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Improving User Environment Detection Using Context-aware Multi-Task Deep Learning in Mobile Networks

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Abstract—Cognition of user behavior can make future mobile networks more intelligent and flexible. Knowledge about users’ habits can be used to personalize services and intelligently manage network resources. However, inferring this key information with a low-cost signaling implementation, and avoiding constant user interaction, is crucial for Mobile Network Operators (MNOs). With this motivation, this paper investigates the detection of the real-life mobile user environment using context-aware detection via multi-task learning (MTL).

We propose models that are able to automatically detect up to eight distinct real-life user environments. We also improve the detection accuracy with the assistance of the mobility state profiling task. We associate both environment and mobility tasks because they correspond to the main attributes of user behavior and, additionally, both of them are correlated. Using MTL, the task of detecting environment corresponds to simultaneously answering the questions: “how and where mobile user consumes mobile services?”.

We build models using real-life radio data which is already available in network. This data has been massively gathered from multiple diversified situations of mobile users. Simulation results support our claim to detect several environment classes in network infrastructure with improved UED accuracy.

Index Terms—Context-assisted, User Behavior, Environment Detection, Indoor/Outdoor, Multi-task Deep Learning

I. INTRODUCTION

New 5G and beyond networks will bring new services, new technological advancements and will be increasingly human-centric. However, their growing levels of complexity and traffic volumes, combined with high diversity and big size, brings a new set of challenges for operators managing the network. So, the coming of 5G triggers a need for a full end-to-end automation for 5G and beyond [1]. On the other hand, with every advance in the generation from 3G to 4G and reaching 5G, users are more and more asking for better services, with the highest possible quality with lowest cost. Thus, mobile networks are expected to accommodate the ever-growing user-demands by guaranteeing personalized services/applications and better Quality of Experience (QoE). This signifies a shift in the objectives of network self-management and decision-making processes from a network-centric to a more user-centric view. “*Network as a sensor*” is one of the future vision

in which the mobile network will sense the environment, while becoming a center of situational information as well as collection and processing of signals and data. One of the idea towards realising above is to design mobile networks which are aware of the context in which the mobile devices are used. This will make the network be more intelligent and more aware of the situations in which mobile users consume, or prefer to consume their services and applications. By anticipating mobile users’ behavior or users’ consuming habits, the network will be able to efficiently take appropriate decisions in the face of variable network conditions (such as changing traffic and data rate) and users’ needs. However, inferring the service consumption habits of users is a very complex problem. It is particularly problematic when the objective is to detect the personal usages or preferences without requiring constant user interaction through personalized and refined questions. Indeed, context is broadly defined and complex. It includes contextual information in the form of temporal information, spatial location, social situations, or other relevant contextual information corresponding to the user’s activities such as the environmental situation. A lot of research has already been done on use context detection in mobile environments, especially in the domain of context-aware rule learning which is detailed in [2]. The goal is to derive useful information on usual/preferred behavior of users in multiple situations. Among the contextual information, the environmental situation constitutes a relevant information about user’s activities.

Recently, some works showed that it is possible to beneficially exploit the knowledge about the user environment context for enhancing network operations, for example when a user changes environment from outdoor to indoor or from vehicular to pedestrian mode or vice versa. This information can be used to provide better QoE for video applications [3], accurate user localisation detection [4], improved handover process [5], slice selection to switch from a slice with more flexible resources to a resilient one [6], etc. So, having knowledge about user environment in advance can help operators to configure or optimize their networks/services or to prepare data efficiently. Indeed, the environmental situation of user constitutes both an high level indicator of the radio coverage quality and a precise information of use context.

Therefore, there is a need to design a new functionality,

This research work was carried out during Illyne Saffar’s stay at Nokia under the collaboration with University of Rennes and Saint-Etienne

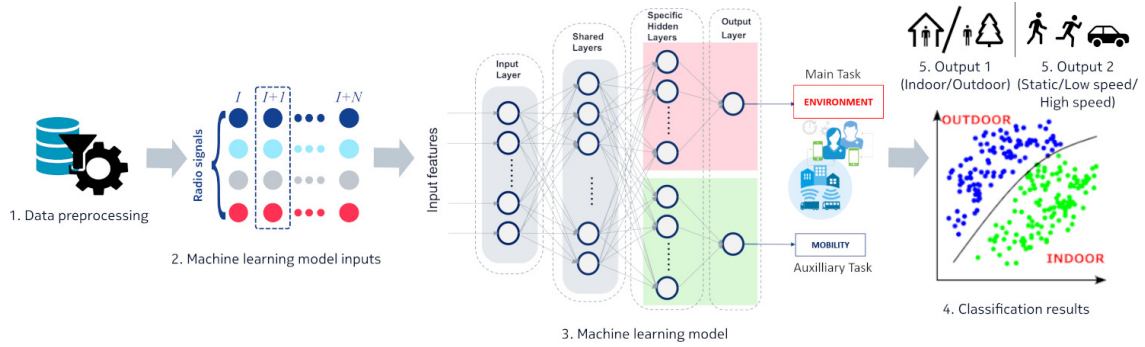


Fig. 1: Automatic User Environment Detection (*UED*)

which can accurately and automatically detect where does a mobile user like to consume mobile services. For this, the functionality is required to be placed close to the network functions using environment information to have a win-win situation for Mobile Network Operators (MNOs). Furthermore, ensuring a full automatic process, the functionality should work without requiring constant user interaction. MNOs also prefer to avoid intrusive installations on mobile devices. Hence, we would like to design a *network side* solution, which will have the following advantages: it will avoid overloading User Equipment's (UEs) with installations, additional computations and will avoid costly additional signaling of environment information to the network. Note that UEs often have limited uplink bandwidth, computing power and energy. So, the challenge is to develop an automatic functionality that is able to detect real-life environments of connected users with the highest detection accuracy from the network side. But, this is a hard task because there exist various as well as complex real-life environmental situations. They also vary from one user to another, depending on his/her location and activities.

User Environment Detection (UED) refers to the detection of the environment type of mobile users [7]. In this paper, and as described in Figure 1, we propose a solution for automatic UED. It operates at network side. As compared to state-of-art, we study how using Multi-Task Learning (MTL) can help in increasing accuracy in UED detection. Multi-task Learning is a sub-field of transfer learning in which multiple learning tasks are solved at the same time, while exploiting commonalities and differences across tasks. This results in improved learning efficiency and detection accuracy for the task-specific models when compared to training the models separately [8]. Our motivation to investigate MTL architecture for UED relies upon its effectiveness to generalize better with the introduction of auxiliary learning tasks [9].

In this work, the UED task is assisted with the *Mobility Speed Profiling (MSP)* task using MTL architecture. MSP refers to the estimation of the speed ranges of a mobile user. The idea here is to use MSP information for aiding the classification of different outdoor environments. It will help to classify ambiguous measurement points which have low received power values, but do not correspond to indoor. For example, when a user is moving at high speed, the radio signal quality can degrade (which is also the case for indoor users), but speed profile information can aid MTL to correctly classify such points as outdoors. Thus, we focus on two

contextual attributes *Environment and Mobility* for improving UED accuracy. Consequently, with MTL, both the tasks are then jointly solved. MSP is considered as an auxiliary task and is referred as Auxiliary Learning. Both of them deeply impact the user behavior (at service and QoE level) and are strongly correlated, e.g., an indoor user can't be in high speed state. UED assisted with MSP is also linked to conjointly answer the following questions about a user: the where? and the how?

