Correlation-Based Feature Mapping of Crowdsourced LTE Data

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***Abstract*—There have been efforts taken by different research projects to understand the complexity and the performance of a mobile broadband network. Various mobile network measurement platforms are proposed to collect performance metrics for analysis. Data integration would provide more thorough data analyses as well as prediction and decision models from one dataset to another. The crucial part of the data integration is to find out, whether two datasets have corresponding features (performance metrics). However, finding common features across datasets is a challenging task. For example, features might: 1) have similar names but be different metrics, 2) have different names but be similar metrics, or 3) be same metrics but have differences in the underlying methodology.**

We designed a feature mapping methodology between two crowdsourced LTE measurement-based datasets. Our method is based on correlations between the features and the mapping algorithm is solving a maximum constraint satisfaction problem (CSP). We define our constraints as inequality patterns between the correlation coefficients of the measured features. Our results show that the method maps measurement features based on their correlation coefficients with high confidence scores (between 0.78 to 1.0 depending on the amount of features). We observe that mapping score increases as a function of the amount of features. Altogether, our results show that this methodology can be used as an automated tool in the measurement data integration.

I. Introduction

There have been efforts taken by different research projects to understand the complexity and the performance of a mobile broadband network. Various crowsourced-based platforms such as Netradar [1], RTR Nettest [2], Mobiperf [3], OpenSignal [4], and Speed Test [5] have been developed to collect network related metrics from different vantage points. Also, controlled cross-operator measurement test platforms, such as the MONROE [6] has been built for the same purpose. These platforms are collecting measurement metrics independently. It is possible to use each of this measurement dataset separately for analyzing the behaviors of mobile broadband networks, as it is recently done by several research groups [7], [6].

However, to enable the richer use of the collected data, the data sources should be integrated. The data integration would provide more thorough data analyses, for example with a wider range of Mobile Network Operators (MNO)s included in the data. Moreover, the data integration would provide the dynamic adaptation of prediction and decision models from one dataset to another. The integration of the dataset needs to find the features (performance metrics) that are common to these separate datasets, such as throughput, latency, and network-level metrics. For instance, the EU project about mapping of broadband services in Europe [8] shows currently separate datasets by country level. One reason of displaying such different datasets separately is that there is no easy solution to find similar features and to merge them. Therefore, such projects would also benefit by applying a feature mapping method that enables integrating datasets into a single country-level view.

The crucial part of the data integration is to find out, whether two datasets have corresponding features (performance metrics). The challenge in finding similar features rises in comparing whether they have: 1) similar names but different metric (such as "download speed" depicting either the throughput or average bit rate), 2) different names but similar metric (such as "latency" and "ping duration"), names, and 3) same metrics in general but measurements have differences in the underlying methodology (such as latencies measured with different protocols). Our objective is to automatically analyse and map similar features across platforms, without a need for manually analyse their similarities and solve the above-mentioned vagueness.

Our approach addresses these issue by mapping features between crowdsourced datasets. We use platform-specific correlation coefficients between features and try to find the same correlation patterns from another dataset. In the mapping, we assume that ranking between coefficients is domain invariant. In other words, the ranking order of the coefficients is more or less the same in both datasets. We present a methodology for measurement-based feature mapping of different data sources only using the correlations between the features. Thus, our method is independent of the actual feature

values which might be biased between the datasets. We find mappings between performance metrics computed under different conditions, such as different protocol in latencies (TCP and UDP) and between biased metrics that at first seems different, such as Reference Signal Received Power (RSRP) and Arbitrary Strength Unit (ASU). The results show that the method maps measurement features based on their correlation coefficients with high confidence scores (between 0.78 to 1.0 depending on the amount of features). The applicability of our methodology is that it can be used as an automated tool in the measurement data integration.

This paper is structured as follows: Section II presents the related work in feature mapping, Section III describes two datasets, Section IV explains our methodology, Section V presents the results of our approach, and Section VI concludes the paper.

II. Related Works

Our work is mainly related to studies which have the research objective of integrating measurement data from different sources and need to solve the problem of mapping the features across datasets.

