I'm Only Unhappy When It Rains: Forecasting Mobile QoS With Weather Conditions

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***Abstract*—Global increase in the use of mobile Internet service generates interest in mobile network studies to determine and forecast the QoS provided by mobile operators. This study proposes different methods to forecast signal strength, one of the most important mobile Internet QoS indicator, based on time series analysis and considering external information about weather conditions as temperature, humidity and precipitations due to the effect they cause on mobile Internet QoS. This work shows the feasibility of forecasting mobile signal strength using crowd data corresponding to mobile devices in Santiago, Chile and that the inclusion of weather information generates more accurate forecast models for a given geographic area, obtaining good performance by all models used at comparing their forecast error values for weekly predictions. To the best of the authors' knowledge this is the first attempt of using weather information together with real data gathered from user devices in order to forecast mobile signal strength.**

I. Introduction

During the last years, the use of mobile Internet service has been increasing globally, which is reflected in Chile, where during the first quarter of 2017, 75.8% of total Internet access was made through mobile devices [1]. Given the great magnitude of the current use of mobile Internet, it is important to carry out studies to determine the quality of this service provided by mobile phone operators, and it is also important to develop predictive methods of mobile Internet QoS, so that both counterparts (companies and customers) can anticipate possible declines in the quality of mobile Internet for a given time and place.

Between all mobile Internet QoS indicators, signal strength is one of the most important, mainly because it directly influences other important QoS indicators such as latency, number of lost packets and throughput [2]. Signal strength data used in this paper, come from a passive Android monitor of mobile Internet called *Adkintun Mobile* [3], using a crowd measurement method.

It is important to take account of weather conditions at forecasting signal strength due to their effects on mobile phone network QoS. The weather effect on signal strength received occurs partly because raindrops and fog absorbs power from the radio wave and dissipates the power by heat loss or by scattering [4].

Therefore, this work studies the effect of weather conditions on mobile Internet QoS forecasting, evaluating the prediction of the most used mobile network technologies: UMTS and LTE; using *AutoRegressive Integrated Moving Average* (ARIMA), *Seasonal ARIMA* (SARIMA) and Deep Learning models. The results obtained show that it is possible to carry out good performing predictions, since all tested methods outperformed a Naïve model of comparison. It was also observed that ARIMA and SARIMA solutions obtain better accuracy measures than Deep Learning based methods, but describe smoother and less risky time-series.

To the best of the authors' knowledge this is the first attempt of using weather information together with real data gathered from user devices in order to forecast mobile signal strength.

II. Related Work

With the growth of the mobile phone network during the last two decades, different studies have focused their work on the analysis of the services delivered, and on the development of prediction methods for certain measurable parameters in mobile networks. Some of these works have implemented predictive models to forecast network congestion in a specific geographical location through the analysis of time series, such as the prediction of call traffic using ARIMA models [5], and through the use of chaotic analysis [6]; and the prediction of mobile Internet data traffic using SARIMA models [7] [8] [9]. These studies support the idea of forecasting mobile Internet QoS since the amount of traffic present in the cellular telephone network can directly affect QoS in a specific location, given the high levels of network congestion that may occur. They also show the impact on the use of the network (calls and mobile Internet traffic) due to the occurrence of natural phenomena such as heavy rains or snowfalls, which also supports the inclusion of weather conditions to predict QoS indicators.

All these studies use data coming directly from mobile service provider companies, so they have complete information about network usage from all devices belonging to those companies, which is important for having a well detailed data set and to avoid possible biases. Contrary to the previous, this work is based on data collected directly from user devices, due to measuring QoS has more relevance and makes more sense if the measurements are taken by the devices that are receiving these mobile services. In the same line, other studies have also been accomplished with data obtained by a group of testing mobile devices, which typically have installed an application developed specifically to perform some tests and obtain the required data. Among these studies is the prediction of download speed for 4G LTE network through the application of active measurements using a variation of ARIMA model [10] and the prediction of QoE through the application of passive measurements [11].

In other works it has been studied in depth the correlation that exists between weather and Internet QoS, measuring the connectivity of residential Internet during periods of severe weather, showing the increase of Internet outages during these events [12] and showing the effect of air temperature and humidity on signal strength received from Wireless Networks [13], so that changes in radio signal strength can be explained by the levels of temperature and humidity measured at that time. Contrary to these researches that use measurements from a very controlled space, this paper aims to show the correlation between mobile network signal strength and weather using real crowd data from multiple Android devices, and to use this information to make accurate predictions about signal strength for a geographic location.