Thus, the challenge is to design a unified system that can simultaneously infer the environment type and the mobility state (speed range), in an automatic synchronous way. This problem is complex and difficult to model mathematically. For this, we are interested in Deep Learning (DL) techniques. They can learn in an automatic way, in real-time, and benefit from the value added by the massive data. DL outperforms the traditional models/algorithms of Machine Learning (ML) [10]. Furthermore, they are also able to deal with complex problems and to characterize inherent relationships between the inputs and outputs of a system without human involvement [11], [12]. Our motivation is to develop a practical approach with high accuracy which exploits radio data available in the Radio Access Network of mobile network to detect several UED classes. The multi-task deep learning model is then extensively evaluated via two large scale datasets composed of real radio data as defined by the 3rd Generation Partnership Project (3GPP). This data corresponds to radio signals measured by UEs which are either reported to mobile network or are derived inside base stations. Results demonstrate that UED with Environment and Mobility Detection task-based MTL is achieved with significant improvements in terms of Accuracy and F1-Score, compared with the state-of-the-art baseline. Moreover, these results are obtained on distinct large-scale datasets which contain radio data captured from situations capturing different real-life activities.

Paper Contributions:

The novelty and contributions of this work as compared to state of the art are as follows. We provide detection of more UED classes. We improve UED accuracy thanks to the use of MTL because UED task is assisted by mobility task. We perform UED at the network side where there is less information about the user environment as compared to the raw information present on UE. We use data produced from real life activities which is more representative of user environments as compared to drive tests. Finally our contribution can be seen as a step towards intelligent 5G network. These

contributions are further elaborated below:

1) *Improved UED with more granular detection of environment*: As compared to detection of just 2 or 3 environment states in state-of-art, we propose schemes with up to 8 classes and achieve more granular detection of environment and mobility of mobile users. This granular division of classes is derived from a finer analysis of user activity and service consumption under different environment and mobility conditions. The detection of more than 2-class schemes becomes a multi-output classification problem. UED is performed using supervised deep learning classification methods. We introduce some input signal features for UED, which are compliant with the 3GPP standard and available *from the network side*. It should also be noted that performing UED from the network side is different from other state of the art works. Network side UED has some advantages as discussed in the introduction.

2) *Better accuracy for user environment detection*: The accuracy of environment detection is improved thanks to additional knowledge captured from auxiliary tasks such as mobility detection or MSP. This is because we use MTL. With MTL structure, both tasks share data inputs and information which bring meaningful additional information to UED. This is shown during evaluations where we investigate UED with (using MTL) and without the help of MSP.

3) *Strategies to deal with noisy and imbalanced real-life data*: Data is collected during various activities of mobile users: while being static, while moving with different speeds and at various diverse cities/places. This allows to gather data which is more representative of real life activity of mobile users. Unlike classic approaches (e.g. drive-test mode), this allows to examine more multiple and varied real situations with users connected to cellular networks, while experiencing a service or using an application. One problem faced when training DL models using real data is that we have to deal with imbalanced, corrupted and noisy data. People spend most of their time indoor or static than in mobility or outdoor. The noise can be due to users unwilling to share their accurate positions. Thus, we also propose some data pre-processing strategies to deal with these problems.

4) *A step towards Intelligent 5G network*: Our proposal for UED task can be implemented in the management plane of 5G and beyond networks. It fits the first steps of the whole cognitive network cycle vision: observe, detect and analyse, plan and decide, act. In this work, we are currently in the steps of observe, detect and analyse. In the next steps left for future work, the network will use the detection and estimation knowledge to plan and decide. Next, the network will take actions to optimise the user experience as well as network resources at the same time. For example, depending on whether a user is indoor or outdoor, the functions such as mobility management or virtual content distribution network can be switched on or off.

This paper is organized as follows. Section II presents the background and introduces the prior related work; Section III discusses data collection and data pre-processing. Section IV defines different classification schemes. Section V-D proposes a comparison study of multi-task learning for user environ-

ment detection. Finally, Section VI concludes the paper with discussions and future work.

II. RELATED WORK

A. User behavior modeling

The [ISO 13407:1999] standard [13] defines the context of use as the whole situation relevant to an application and its set of users. Extending the definition of context from [14], we include the user behavior model as the direct reflection of all the usage situations of mobile services or applications, and the users themselves. This model provides a picture of the consuming habits or preferences of users. The user behavior model should be *an abstraction of the diverse usage situations experienced by mobile users*, inside the mobile services delivery zones, while a user is using his phone. It should also be exploitable in order *to bring a positive impact on QoE* with the intelligence extracted from user behavior.

We consider the user behavior modeling by two QoE-influencing features related to mobile use context: the *user environment* and *mobility*. These factors give information about the situation of the mobile user while he is using the phone. These factors are defined as follows:

- 1) **Where** is the user? $\xrightarrow{\text{answer}}$ Environment (indoor/ outdoor/ etc.)
- 2) **How** is he using it? static or moving? $\xrightarrow{\text{answer}}$ Mobility State and Speed (low/ high/ etc.)

The choice of these factors is motivated by their relevance with QoE. For example, an indoor user would experience a very different service quality as compared to an outdoor user, all else being equal. During day, a user can be in different situations (walking outdoor, car, at home or in a pub) Statistical studies show that mobile phones are mostly used in a building for internet service (80%) and for a call (70%) [15]. This can be explained by the fact that the different use contexts pose their own limitations and, thus, impact the potential application usages.

B. Environment awareness for enhancing network operations

Many works investigate the beneficial exploitation of using context, especially the user's environmental situation, characterizing the phone usage habits of users, for enhancing network operations. For example in [16], the authors focus on profiling the usage patterns of mobile applications and investigates where, how, and when smartphone applications are used from spatial, temporal, and user perspectives. They evaluate how such characterization can positively impact network operations. In [17], the context of use, notably the environmental

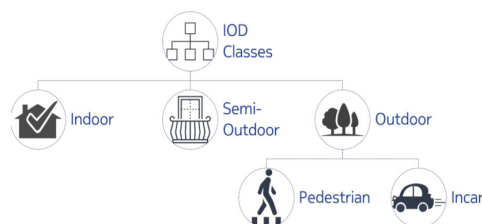


Fig. 2: State of the art scheme with 3 main classes

factor, is seen as a potential information in developing new, more personalized mobile services and applications. In [4] authors enhance QoE by anticipating the change in user environment, or a coverage hole, and accelerate the filling of video application layer buffer. They show that knowing the user environment change in the few coming seconds can enhance user's QoE. Other researchers [3] show some improvements in user localization accuracy by using the knowledge on whether a user is indoor or outdoor.

As a matter of fact, knowing the user environmental situation can help networks to conduct their operations efficiently.

C. User Environment Detection

The user environment detection issue has been largely studied. So far, what has been carefully studied in literature, is Indoor/Outdoor Detection (IOD), with works divided into two categories. IOD is either considered as a statistical issue where a weighted score or a threshold is defined to determine the mobile environment, or as a classification problem sorting mobile users between multiple classes. In most of these works, only two classes are considered (Indoor/Outdoor), but in some works, three or four classes are selected (e.g. Light and Deep Indoor/Semi-Outdoor/Outdoor [18] or static/Pedestrian/Incar [5]). Figure 2 illustrates the synthesis of the main 3-state classification schemes used for IOD in the state of the art. Unlike above, we will now also categorise the works depending on whether detection is done from the mobile terminal side or from the mobile network side. The operators prefer network side solutions to avoid burdening the mobile devices with installations, computations and additional signalling.

In first category, works of environmental context detection is done in mobile device using sensors data [19]. In [20], the authors propose to use thresholds, derived from a set of signals: radio signals, cell signal strength, light intensity as well as the magnetic sensor to infer whether the mobile user is indoor or outdoor. Similarly, [21] also addressed IOD using the same set of sensors and some more like sound intensity, battery temperature and the proximity sensor. Recently, [22] proposed to use random forest and AdaBoost classifiers that use mobile device sensor data to classify the environment. [23] developed an ensemble learning model based on stacking and filtering the detection results with a hidden Markov model. An indoor/outdoor classification system using light measurements and ML is proposed in [24].

