "RAM names" item, then the intent is classified as a RAM request having specified the required RAM amount"*. Notice that various second-level rules could be applied in parallel and coexist, allowing a more sophisticated understanding of the user intent. Thus, in most cases, a second coexisting rule was applied too like the following: *"if a word combination is provided, consisting of a possible "RAM names" item, a numerical value, a "Quantity types" item, and a random word, then the intent is classified as a RAM request having specified the required RAM amount."*. Essentially, in this case, the second rule defines a new grammar definition or syntax for the same type of intent.

Similar to the previous example, various rules can be constructed describing a big variety of user intents. Key points of the RITA implementation are the ease of construction and expandability, e.g., rules can be easily edited, and expanded. It should be noted that the same set of rules was applied in both pattern recognition techniques (SpaCy and RegEx).

V. Performance Evaluation

This section details the evaluation of the discovery application, focusing on the performance of the clustering, classification and intent recognition functional entities.

A. Training and Inference Time Analysis

This analysis studies the time taken to train the clustering and the random forest ML models, as well as the time dedicated to data preprocessing. The system used for the analysis consists of a Kubernetes cluster, where the pod hosting the components counts with 2 CPUs at 2.10GHz and 4GB RAM. Fig. 3 depicts the results of the various processes with a training dataset comprising 15K entries. The training and preprocessing tasks are repeated 10 times to ensure that no significant deviations are obtained, the results plotted being the average of those 10 executions with 95% confidence intervals. In particular, it can be seen how the preprocessing step is the one consuming more resources due to the time taken to clean and format the entries. By contrast, the RF model's training is the one taking less time, achieving values below 30 s.

Evaluating the time consumed by the recognition phase of the intent-based frameworks, for a given intent format as stated in section V-C, the average execution time consumed by the SpaCy framework was 9-10 times slower than RegEx (0.007 vs 0.0008 seconds). In both methods the models where preloaded in the memory. The spaCy's ML model is a Convolutional Neural Network, while RegEx technique compiles into Deterministic Finite Automata. As shown in section V-C, the trade-off between accuracy and speed justifies the choice of the ML approach, since it outperforms the RegEx approach in terms of recognition rate. Generally, the amount of first and second-level rules affected the speed of both models, showing a linear increase in execution time for each added rule.

B. Accuracy of the clustering and classification methods

Fig. 4 illustrates the accuracy of the ML models for clustering and classification of the validation data. The results for the clustering model are shown on the left in terms of Sum of Squared Errors (SSE) regarding the number of clusters for each offer type. The error converges to a value close to zero in all cases, except for the NS offers. Being a more

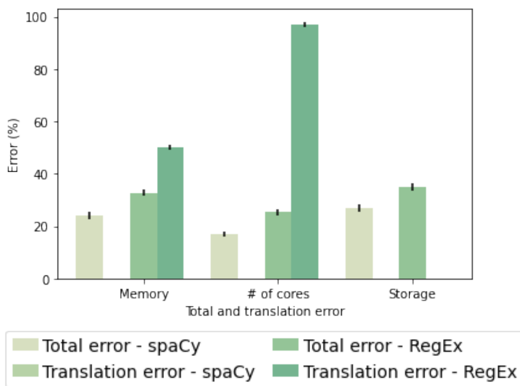

Fig. 5: Accuracy results of spaCy and RegEx approaches.

complex offer composed of several features with very wide value ranges, makes it harder for the algorithm to find patterns, and therefore, to provide the same accuracy as the rest. The accuracy of the RF model is depicted in terms of log loss on the right plot. The log loss presents the expected classification loss, showing low results for all offer types. This metric depends on the number of classes (in this case, the number of clusters), and even if the loss is slightly higher for the NS case, this is still negligible for the model's accuracy.

It should be noted that although the time taken by the ML models' training (Fig. 3) can differ based on the hardware specifications, we have obtained similar accuracy results using different testing platforms.