Mapping of performance metrics and QoS features in the LTE networks is addressed in earlier mobile network research. Malandrino et. al [9] have the similar objective of merging two crowdsourced LTE measurement datasets. Their focus is however on using human expertise in order to map the metrics from the datasets, whereas we present a method that analyses the data and proposes the mappable features without manual analysis.

Lipenbergs et. al [10] address the European-wide broadband mapping task [8] and analyse the data representation of broadband mapping. Apajalahti et. al combine statistical correlations and human-defined semantic dependencies to enable cross-domain mappings between LTE performance metrics of different network providers. Li et. al [11] map QoS parameters across LTE network components, such as the Evolved Universal Terrestrial Radio Access Network (E-UTRAN), Backhaul transport network, and Evolved Packet Core (EPC) network. All of these works propose models where the actual cross-domain mapping is defined by human, whereas our approach aims to find the mapping automatically.

More generally in the field of wireless networks research, there have been approaches to map features across data sources with statistical and machine learning methods. For example, Manco-Vásquez et. al [12] uses a Kernel Canonical Correlation Analysis (KCCA) method for spectrum sensing in the cognitive radio environment. Although the method is also correlation-based, it requires the actual data sources to be in the same environment (the same time periods and/or location), whereas our method is developed to handle heterogeneous data where time periods and locations of the measurements might be unknown or scattered.

Pan et. al [13] present a transfer component analysis method that learns a cross-domain feature space for indoor WiFi localization. Their method differs from ours as it addresses a supervised learning task where the feature mapping is trained with respect to labels (locations) in the training set, which we do not consider.

The concept of feature mapping has also been addressed in sensor networks research, for example, in the human activity recognition task. Van Kasteren et. al [14] map features with manually define mapping functions by first classifying the features by their type. Chiang et. al [15] also define manually the sensor metadata which is then used to calculate the feature similarities across domains. Wen-Hui et. al [16] propose an algorithm based on Kullback–Leibler divergence to map cross-domain features with respect to the probability distributions of the classification labels. In this case, one needs to map the classification labels in order to learn mappings between the features.

Altogether, the related work shows that cross-dataset feature analysis has gained interest in the related research fields, but most of the work relies either on manually defined mappings or on classified data where labels describe the measurements and feature values. The need for automatic mapping of QoS and other LTE-related measurement parameters between data sources has been recognized, but to our knowledge no earlier work for this exists yet.

III. Datasets

For this work, we have used two measurement datasets collected from the first of June to the end of Nov. 2017. The first dataset is `Netradar` [17]. It is a crowdsourced mobile measurement platform that measures and collects metrics related to cellular network performance collected from mobile user devices. It has been running actively worldwide since March 2013. The measurement mainly focuses on the data services and analysis of bit-rates (over TCP), UDP based latencies and the context information related to each measurement including, device model, battery level, location, radio signal strength, date and time, the mobile operator.

We processed the dataset by radio technology type and location. For this, we select measurements under LTE network, which has been collected from Helsinki area, Finland. `Netradar` has a number of measurement metrics related to cellular network performance. In this paper, we use the following metrics: TCP-based downlink and uplink throughput, UDP-based latency, signal strength, LTE ASU, LTE RSRP, LTE Reference Signal Received Quality (RSRQ), LTE Reference Signal Signal to Noise Ratio (RSSNR), battery level, and movement speed.

The second dataset we have used in this paper is `RTR Nettest` [2]. It is a mobile application that collects information from the end user with an open

dataset access. It records features including the downlink and uplink throughput, signal strength, network metrics such as RSRP and RSRQ for LTE, connection error and IP packet loss, ping based latency, testing time, IP address and host name of the computer. It also collects other quality parameters such as Domain Name System (DNS), ports, transparent connection, downloading speed test website and traceroute. `RTR Nettest` provides more than 60 network-related features. For this work, we only focus on metrics collected under LTE network. These are the TCP-based downlink and uplink throughputs, TCP-based ping latency test, LTE RSRQ, and LTE RSRP.