In the second category, i.e., network side IOD, few works have been proposed. [3] used *RSRP* (Reference Signal Received Power) and *RSRQ* (Reference Signal Received Quality) signals and compared Support Vector Machine (SVM), logistic regression and random forest. SVM performed best. As for works in [4], they use a combination of phone sensors as well as *RSRP* and Global Navigation Satellite System (*GNSS*) measurements. This information coming from phone sensors is combined with a joint posteriori probability based on the distributions of *RSRP* and Global Positioning System (*GPS*) measurements to perform IOD. In [25], a semi-supervised learning algorithm using a regression logic model is proposed to estimate the probability that a particular

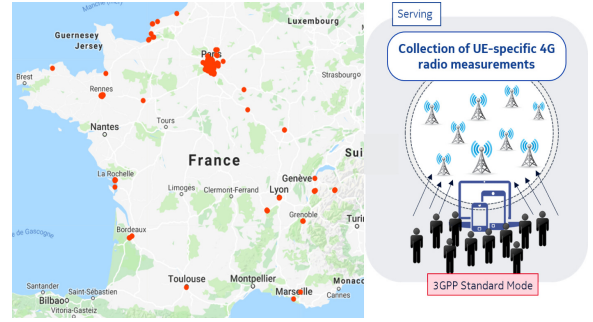


Fig. 3: Data collection modes and places

connection was generated indoors. The detection is based on 4G Long Term Evolution (LTE) measurements from radio connection traces. [26] performs a complete study of an ensemble learning schemes applied for IOD. [27] studied quantum machine learning approaches applied to IOD. [28] investigates a deep learning algorithm, based on large-scale radio data including temporal and mobility indicators. The authors show that the multi-output classifier achieves high accuracy for a relatively complex environment classification, considering multiple environments. In [5], the authors estimate the signal attenuation in different situations of mobility with varying speed (low, medium, high). This in turn helps them to efficiently classify the mobile user environment in outdoor situation (pedestrian, in-car or non-moving) and finally to improve the handover process. It illustrates the link between mobility and environment relying on signal power attenuation.

Indeed, the links also allow us to envisage a beneficial help of MSP task for UED task within MTL system considering multi-output classification tasks.

III. DATA DESCRIPTION

We now describe the data collection process, features and pre-processing techniques to tackle noisy and imbalanced data.

Data	Period	Device	Location	User
130K	15 months	Samsung S4	Urban, indoor, beach, mountains	Regular habits
82K	8 months	Nokia 8.3	Urban, indoor, beach, forest	Regular habits

TABLE I: Measurement configuration: Dataset 1 / Dataset 2

A. Data Collection: data representative of real life

Data collection being the first step for ML, we collected data using the crowd-sourcing mode [29] to build our models. In this mode involving volunteers, the collection is provided by applications running on end-user devices and performing active, passive or both types of measurements in real time. The mobile phones are almost always with users for 24/24h and 7/7 days, during their various activities, moving or not. This enables us to build two datasets (referred as Dataset 1 and Dataset 2 with representative data for training and evaluation as close as possible to the complexity and the variety of usage situation of mobile users and their movement in real world. Thus, after cleaning and pre-processing, for training our models, we use many instances of UE-specific 4G data

(as 5G was not available at that time). So, the two datasets used for training and evaluation have been collected with the characteristics detailed in Table I. Both the datasets are collected from several locations in France (red dots in Figure 3) which were visited by the volunteers. The 2 datasets are distinct due to different timelines, device types, diverse cities and places where measurement points are done.

B. Data Features

Let us first recall shortly indicators/parameters/signals that are commonly used in mobile networks' context. They are Key Performance Indicators reflecting the behavior of users. They are power, quality, location and mobility signals respectively.

- *RSRP*: It is the average received power of a single Reference Signal (RS) resource element [30].
- *CQI*: Channel Quality Indicator is used to indicate the most appropriate transmission modulation and coding scheme to be used [31].
- *TA*: Timing Advance is used to control UL signal transmission timing [32].
- *MI*: Mobility indicator refers to the number of Cell ID changes in a sliding window of a given duration (TCR_{max}) [33]. To estimate its value, TCR_{max} is fixed to 100s [34].
- *ST*: Sojourn Time in a cell.

For UED task, we opt for a dataset composed of four features, 3GPP standard radio signals (defined above), to help efficiently classify the ambiguous points: *RSRP*, *CQI*, *TA* and *MI* [7]. For the auxiliary MSP task, we use the same dataset as UED, adding Sojourn Time *ST* and some new features defined below [35]. In addition to these UE-specific 4G radio measurements, metadata such as GPS coordinates is also collected and registered along with the other signals. Our purpose to use *GPS coordinates* is just to help in automatically computing labels for MSP task and verifying and correcting labels for both tasks. Unlike MSP, the environment is labelled manually.

Thus, our whole data-set is composed of a vector of following features (4 features for UED in single-task and 6 shared features for MTL-based UED) plus labels. We consider *RSRP*, *CQI*, *TA*, *MI*, *ST*, and extra engineered features: signals derived from *RSRP* and *TA* to exploit their temporal variation during a sliding window of duration TCR_{max} . These two additional parameters are also considered:

- Time: Recording time of signal or burst data arrival (ms)

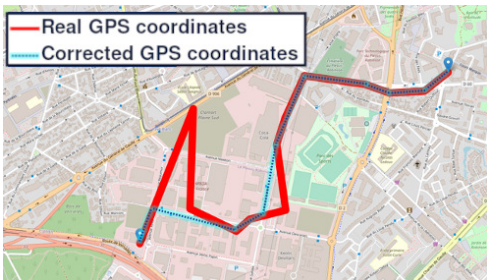


Fig. 4: Real data (noisy) in red and corrected trajectory in blue

- GPS coordinates: to automatically label and clean data.

As we are dealing with a supervised method, environment or/and mobility state labels are used to train the MTL models.

C. Imbalanced noisy data and cleaning of noisy labels

Note that our dataset built using crowd-sourcing collection mode in real-time is inherently not strictly controlled during the data collection. It suffers from two problems: imbalanced data classes and noisy data. People spend most of their time indoor or static than in mobility and outdoor. Consequently, outdoor data is less represented than indoor data when considering phone usage (detailed in section II-A). Sometimes, this imbalance is also a by-product of data cleaning, which in turn is required to overcome the noise inherent to real data. Actually, different techniques can be found in literature to solve [36]. A simple and a popular one is used here to artificially oversampling the minority classes (or artificially under-sampling the abundant classes) in the dataset.

In addition, our data collection suffers from a problem that is related to the signal recording tool. A mobile application is used to automatically record various cellular or data signals during a given time slot. The recorded values are stored in files on the mobile or sent directly to a data platform. During short disconnection events, the signals values are found to be empty, random, default or duplicate values. These erroneous values were either be discarded or corrected using interpolation.