C. Intent Recognition Accuracy: spaCy vs RegEx Frameworks

The term *accuracy* refers to the divergence between the requirements set in the intent and the returned offers, represented by the total error. The translation (comprehension) error represents the accuracy of the NLP model. Fig. 5 showcases those errors for the intent frameworks. To compare the two frameworks, the same set of first and second-level rules was applied. The spaCy method provided an increased recognition rate against the RegEx-based implementation, although suffering from a small but reasonable speed slowdown.

The power of the spaCy framework is shown in the understandability of the intent. If the intent is defined as in the example *"Two cores ten GB of RAM"*, the spaCy framework will classify it exactly as a two cores request, which is naturally closer to the physical language. The RegEx implementation instead will suggest that the request is either for two or ten cores. Different physical language spaCy models were utilized and compared, but the comprehension ability of all of them showed minimal variation for the scope of this work. Thus, the minimum-sized language model was chosen.

For the accuracy comparison between the two frameworks, a wider set of first-level rules defined as: "CPU names", "RAM names" and "Storage names" were applied. In particular, ten auto-generated user intent examples with a specific format were used, all requesting edge offers specifying the number of cores, RAM, and storage requirements. The intent format used was: number 1 + "cores" + number 2 + "MB of RAM" + number 3 + "GB of storage". The ranges defined were [1, 10] for the number of cores, [2000, 16000] MB for RAM and [1, 180] GB for storage. Considering the label-value and vice-versa query format explained in subsection IV-B, two second-level rules were defined for each requirement, making a total of six second-level rules. The definition of more complex rules would make the physical language meaning increasingly subjective, so this is to be explored in later studies.

The translation error of the spaCy method is zero in all cases in Fig. 5, while for the RegEx method this is only true in the Storage case since it is the last sub-string in the intent. The total error between the returned and the requested resource amounts of the RegEx method is larger than the spaCy method, due to its smaller comprehension ability. That was because two second-level rules were defined for the specified CPU and RAM, essentially describing that their amount could be inserted before or after the item, as showcased previously. For the Memory and Cores cases with RegEx, the total error is lower than the translation error, which is a priori contradictory. This is because the misinterpretation incurred by this approach leads to unfeasible RAM and CPU requirements, which do not exist in our dataset with real-world examples, thus they could not be returned and as such this is not impacting the total error. Finally, reducing the number of second-level rules to the one that best matches the intent example format for each requirement, could lead to increased accuracy in ReGex, but also to incomprehensibility for other types of intents, like: "RAM: 16 GB", or "16 GB of RAM", depending on the removal.

VI. Conclusion

Enabling resources and services sharing via multi-party distributed Telecom Marketplaces is a growing demand to realize the envisioned capabilities for B5G/6G systems. Towards such a goal, this paper provides insights into the design and implementation of the Smart Resource and Service Discovery application that enables stakeholders to search available offers via high-level intent-based queries. The proposed solution employs intent recognition techniques together with clustering and classification models to identify groups of offers according to their features, providing a clustered dataset consumed on-demand by the translated intents. Experimental results demonstrated the ability to match the requirements of the Marketplace requests and the specifications of the returned offers, and the high accuracy of the clustering and classification ML methods to minimize the online search time of the intent. In our future work, a robust after-clustering ranking system will be specified, increasing the recognition accuracy of the network business-level intents. Moreover, we will study the ability of other ML algorithms to suit the requirements of the problem and explore online re-training methods for accuracy assurance over time. Furthermore, towards increased user-centricity in next generation networks, we plan to enhance our discovery mechanisms with personalized recommendations for end-users/prospective service consumers, to also consider business context, user profiles and situational awareness. Additionally, we will investigate techniques for the historical usage-based evaluation of available services in the Marketplace, with particular focus towards embedding trust and security. Finally, to facilitate open innovation and ensure fair inclusion of stakeholders in formed networking ecosystems, we will examine methods for explainable and transparent decision support, especially in the process of unbiased service ranking.

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