IV. Methodology

This section presents the method that maps the measurement-based features between two crowdsourced LTE data platforms, RTR Nettest and Netradar. Thus, the features are performance metrics and QoS parameters collected via end-user measurements. The main problem is to find and map corresponding features between two platforms by only analysing their correlation coefficients with other features. The hypothesis is that we can find feature pair-specific patterns from the correlation coefficients which occur in both platforms. The objective of the method is to rank the coefficient values and represent every coefficient pair with inequalities, such as $r(f_x, f_y) < r(f_y, f_z)$ stating that correlation between f_x and f_y is lower than f_y and f_z. For example, our analysis shows that we can make a general rule $r(latency, downlink) < r(downlink, uplink)$ (see Section V for more information).

A. Preparing measurements into correlation coefficient rankings

In order to find regular patterns regarding the coefficient rankings of a large dataset (data available from RTR Nettest or Netradar), we need to preprocess the data. Figure 1 shows the preprocessing phase. First, the dataset is split into smaller monthly subsets (step 1). Next, a correlation matrix R_i is calculated for each subdataset (step 2). For evaluation purposes we use both Pearson's linear and Spearman's non-linear correlations. Finally, for each subdataset we calculate coefficient rankings as a set of inequality clauses (step 3).

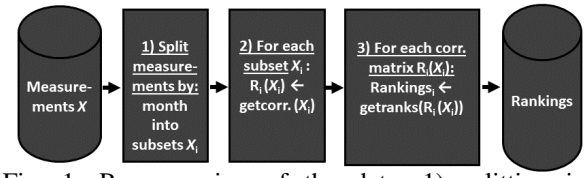

Fig. 1: Preprocessing of the data: 1) splitting into monthly subsets 2) calculating correlation matrices 3) listing the rankings between the correlation coefficients.

B. Correlation-based feature mapping

The output of the preprocessing task (Figure 1) is used for the actual mapping. Figure 2 shows an overall picture how the features are mapped across the platforms. The earlier described data preparation are made separately for both source and target platforms. From the source platform, we also need to learn which of the coefficient inequalities are more regular than others regarding the N subdatasets (step 1). We add an inequality $r(f_x, f_y) < r(f_y, f_z)$ between correlation coefficients of features f_x, f_y, and f_y,f_z into the constraint base, if the inequality occurs in majority (more than 0.5 times) of the subdatasets. After learning the constraint base we use it to find similar patterns from the target platform (step 2).

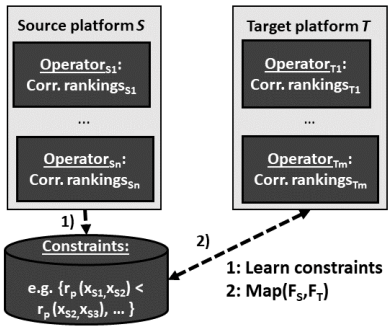

Fig. 2: Steps in the mapping procedure: 1) learning the constraints from the source platform and 2) mapping those to correlation coefficients from the target platform.

Technically, our feature mapping method is solving an approximation of a well-known constraint satisfaction problem (CSP). A CSP is a problem in which values need to be assigned to variables so that given constraints are satisfied. [18] In our case, the constraints are the inequalities that we learn between the correlation coefficients of the source platform and variables the feature pairs of the source features F_S. The problem is then to assign feature pairs from the target platform (features F_T) as variable values to the constraint base (replacing F_S with F_T) so that the assigned feature pairs maximize the number of truth statements when comparing the constraint base to the target datasets. Assuming that a set of features would have a similar ranking of the coefficient values across platforms, the solution of the maximum CSP problem would then also be a mapping of features between F_T and F_S.

Algorithm 1 demonstrates at a high level how the maximum CSP is adapted to the feature mapping. Basically, we try every possible mapping combination between a set of target and source features, and try to maximize the truth statements that the assignments (mapping) in the constraint base will produce while comparing the assigned constraints to the correlation data from the target platform.