To automatically label as well as clean the data for training, GPS measurements is used. They are mostly used to calculate the speed labels for MSP and to check the correctness of labels for UED (e.g., the labels should not show indoor where the GPS coordinates show the user on highway). However, noisy and missing measurements will cause problems mainly for MSP task. From ML point of view, label noise leads to labels of given classes assigned to another classes. For example, Figure 4 shows a moving pedestrian with a real speed not exceeding 3 kmph, while a speed between 15 kmph and 30 kmph has been erroneously detected with the collected GPS measurements. As a first step, for reliable measurements, we have used an indicator “GPS-on” to check if a given GPS measurement was reported with the GPS turned on. If the indicator “GPS-on” is activated such measurement is considered reliable and kept. Otherwise it is dropped. In order to automatically label speed, a typical approach [35] is to transform the series of measurements that record position points (latitude and longitude), at regular time intervals, to coordinates (x, y) in km. To derive the average mobile user speed v , we use a succession of N coordinates (x, y) derived from GPS information. Suppose that the mobile user moves along a path P from point A to point B . To link these two extreme points, the user goes through $N - 2$ intermediate points belonging to $S = \{a_i\}_{i \leq N-1}$ at time $\{t_i\}_{i \leq N-1}$. Let TCR_{max} be the time elapsed to go from A to B : $t_N - t_0 = TCR_{max}$. L is the total distance and δt_i is the elapsed time: $t_i = t_i - t_{i-1}$. Let l_i be the distance between points $\{a_{i-1}, a_i\}$:

$$l_i = \sqrt{(x(t_i) - x(t_{i-1}))^2 + (y(t_i) - y(t_{i-1}))^2} \quad (1)$$

The point a_i has the following coordinates $(x(t_i), y(t_i))$. The average speed \hat{v} , is approximated as:

$$\hat{v} = \frac{1}{N-1} \sum_{i=1}^N \frac{l_i}{\delta t_i} = \frac{1}{N-1} \sum_{i=1}^N \hat{v}_i \quad (2)$$

Another step of *cleaning* the labeled data is primordial since it ensures the integrity of the ground truth used for labeling. For this, let σ be the threshold that sets a confidence interval. At t_i , if $l_i \in [L \pm \sigma]$ then $a_i \in S$ otherwise $a_i \notin S$. The distance l_i between 2 successive points should be bounded by L to be used for the average speed derivation. Otherwise the measurement at time t_i considered as an outlier is excluded.

IV. CLASSIFICATION SCHEMES

Each task, UED or MSP, is represented as a multi-output classification problem. This section proposes different classification schemes with varying levels of granularity.

A. Classification granularity level

The more granularity we have for environment and mobility, the better it is for capturing the user behavior. Indeed that would reflect more the complexity of a user's daily life and capture better the variety of his movements in real world. Thus, more schemes will lead to a more precise description of user situations and describe the diversity of the environment or mobility situations of a user. However, increasing too much the number of classes groups the data instances in unequal manner between the different categories. This trade-off makes it challenging for ML. This observation asks for determining the appropriate granularity level (level of details). Can we classify the user environment or speed range with detailed classes and with good performance? For this purpose, we will look for a best trade-off between more granularity and performances in terms of Accuracy and $F1 - score$ metrics.

For UED task, we investigate the eight categories of environment proposed in [7]: [*Work, Home, Building, Mall, Pedestrian, Bus, Car, Train*]. The categories have been chosen for labelling the data since they are the typical environment most frequented by the users of our two datasets. For MSP task, we consider eight speed categories proposed in [35] for profiling the mobility state of mobile users connected to 4G network. The boundaries (defined by minimal and maximal speed value) of each category are extracted from the following set: $\mathcal{B} = \{0, 1, 2, 3, 10, 30, 40, 90, \infty\}$ (in kmph). They were selected to reflect the complexity of user's daily life and capture variety of his movements in real world. They represent the typical speeds [37], related to various user environments (highway, road, pedestrian, bus, car and train).

B. User activity versus environment and versus speed range

Figure 5 depicts the user activity by plotting the phone usage ratio versus the eight environment categories and versus the eight speed categories. The phone usage ratio is measured as the ratio between the number of instances the user has been using his phone effectively and the total number of instances.

Precisely, the figure illustrates then the percentage of total time the user is connected to 4G network and exchanges data.

Analysing these graphs gives us a clear picture of mobile phone usage in different situations of environment and mobility. We observe that most of the activity is spent indoor (70%), mainly at home and at work. We notice that most of the user activity occurs when the user moves at a speed lower than 1 kmph (75% of activity), which is mainly when the user is indoor or is walking as a pedestrian. These observations highlight the user activity trends that we can find in the statistical analysis on mobile user behavior provided in literature (as detailed in Section II-A). Practically, mobile users' preferences for certain applications or contents are linked with their current usage situation [38]. Moreover, it may also be linked to the factor that when the user speed increases, the network quality may also deteriorate. Consequently the user may do handover from 4G to 3G or even to (rarely) 2G.

Therefore, the data instances are distributed unequally between the different categories in both cases. The data proportion for *Train, Bus, Mall, Building* or *Pedestrian* is very low compared to the other remaining groups. Thus, designing an environment and/or speed classification scheme will face the problem of unequal data distribution in classes.

C. Relation between environment and speed

With classification of environment in mind and with the help of speed, lets see which factors and boundaries are important. We plot the environment type distribution versus the speed category in Figure 6. We observe 3 easily distinguishable zones which are separated by 2 speed boundaries: 10 kmph and 40 kmph. The 10 kmph boundary makes a clear split between sets of indoor and outdoor classes, which are two distinct environment types with different physical characteristics. Below 10 kmph measurement points have been collected mainly inside buildings. Above 10 kmph the instances have been mostly

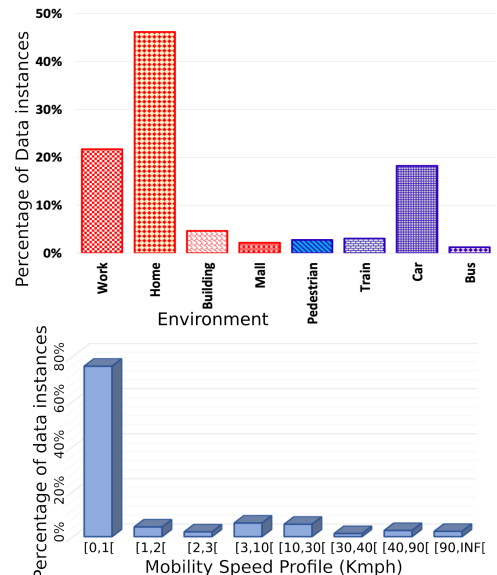


Fig. 5: User activity per environment (above) and speed category (below)

collected outdoor: between 10 and 40 kmph in cities and above 40 kmph on highways. We can notice that the speed boundary of 40 kmph is directly linked to user location (urban or rural). This is because some speeds are inherently linked with certain types of environment and, thus, are linked to speed boundaries that separate such environments. For example, a speed of 30 to 50 kmph is linked to cities and 70 kmph is linked to rural places. Besides, the maximal speed (30, 50, and 70 kmph) in cities or road depends upon geographical location. Thus these borders will play a key role for improving performance.

Figure 6 shows clearly that environment and mobility are related. These results confirm the interest to use MTL architecture to learn the user behavior. We also notice some errors in Figure 6 in the highest speed zone. We observe indoor instances in 2 types of highways denoted either national routes or expressways. However, the speed is higher than 40 kmph which is logically impossible. This is addressed by data cleaning algorithms (see Section III-C).

D. Classification Schemes

There is a trade-off between a simple classification scheme, with few classes, and a more complex classification scheme with a higher number of classes.

Indeed, a classification scheme should be able to efficiently depict situations of real mobile user activity, with a fine granularity to hold detailed user behaviour information and a low decision error. The method to smartly regroup the various environment types or speed categories to build classification schemes is described in [7] and [35] respectively. For efficient classification schemes with detailed situations of users, a trade-off to limit this inherent data bias for different classes is found. To do this, the authors first analyse the empirical cumulative distribution function (CDF) curves of the most contributing collected data $\{RSRP, MI\}$ for each category of UED and MSP tasks. Then, the UED investigation is completed by an additional comparative analysis of the phone activity variance of all groups. CDF curves are depicted in Figure 7.

Analysis of the CDF curves of $RSRP$ and MI shows some clearly separated groups of curves in both cases. For the environment, a clear split can be seen between the curves corresponding to indoor (indoor categories) and outdoor (outdoor categories). For environment and mobility cases, clear split in 2 groups is observed: one associated to users moving very

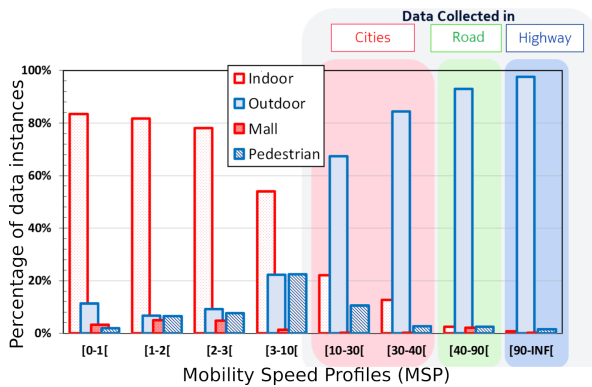


Fig. 6: Environment distribution vs. speed category

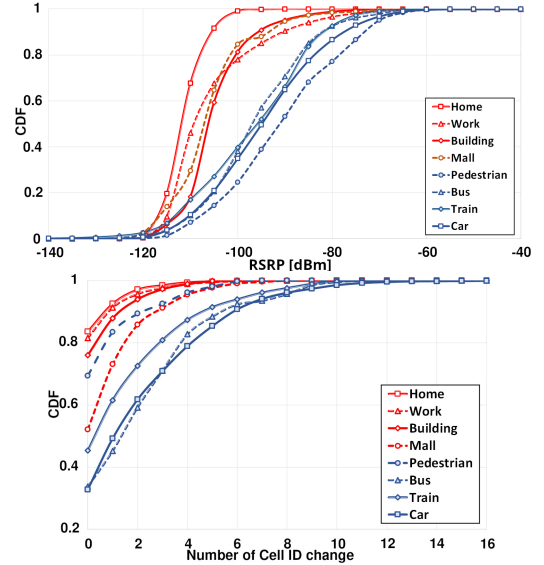


Fig. 7: Empirical CDF of $RSRP$ and MI per environment

slowly (walking or static) and the others moving at high speed. Based on these observations, [7] and [35] propose multiple classification schemes for both tasks. For this, they consider different possibilities, ranging from a simple 2-state to a 8-state classification of a user's environment or speed.

1) *Environment*: The 8 environment schemes studied from [7] are shown in Table III (results will be discussed later see Section V-C). The label “Indoor” refers to [*Work, Home, Building, Mall*]. The label “Outdoor” contains [*Pedestrian, Bus, Car, Train*]. “Transport” includes [*Bus, Car, Train*]. “Buildings” contains remaining indoor locations and various “Buildings”. The scheme name of environment classification is UED_{nC_m} where n is number of classes, m refers to index in case of multiple schemes for same class n . Note that m is omitted if only 1 scheme per class. Figure 8 shows examples of 2 schemes of $n = 5$ classes, called UED_{5C_0} and UED_{5C_1} .

2) *Mobility*: We propose to investigate 4 mobility schemes from the best schemes depicted in [35] to model the diversity of speed situations and to find the optimal boundaries among them. They are shown in Table IV (results will be discussed later). For comparison, we name the schemes of mobility classification as MSP_{nC} where n is number of classes. Let j^{th} scheme $MSP_{nC} = \mathcal{S}^j$ have a total of n classes. Each scheme \mathcal{S}^j is associated with a set of boundaries

$$\mathcal{B}^j = \{B_1^j, B_2^j, \dots, B_k^j, \dots\}_{k \leq n+1} \quad (3)$$

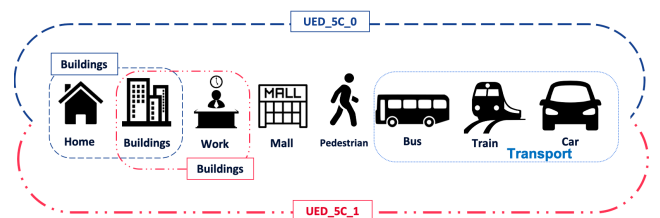


Fig. 8: Example schemes UED_{5C_0} and UED_{5C_1}

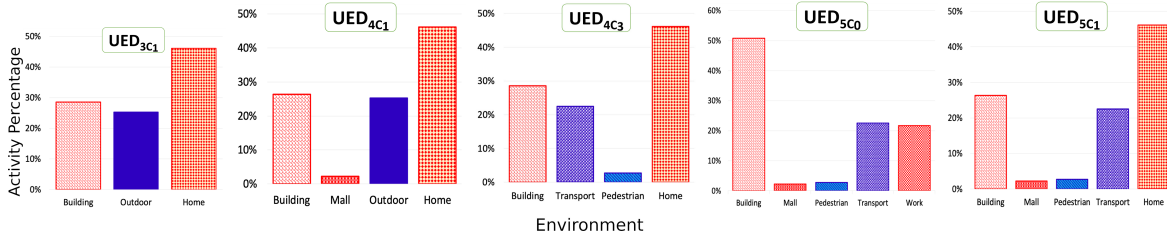


Fig. 9: Phone activity percentage for various classification schemes of environment

with B_k^j the speed value in kmph. The last boundary of a class is always ∞ . They become the minimum and maximum boundaries of each class of $MSP_{nC} = S^j$, namely

$$[B_k^j, B_{k+1}^j] \quad \forall k \leq n. \quad (4)$$

V. MULTI-TASK LEARNING BASED UED

A. Multi-task learning architecture

Using multi-task learning to share knowledge among different tasks is very useful especially under the assumption that the tasks used in multi-task learning are very similar or closely related. If the tasks are unrelated, MTL can cause a phenomenon known as negative transfer and hurt the overall performances [39]. The classic definition from [8], [40], defines two tasks to be similar or related if they use the same features to make a decision. Hard parameter sharing architecture is the most commonly used for MTL with neural networks. Generally, some hidden layers are shared between all the tasks in order to learn a common space representation for all tasks. The neurons in these layers and different parameters are same for all the tasks. Meanwhile, there are also several task-specific hidden layers, for example the pink and light green layers in Figure 10. The layers, neurons and different parameters are different for different tasks. The interest with such structure is to reduce the risk of overfitting and at the same time benefit from the gain brought with related learning tasks. Thus, we opt for hard-parameter sharing architecture of MTL for UED as described in Figure 10. Unlike separate detection of some user attributes in existing works, the obvious correlation between UED and MSP tasks motivates us to propose MTL solution for UED. Unlike single task model, the MTL-UED model looks for minimizing two cost functions corresponding to

environment and mobility. Equation 5 shows the loss function, which is a weighted addition of both the cost functions.

$$L = \alpha \frac{1}{N} \sum_{i=1}^N \sum_{k=1}^{K_{Env}} [Env_{ik} \log(\widetilde{Env}_{ik})] + \beta \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^{K_{Mob}} [Mob_{ik} \log(\widetilde{Mob}_{ik})] \quad (5)$$

where Env corresponds to environment label and Mob to mobility label respectively, while \widetilde{Env} and \widetilde{Mob} correspond to the model output. N corresponds to the data size and K corresponds to the number of classes.

The MTL architecture uses DL, which is appropriate for problems where modeling relationships between large number of features is not tractable. The model has to extract the complexity and variety of different environment and mobility situations met by mobile users.