Algorithm 1 Pseudoalgorithm demonstrating the functionality of the feature mapping.

for each possible mapping $Map_i(F_T, F_S)$ **do**
  Assign features F_T to the constraint base wrt. Map_i
  for each monthly-based correlation matrix in the target platform **do**
    Count, how many times constraints are satisfied in the target platform with the current assignment.
  end for
end for
return Mappings having the highest count of truth statements

The algorithm returns a list of possible mappings, that have the highest satisfiability count. For every possible mapping between features $f_T i$ and $f_S j$, we define a mapping score which is a portion of their occurrence in the returned list. For example, let us consider a mapping case where the problem is to map three features between platforms S and T: F_s = $\{x, y, z\}$ and F_T = $\{a, b, c\}$. The algorithm returns two lists of mappings: $Map_1\{(x, a), (y, b), (z, c)\}$ and $Map_2\{(x, a), (y, c), (z, b)\}$. For this example case, the mapping scores would be: (x, a) = 1.0 and 0.5 for $(y, b), (y, c), (z, b)$ and (z, c). The scores indicate that x and a could be mapped with each other while other mappings can not be deduced from these results. Generally, as the method requires inequalities between coefficients, at least three features from both platforms are required at minimum and a higher number of features would provide a richer set of constraints for the analysis.

V. Results

This section evaluates the feature mapping method. The datasets, Netradar and RTR Nettest, are separated into six monthly sub-datasets in order to analyse the variation of the correlation coefficients. With respect to the documentations of the two platforms (Netradar, RTR Nettest), we define the common features as: (dowlink, download_kbit), (uplink, upload_kbit), (latency, ping_ms), (RSRP, RSRP), (RSRQ, RSRQ). These pairs are assumed to be matched with our feature mapping methodology.

A. Correlations

First, we report and analyse the correlation matrices for the features from both platforms. For evaluation purposes we have applied Pearson's correlation method for analysing possible linear relations and Spearman's for non-linear relations between the features.

1) Pearson: Figures 3 and 4 show Pearson's correlation matrices of monthly based data for the Netradar and RTR Nettest platforms. Figures show heat maps with blue indicating positive correlation (1.0 as a maximum value), white no correlation (0.0) and red negative correlation (-1.0 as a minimum value). In Figure 3, the correlations between the common five features are presented in the first five rows and columns.

From the figures can be seen that all five common features clearly have regularities among each other; inside every correlation matrix, the relative positions of the coefficients stay mostly the same. For example, latency (corresponding to ping_ms) and downlink (download_kbit) have mainly lower negative correlation than latency and RSRP in both platforms. Moreover, RSRP has mainly a stronger positive correlation with uplink (upload_kbit) than with downlink in both platforms.

From the Netradar correlation matrix (Figure 3) can be seen that RSRP, signal strength and LTE ASU have 1.0 correlations between each other. This indicates that the features present redundant information about the signal strength. In our method, this would mean that our method maps RSRP features from the source and target platforms with equivalent scores than with LTE ASU and signal strength. This is important to consider, because some platform might not have RSRP present in the measurement data, but only LTE ASU or signal strength.

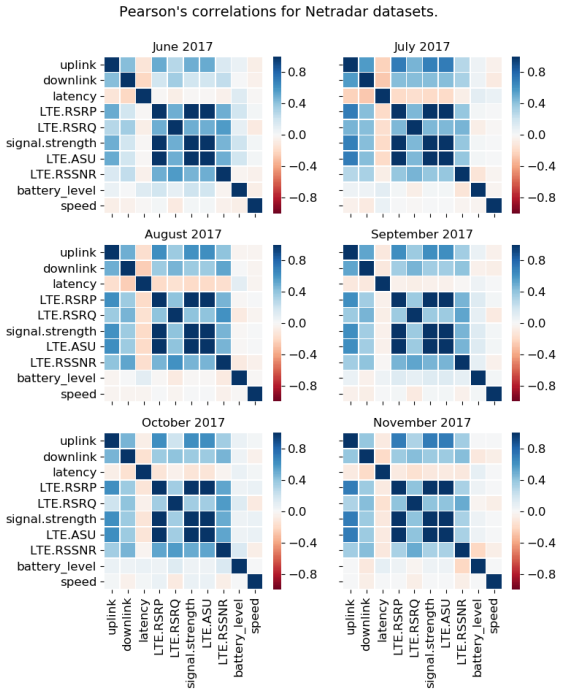

Fig. 3: Pearson's correlations in the Netradar platform. First five rows and columns show the correlations between the common features: uplink, downlink, latency, RSRP, and RSRQ.

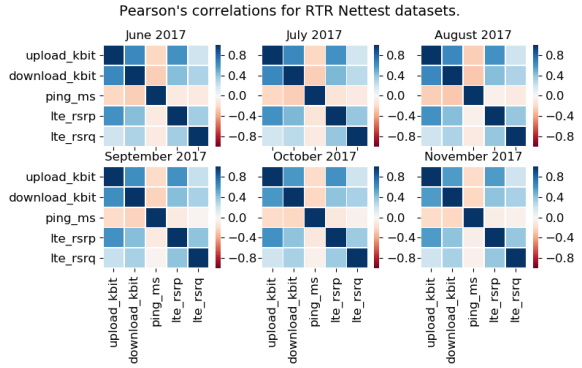

Fig. 4: Pearson's correlations in the RTR Nettest platform.

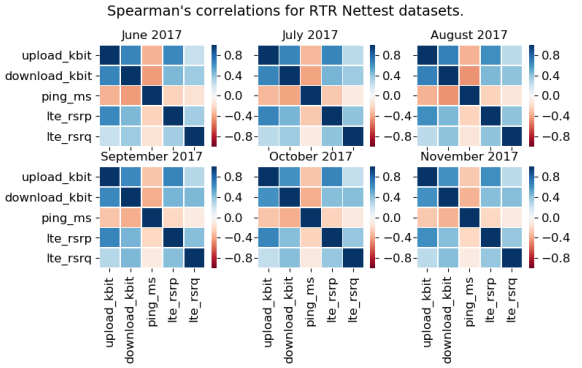

Fig. 6: Spearman's correlations in RTR Nettest platform

2) Spearman: Figures 5 and 6 show the Spearman's correlation matrices for the Netradar and RTR Nettest platforms. Although the actual coefficient values vary between Pearson and Spearman, the relations between the features stay the same. Again, from figures can be noticed that latency correlates stronger with downlink than with RSRP. RSRP in turn correlates stronger with uplink than downlink. Also, Figure 5 shows that the Spearman correlation between RSRP, LTE ASU, and signal strength is 1.0.

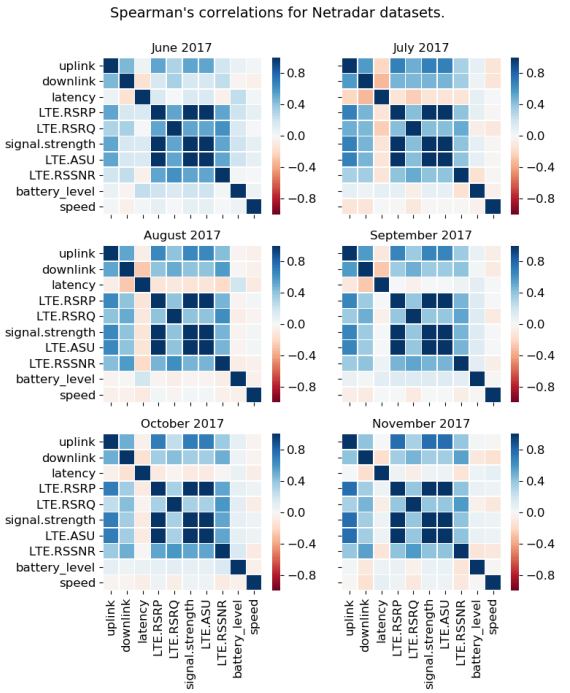

Fig. 5: Spearman's correlations in Netradar platform. First five rows and columns show the correlations between the common features: uplink, downlink, latency, RSRP, and RSRQ.

Altogether the correlation matrices in Figures 3–6 support our hypothesis that regular patterns between coefficients can be found. Next, we evaluate our methodology with mapping scores for all mapping combinations between the platforms.