B. Experimental Setup: Training configuration

Table II describes the experimental setup for cases of single task (STL) and multi-task (MTL) learning. It summarizes the sets of optimized hyper-parameters (e.g. shared and hidden layers, batch size, epoch size) used in both cases. The hyper-parameters for each of the investigated schemes (see Table III for STL and Table IV for MTL) have been optimized with Bayesian optimization. The UED STL model is trained with 4 features and the MTL model is trained with 6 features shared between two learning tasks (described in section III-B). Both cases use a Feed-Forward Neural Network (FNN) model composed of 3 main parts. (i) Input: A first input layer fed with 4 or 6-features. (ii) Core: hidden layers as well as a dropout layer to regularize and minimize the over-fitting. (iii) Output: An output layer with either 2, 3, 4, 5 or 8 classes (according to classification scheme and task). Layers with dropout and early stopping were used to avoid over-fitting.

The metrics: Accuracy and $F1 - score$ (eq. 6) are used to evaluate the UED performance for both STL and MTL.

$$F1 - score = 2 \frac{Precision \cdot Recall}{Precision + Recall} \quad (6)$$

It is a more appropriate metric to evaluate the performance in case of imbalanced data. Accuracy can be misleading in case of imbalanced datasets. The success-criteria is set out to 95% of $F1 - score$ in order to accept a task with a failing-rate ($1 - F1 - score$) of 5%. It is indirectly inspired from assumptions of mobile network dimensioning, where an error up to 5% is qualified as an admissible error rate. Following text looks for a best trade-off between more granularity vs. performance.

C. User Environment Detection: single task learning

First we investigate STL based UED [28] using supervised DL. Table III presents the performance results of multi-output

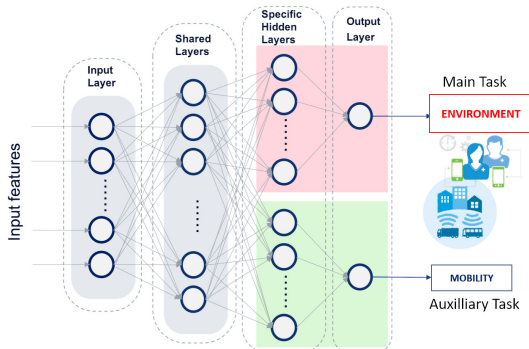


Fig. 10: Hard parameter sharing for multi-task learning

UED task	Learning / Evaluation	Optimizer	FNN model	Drop.	Valid.	Epoch	Batch	Activation
STL	75% / 25%	Nadam	7 hidden layers	0,1-0,4	20% - 30%	70 -200	100	tanh
MTL	75% / 25%	Adam	4 shared layers & 4 specific layers	0,2	30%	100	100	tanh

TABLE II: Experimental Setup: training configuration for single task (STL) and multi-task learning (MTL)

classification for environment detection. We observe that all schemes deliver $F1 - scores$ higher than 90% which we find as an acceptable classification performance. However, among all the schemes, the 2-class scheme UED_{2C} (corresponding to classical IOD) and the four-class schemes UED_{4C_2} and UED_{4C_3} give the best performance.

As shown in Table III, $F1 - score$ of 2-class scheme is equal to 95.76%. $F1 - scores$ of UED_{4C_3} and UED_{4C_2} are equal to 94.28% and 93.11%, respectively. We notice a slight improvement of $F1 - score$ with the two-class scheme as compared to $F1 - score$ obtained under same conditions as in [7]. It is because now the algorithms process two times more data, impacting the performance in a favorable way. We also observe a loss of up to 6%, approximately, when using a five-class scheme as compared to the binary classification. But, when using the 4-class schemes as compared to the binary classification, the loss decreases to around 1.4% with UED_{4C_3} or to 2.6% with UED_{4C_2} . Thus, the experimental results demonstrate that a more detailed learning can be achieved with a very minimal loss of performance. This is mainly obtained using the schemes with 4 classes, where the group “Outdoor” is split into *Pedestrian* and “Transport” classes. As an example, Figure 7 shows a CDF curve related to *Pedestrian* that is distant from the other CDF curves of other outdoor environments.

D. User Environment Detection: multi-task learning

We now investigate MTL based UED, which is done with the assistance of MSP using supervised DL. We then compare the results when UED is done with the help of MSP vs. when UED is done as a single task. Then, the analysis of the gain brought by the MTL architecture is done by investigating best classification schemes, having between 2 to 8 classes, which were picked from UED STL and MSP, (see Table III and [35]).

Table IV compares performance between the single task and multi-task models, while considering optimized model in each classification scheme investigated. The first case presents the detection performance obtained with STL and MTL for a combination of two classical state-of-art schemes for environment or mobility state classification issues. They correspond to scheme combinations of Indoor/Outdoor and 3-state profiles and are denoted as $UED_{2C} - MSP_{3C}$. With MTL, we observe that $F1 - score$ increases by 3.4% in case of Indoor/Outdoor classes compared to UED STL (Table III).

We further investigate the classification using MTL while considering other combinations of best classification schemes found for UED STL and MSP. UED MTL is then investigated by considering new classification schemes as compared to state-of-art. Table IV shows the detailed performance results (Accuracy and $F1 - score$) of UED obtained with Dataset 1 for the various MTL classification schemes. For the best

MSP schemes, [35] shows that the single DL-based MSP task gives an accuracy higher than 93% and average $F1 - score$ of 90%. To deeply analyse the results presented in Table IV, Figure 11 draws $F1 - score$ of STL (full line) vs. MTL (dotted line) for the studied classification schemes. We notice that the curve in full line decreases with the class number of UED task. It shows that $F1 - score$ of UED STL is inversely proportional to the number of classes. However, $F1 - score$ remains unchanged with an increase in class number of MSP task since this task isn’t involved in UED STL. In Figure 11, we notice also that $F1 - score$ of UED is higher in MTL case (dotted line) than in STL case (full line) for all schemes. With MTL, $F1 - score$ increases up to 8% approx. as compared to UED STL. Thus, joint learning in a hard-parameter sharing architecture turns out to be beneficial for UED task. This is because with such structure both tasks share data inputs and information which bring meaningful additional information to UED. The performance increase from STL to MTL also empirically shows that the 2 tasks are similar and correlated. With MTL, the success criteria of 95% $F1 - score$ is reached and we also managed to simultaneously detect the user’s environment as well as the user’s mobility. $F1 - score$ in MTL decreases from 99.03% to 97.37% for the classification schemes of 2-classes and 8-classes, respectively. This high performance can be explained in the way the UED model has been assessed. This is a model that is trained using a dataset capturing only regular life user profiles. In other words, such users always crossed similar environments at almost the same times during their work week as well as the week-end: e.g., work between 9 a.m. and 6 p.m. or home between 9 p.m and 6 a.m during the work week and so on. We also observe

Scheme	Environment	Dataset 1	
		Acc.	F1-S.
UED_{2C}	Outdoor / Indoor	95.8%	95.76%
UED_{3C_0}	Outdoor / Buildings, Work	91.89%	91.84%
UED_{3C_1}	Outdoor / Buildings, Home	92.06%	92.04%
UED_{4C_0}	Outdoor / Buildings, Work, Mall	91.58%	91.53%
UED_{4C_1}	Outdoor / Buildings, Home, Mall	91.42%	91.38%
UED_{4C_2}	Pedestrian, Transport / Buildings, Mall	93.18%	93.11%
UED_{4C_3}	Pedestrian, Transport / Buildings, Home	94.31%	94.28%
UED_{5C_0}	Pedestrian, Transport / Buildings, Work, Mall	90.70%	90.69%
UED_{5C_1}	Pedestrian, Transport / Buildings, Home, Mall	90.79%	90.72%
UED_{8C}	Pedestrian, Car, Bus, Train / Building, Home, Work, Mall	89%	89%