B. Average scores of the feature mapping

To evaluate the feature mapping method, we include all the five features from the RTR Nettest (upload_kbit, download_kbit, ping_ms, lte_rsrp and lte_rsrq) and following eight from the Netradar: uplink, downlink, latency, RSRP, RSRQ, RSSNR, battery_level, and speed. We leave LTE ASU and signal strength out from the evaluation because the correlation matrices clearly indicate that they would give exactly the same results as the RSRP (which is also the desired outcome of the method). The higher number of features in the Netradar dataset allows us to evaluate the mapping in situations when there is not a simple one-to-one mapping between the features, but also some "noisy" features that should be left without a mapping.

For evaluation purposes, we define a mapping score between F_T and F_S for a single mapping case as follows: $\frac{1}{M}\sum_{i=0}^{M} score(f_{Ti}, f_{Si})$, where M is the number of common features between the sets ($M = |F_T \cap F_S|$), f_{Ti} and f_{Si} are the ith common features from the F_T and F_S. As defined in Section III, the common feature-pairs are defined as: (uplink,upload_kbit), (downlink, download_kbit), (latency, ping_ms), (RSRP, lte_rsrp), and (RSRQ, lte_rsrq).

We evaluate the overall performance of the mapping by generating all possible mapping combinations between the source and target features in order to examine how our method catches the different levels of similarities between the feature sets. We present the overall results in plots that show average mapping scores as a function of the ratio of common features. This means that we group all mapping cases that have the same ratio of common features and calculate the average mapping score over those. For example, the mapping of three features means that there are 560 mapping combinations

$(\binom{5}{3} \times \binom{8}{3})$ in the plot and the point where the common ratio is 3/3, the value is averaged over 10 $(\binom{5}{3})$ different mapping combinations.

Figure 7 shows the average scores of the feature mapping while RTR Nettest is the source and Netradar the target platform. Figure has three subplots separating the mapping results between the mapping of three, four, and five features. All the subplots show that the average scores of perfect mappings (common ratio is 1.0) can clearly be distinguished from imperfect mappings (common ratio is lower than 1.0). Moreover, the increasing trend of the scores as a function of the common ratio can be noticed. This shows the desired outcome that the feature mapping method gives better scores when higher portion of common features are mapped. The different correlation methods, Spearman, Pearson, and their combination (both of them are used in the constraint base), give rather similar results, meaning that linear relations can be used as well as non-linear.

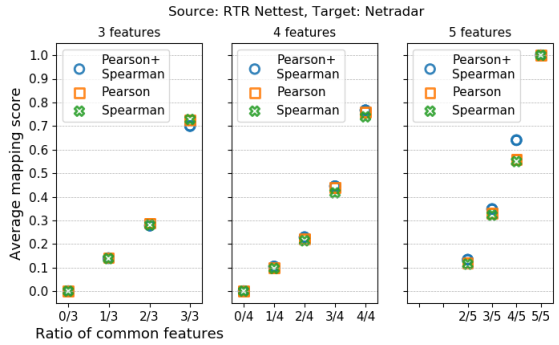

Fig. 7: Average mapping scores when mapping from RTR Nettest to Netradar. The score increases as a function of the common ratio. The perfect mappings (ratio of 1.0) outperforms the incomplete mappings.

Figure 8 shows the mapping results when Netradar is the source, and RTR the target platform and the same features are included in the evaluation. Apart from a small variation, the scores are rather equal to the earlier mapping case shown in Figure 7.

Altogether, the average scores show that the feature mapping method is able to distinguish incomplete mappings from the perfect mappings. Regardless of the amount of mapped features, there is a remarkable gap in the scores between the incorrect mappings and correct mappings (between the scores having a common ratio of 1.0 compared with lower ratios). Moreover, we can see that also the scores of the incorrect mappings give an insight of how many correct features there might be between the platforms, as the average score clearly correlates with the common ratio.

C. Feature-specific scores

Next, we evaluate our method from the perspective of the common features in order to report the differences between the features. We define a feature-specific mapping score as an average over all mapping cases, in which the common ratio is 1.0. As we have 16 such cases $(\binom{5}{3} + \binom{5}{4} + \binom{5}{5})$, the feature-specific score of the ith common feature (f_{Ti} and f_{Si} respectively) is $\frac{1}{16}\sum_{j=0}^{16} score(f_{Tij}, f_{Sij})$.

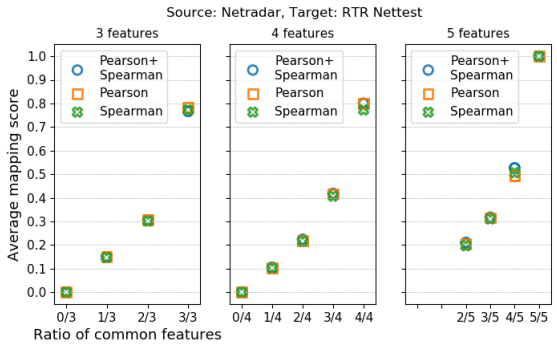

Fig. 8: Average mapping scores when mapping from Netradar to RTR Nettest. The score increases as a function of the common ratio. The perfect mappings (ratio of 1.0) outperforms the incomplete mappings.

Feature-specific scores of the mappings can be seen in Figure 9. This plot shows that there are more variations between the correlation methods and between the feature scores than that could be seen from the earlier overall results. The combined method (Pearson + Spearman) gives rather stable scores regardless of the source and target platform. The highest difference in the performance is in the uplink scores; uplink gets a score of 0.8 while RTR Nettest is the source platform, but 0.96 while Netradar is the source platform.

The latency outperforms all other features having the highest possible mapping score of 1.0. This result is expected as the earlier correlation matrices (Figures 3 – 6) show that latency clearly has the lowest correlations with all the other features, which makes it easy distinguish it with respect to our method. Another finding of these plots is that RSRP and RSRQ are more difficult to map than the other features, as their scores are lower. A closer look to the individual mapping cases shows that RSRP and RSRQ are sometimes mixed up together when only three features were mapped.

Altogether, we may conclude that the feature-specific figure scores are high enough to make correct mappings between all features, but there are some variations between the feature scores. For example, RSRP and RSRQ have lower scores, whereas latency clearly has the highest scores of 1.0. All scores are acceptable as the scores do not present the accuracy, but rather a "voting" score, as explained in Section IV. Thus, any score higher than 0.5 for a common feature implies that on average we would select a correct mapping. Moreover, it should be noted that a random guess would have a mapping

score of 0.33, 0.25, or 0.2, depending of the amount of features ($1/N$, in general).

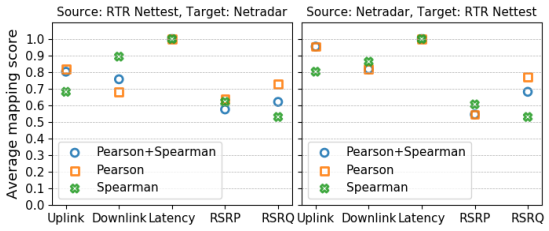

Fig. 9: Feature-specific mapping scores. The scores are high enough to make correct mappings for all features but there is variation between the features.

VI. Conclusion

In this work, we designed a feature mapping methodology between two crowdsourced LTE measurement-based platforms. Our objective is to automatically analyse and map similar features across platforms, without a need for manually analyse their similarities. Our method is based on correlations between the features and the mapping algorithm is solving a maximum constraint satisfaction problem (maximum CSP). We defined our constraints as inequality patterns between the correlation coefficients of the measured features.

Our results show that the method maps the common features with high confidence scores (between 0.78 to 1.0 depending on the amount of features). As a desired outcome of the method, the average mapping score increases when more similar features are involved. The results also indicate that there is no significant difference in the average results between using Pearson, Spearman, or their combination. However, some individual features perform slightly better using Pearson (uplink and RSRQ) and some other using Spearman (downlink). Some issues were noticed between features having similar patterns, for example RSRP and RSRQ. However, even then the scores are promising and our results show that this methodology can be used as an automated tool in the measurement data integration.

In the future work, we will include more measurement datasets in the feature analysis. Moreover, with the merged datasets we may do cross-dataset analysis, for example by using the transfer learning paradigm [19] from the machine learning.

Acknowledgements

This work is partially funded by Nokia and the FP7 Marie Curie Initial Training Network (ITN) METRICS project (grant agreement No. 607728)

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