TABLE III: $F1 - score$ and Accuracy for single task learning

Scheme	Environment (UED)	Mobility (MSP) kmph	Dataset 1	
			Acc.	F1-S.
$UED_{2C} - MSP_{3C}$	Outdoor / Indoor Pedestrian, Transport / Buildings, Home Pedestrian, Transport / Buildings, Home, Mall Pedestrian, Car, Bus, Train / Building, Home, Work, Mall	{0,10,90}	99.12%	99.03%
$UED_{4C_3} - MSP_{3C}$			99.22%	98.23%
$UED_{5C_1} - MSP_{3C}$			98.92%	97.97%
$UED_{8C} - MSP_{3C}$			98.85%	97.90%
$UED_{4C_3} - MSP_{4C}$	Pedestrian, Transport / Buildings, Home Pedestrian, Transport / Buildings, Home, Mall Pedestrian, Car, Bus, Train / Building, Home, Work, Mall	{0, 1, 10, 90}	98.90%	97.75%
$UED_{5C_1} - MSP_{4C}$			98.96%	97.84%
$UED_{8C} - MSP_{4C}$			98.74%	97.44%
$UED_{4C_3} - MSP_{5C}$	Pedestrian, Transport / Buildings, Home Pedestrian, Transport / Buildings, Home, Mall Pedestrian, Car, Bus, Train / Building, Home, Work, Mall	{0, 1, 10, 40, 90}	98.88%	97.68%
$UED_{5C_1} - MSP_{5C}$			98.90%	97.90%
$UED_{8C} - MSP_{5C}$			98.74%	97.54%
$UED_{4C_3} - MSP_{8C}$	Pedestrian, Transport / Buildings, Home Pedestrian, Transport / Buildings, Home, Mall Pedestrian, Car, Bus, Train / Building, Home, Work, Mall	{0, 1, 2, 3, 10, 30, 40, 90}	98.85%	97.61%
$UED_{5C_1} - MSP_{8C}$			98.86%	97.82%
$UED_{8C} - MSP_{8C}$			98.66%	97.37%

TABLE IV: $F1 - score$ and Accuracy for multi-task learning (MTL) per classification scheme

that $F1 - score$ for UED stays stable with MTL. We remark that increasing the number of MSP classes doesn't negatively impact $F1 - score$ of UED as it might have been expected. Results show that a good scheme in terms of classification performance corresponds to 3 MSP classes with 2 to 8 UED classes. The three classes: "static" or "moving slow" or "moving rapidly" provide sufficient additional information to significantly improve the performance of the UED task. In this case, classification scheme with more classes (more thinner mobility state) for the auxiliary task is not required to ensure high performance of the main task.

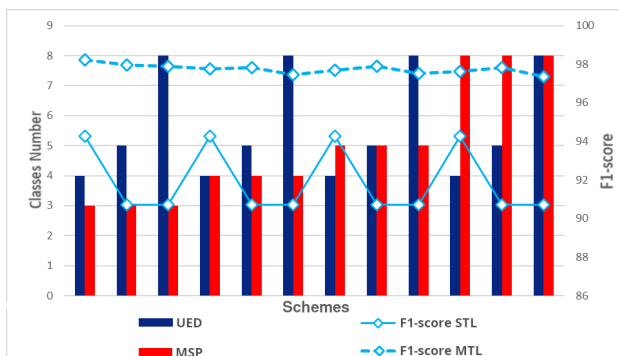
Table V compares the performances of different UED models on the 2 datasets, thus, also including the dataset 2. As described before, this dataset differs from dataset 1 in terms of its timelines, diverse cities, devices used and places where measurements were recorded. We compare the performance for UED task using different models such as FNN multi-task or single task, SVM, logistic regression and random forest. The classic ML models are trained using the same conditions as those used for STL. It can be observed that MTL shows better $F1 - score$ as compared to STL and other classic ML algorithms. For dataset 2, $F1 - score$ with MTL exceeds that of STL by at least 8.30% and at least by 7.83% to that of classic ML algorithms. All models perform worst when the classification scheme involves UED_{5C_1} . This is due to the *Mall* class. Especially Dataset 2 has a very few instances of this class. In general, we also observed that, in terms of $RSRP$ values, the *Mall* class is very similar to some other classes such

as *Building* and *Work*. Note that, in most cases except a few ones, all models perform better on Dataset 1 than on Dataset 2. We found Dataset 2 has significantly more measurement points which correspond to different mobility situations. Thus, STL performs relatively worse on Dataset 2 because STL does not use MSP information. Note that in case of MTL, this additional MSP information helps classification of outdoor class.

VI. CONCLUSION

We proposed to improve the detection of user environment by detecting several environment classes and improving the detection accuracy. For that, we collected real-life radio data from 3GPP UE-specific 4G networks. We pre-processed the data using label correction strategies. As one of the novelties of this work, we then proposed granular environment classification schemes to detect up to eight distinct types of user environments. Using different classification schemes, we compared user environment detection using ML algorithms and DL as a single task model as well as a multi-task learning (MTL) model, with the assistance of mobility speed profiling (MSP) task. We observed improvements in detection accuracy thanks to the assistance of the auxiliary MSP task.

Experiments are run over two distinct large-scale datasets. Results showed that a reliable and profile-specific machine

Fig. 11: Number of classes per scheme and $F1 - score$ for single task (STL) vs. multi-task learning (MTL) per scheme

Model	Schemes	Dataset 1		Dataset 2	
		Acc.	F1-S.	Acc.	F1-S.
FNN MTL	$UED_{2C} - MSP_{3C}$	99.12%	99.03%	99.07%	99.01%
	$UED_{4C_3} - MSP_{3C}$	99.22%	98.23%	98.53%	98.51%
	$UED_{5C_1} - MSP_{3C}$	98.85%	97.9%	98.47%	96.64%
FNN STL	UED_{2C}	95.80%	95.76%	91.27%	90.71%
	UED_{4C_3}	94.31%	94.28%	83.92%	83.63%
	UED_{5C_1}	90.79%	90.72%	84.11%	67.73%
SVM	UED_{2C}	92.86%	92%	83.30%	83.97%
	UED_{4C_3}	77.32%	63.99%	71.99%	50.54%
	UED_{5C_1}	77.08%	57.36%	72.06%	56.58%
Logistic Regression	UED_{2C}	91.20%	90.04%	82.38%	81.58%
	UED_{4C_3}	69.63%	51.55%	63.4%	61.54%
	UED_{5C_1}	69.54%	40.93%	63.53%	49.34%
Random Forest	UED_{2C}	94.84%	94.27%	91.67%	91.18%
	UED_{4C_3}	86.47%	78.66%	83.41%	83.20%
	UED_{5C_1}	85.99%	72.77%	83.40%	66.67%

TABLE V: $F1 - score$ and Accuracy per UED model

learning based model can be trained efficiently for UED task. MTL has its own advantages, such as reduced complexity brought by a unified system. However, as a limitation of this solution, the labeling required for the two tasks implies more human intervention in terms of data preparation and additional signalling. Also, such functionality can disclose indirect information of user's location to Mobile Network Operators, which can raise concerns about user privacy and security in general. This will require the use of additional functionality to ensure the protection of users' identity.

In future, we would like to detect more user behavior attributes, investigate other DL algorithms and semi-supervised methods to exploit the unlabelled massive data. We also target to exploit data coming from more diversified user profiles, with more diverse hourly or daily activities.

REFERENCES

- [1] S. van der Meer, J. Keeney, and L. Fallon, "5G networks must be autonomic!" in *NOMS 2018-2018 IEEE/IFIP Network Operations and Management Symposium*. IEEE, 2018, pp. 1–5.
- [2] I. H. Sarker, "Context-aware rule learning from smartphone data: survey, challenges and future directions," *Big data*, vol. 6, no. 1, pp. 1–25, 2019.
- [3] A. Ray, S. Deb, and P. Monogioudis, "Localization of LTE measurement records with missing information," in *IEEE INFOCOM 2016-The 35th Annual IEEE International Conference on Computer Communications*. IEEE, 2016, pp. 1–9.
- [4] S. Mekki, T. Karagioules, and S. Valentin, "HTTP adaptive streaming with indoors-outdoors detection in mobile networks," in *2017 IEEE Conference on Computer Communications Workshops (INFOCOM WK-SHPS)*. IEEE, 2017, pp. 671–676.
- [5] A. B. H. Alaya-Feki, A. Le Cornec, and E. Moulines, "Optimization of radio measurements exploitation in wireless mobile networks," *JCM*, vol. 2, no. 7, pp. 59–67, 2007.
- [6] E. Pateromichelakis, F. Moggio, C. Mannweiler, and al, "End-to-end data analytics framework for 5g architecture," *IEEE Access*, vol. 7, 2019.
- [7] I. Saffar, M. L. A. Morel, K. D. Singh, and C. Viho, "Semi-supervised deep learning-based methods for indoor outdoor detection," in *ICC 2019-2019 IEEE International Conference on Communications (ICC)*. IEEE, 2019, pp. 1–7.
- [8] Y. Zhang and Q. Yang, "A survey on multi-task learning," *IEEE Transactions on Knowledge and Data Engineering*, 2021.
- [9] S. Wu, H. R. Zhang, and C. Ré, "Understanding and improving information transfer in multi-task learning," in *International Conference on Learning Representations*, 2019.
- [10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [11] E. Brynjolfsson and T. Mitchell, "What can machine learning do? workforce implications," *Science*, vol. 358, no. 6370, pp. 1530–1534, 2017.
- [12] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.
- [13] S. ISO, "13407: 1999," *Human-centred design processes for interactive systems*, 1999.
- [14] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, and et al, "Towards a better understanding of context and context-awareness," in *International symposium on handheld and ubiquitous computing*. Springer, 1999, pp. 304–307.
- [15] D. Lodder, B. Bregen, D. Braunschweig, J. Allen-Smith, and T. Ford. (2015) Understanding the right mobile mix for your venue. [Online]. Available: <https://www.hetnetforum.com/resources/send/2-resources/36-venueconnect-2015-hetnet-forum-presentation>
- [16] Q. Xu, J. Erman, A. Gerber, Z. Mao, J. Pang, and S. Venkataraman, "Identifying diverse usage behaviors of smartphone apps," in *Proceedings of the 2011 ACM SIGCOMM conference on Internet measurement conference*. ACM, 2011, pp. 329–344.
- [17] D. Peraković, I. Forenbacher, I. Jovović et al., "Identification and prediction of user behavior depending on the context of the use of smart mobile devices," *Annals of DAAAM & Proceedings*, vol. 26, no. 1, 2015.
- [18] W. Wang, Q. Chang, Q. Li, Z. Shi, and W. Chen, "Indoor-outdoor detection using a smart phone sensor," *Sensors*, 2016.
- [19] F. Feriol, D. Vivet, and Y. Watanabe, "A review of environmental context detection for navigation based on multiple sensors," *Sensors*, 2019.
- [20] S. Edelev, S. N. Prasad, H. Karnal, and D. Hogrefe, "Knowledge-assisted location-adaptive technique for indoor-outdoor detection in e-learning," in *IEEE International Conference on Pervasive Computing and Communication Workshops*. IEEE, 2015, pp. 8–13.
- [21] V. Radu, P. Katsikouli, R. Sarkar, and M. K. Marina, "A semi-supervised learning approach for robust indoor-outdoor detection with smartphones," in *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*, 2014, pp. 280–294.
- [22] A. Esmaceli Kelishomi, A. Garmabaki, M. Bahaghighat, and J. Dong, "Mobile user indoor-outdoor detection through physical daily activities," *Sensors*, 2019.
- [23] Y. Zhu, H. Luo, Q. Wang, F. Zhao, B. Ning, Q. Ke, and C. Zhang, "A fast indoor-outdoor transition detection algorithm based on machine learning," *Sensors*, 2019.
- [24] M. B. Rhudy, S. K. Dolan, C. Mello, and N. Greenauer, "Indoor and outdoor classification using light measurements and machine learning," *Applied Artificial Intelligence*, 2022.
- [25] J. Bejarano-Luque, M. Toril, M. Fernandez-Navarro, and et al, "Data-driven algorithm for indoor-outdoor detection based on connection traces in a lte network," *IEEE Access*, vol. 7, p. 65877–65888, 2019.
- [26] L. Zhang, Q. Ni, M. Zhai, J. Moreno, and C. Briso, "An ensemble learning scheme for indoor-outdoor classification based on kpis of lte network," *IEEE Access*, p. 63057–63065, 2019.
- [27] C. Frank, R. S. Phillipson, I. Wezeman, and Chiscop, "Indoor-outdoor detection in mobile networks using quantum machine learning approaches," *Computers*, 2021.
- [28] I. Saffar, M. L. A. Morel, M. Amara, K. D. Singh, and C. Viho, "Mobile user environment detection using deep learning based multi-output classification," in *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*. IEEE, 2019, pp. 16–23.
- [29] M. K. Marina, V. Radu, and K. Balampekos, "Impact of indoor-outdoor context on crowdsourcing based mobile coverage analysis," in *Proceedings of the 5th Workshop on All Things Cellular: Operations, Applications and Challenges*, 2015, pp. 45–50.
- [30] *Evolved Universal Terrestrial Radio Access (E-UTRA); Requirements for support of radio resource management*, 3GPP Standard TS 36.133 - Release 8, 2018.
- [31] *Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures*, 3GPP Standard TS 36.213 - Release 8, 2018.
- [32] *Evolved Universal Terrestrial Radio Access (E-UTRA); Medium Access Control (MAC) protocol specification*, 3GPP Standard TS 36.321- Release 15, 2018.
- [33] *Evolved Universal Terrestrial Radio Access (E-UTRA); User Equipment (UE) procedures in idle mode*, 3GPP Standard TS 36.304 - Release 15, 2018.
- [34] D. Herculea, C. S. Chen, M. Haddad, and V. Capdevielle, "Straight: Stochastic geometry and user history based mobility estimation," in *Proceedings of the 8th ACM International Workshop on Hot Topics in Planet-scale mOBile computing and online Social neTworking*, 2016, pp. 1–6.
- [35] I. Saffar, M. L. A. Morel, K. D. Singh, and C. Viho, "Deep learning based speed profiling for mobile users in 5G cellular networks," in *2019 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2019, pp. 1–7.
- [36] P. Branco, L. Torgo, and R. P. Ribeiro, "A survey of predictive modeling on imbalanced domains," *ACM Computing Surveys (CSUR)*, vol. 49, no. 2, pp. 1–50, 2016.
- [37] *Study on scenarios and requirements for next generation access technologies*, 3GPP Standard 3GPP TS 3GPP TS 38.913 - Release 14, 2019.
- [38] S. Ickin, K. Wac, M. Fiedler, L. Janowski, J.-H. Hong, and A. K. Dey, "Factors influencing quality of experience of commonly used mobile applications," *IEEE Communications Magazine*, vol. 50, no. 4, pp. 48–56, 2012.
- [39] R. Caruana, "Multitask learning: A knowledge-based source of inductive bias," in *Proceedings of the Tenth International Conference on Machine Learning*. Morgan Kaufmann, 1993, pp. 41–48.
- [40] C. Shui, M. Abbasi, L.-É. Robitaille, B. Wang, and C. Gagné, "A principled approach for learning task similarity in multitask learning," *arXiv preprint arXiv: 1903.09109*, 2019.