III. Data Set Overview

This paper is based on the data collected by chilean Android app *Adkintun Mobile* [3], a mobile monitor, that takes passive measurements about mobile Internet status. The app informs about all the antennas to which mobile devices connect, reporting signal strength, type of network (UMTS, HSPAP, LTE, etc) and antenna identifiers such as Location Area Code (LAC) and Cell ID, in order to make antenna geolocation possible. Also, the app reports the amount of bytes sent and received by each installed application and monitor the Internet connectivity status, which allows to know when users were connected to the Internet through the mobile network and when they suffered a disconnection event. All this information is stored with a timestamp, so each measurement is able to be mapped to a specific time and specific location (due to antenna geolocation). The data collected by *Adkintun Mobile* used in this paper belongs to the city of Santiago, Chile as of October 2016, from approximately 300 mobile devices in that location. To forecast signal strength values, only measurements from users connected to antennas in an area of 15 km^2 in the middle of Santiago city, where approximately 100 users move inside daily, were considered; obtaining near to 20000 signal strength measurements for each day.

In addition to *Adkintun Mobile* data, this paper uses data from a weather station of the Ministry of Public Works of Chile located in Santiago, Chile [14], in the center of signal strength measurement area mentioned above, as showed in Figure 1. This station makes hourly reports about values of air temperature, humidity and precipitation. Also, values for change of temperature and humidity (Δ) were calculated every hour, as they were included in previous analysis of

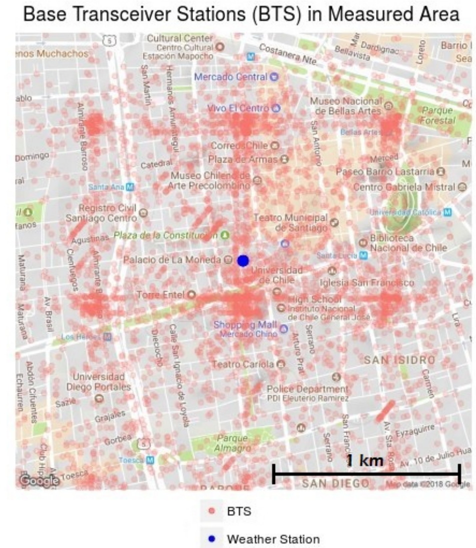

Fig. 1. Geographic position of Weather Station and Base Transceiver Stations in Measured Area.

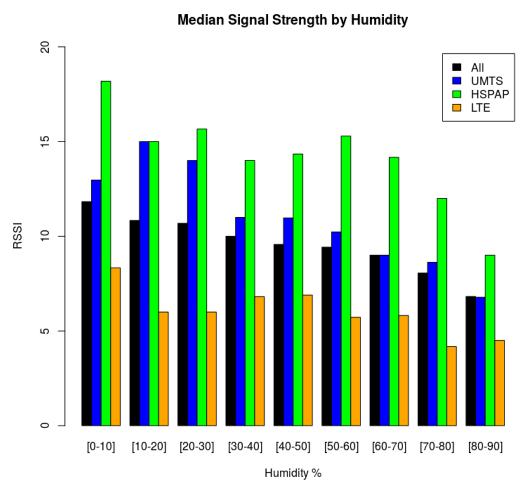

Fig. 2. Signal Strength trend according to relative humidity levels.

signal strength [13]. Like app data, these values are obtained as of October 2016.

Figure 2 shows the relation observed between signal strength and humidity after joining both data sets, where the humidity values are grouped in 9 intervals and, for each interval, the median of signal strength values is reported. Additionally, signal strength values are grouped for the three most used mobile network technologies in the data set (UMTS, LTE and HSPAP), and their median values are also reported for humidity intervals. The figure shows a trend for all mobile network technologies to decrease their signal strength when the humidity increases. These results serve as validation to the addition of weather conditions as external regressors to forecast signal strength in mobile phone network.

IV. FORECAST MODELS

To forecast signal strength values in the mentioned area, the data was aggregated over two hours and median values were reported. Since in each interval an user could have been connected to multiple antennas and received different signal strength inside the area, median values are calculated by pondering each signal strength value with the time (in seconds) in which the user had been receiving that signal strength. The 2-hours signal strength aggregated data is represented as a time series and the 2-hours weather conditions aggregated data are given as external regressors for the main time series.

In order to follow related work, the use of ARIMA and SARIMA forecast methods are proposed. As well as the use of some Neural Network architectures commonly used for time series analysis.

To evaluate these forecast models, a Naïve Persistent Method is proposed for establishing a comparison on some forecast errors indicators obtained at predicting signal strength, which are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) in logarithmic *dBm* scale, and Mean Absolute Percentage Error (MAPE) in normal *Watt* scale.

A. ARIMA

ARIMA models, also called Box-Jenkins models, are models that include autoregressive terms, moving average terms, and differencing operations. An ARIMA(p, d, q) model, where p is the order of the autoregressive part, d is the degree of first differencing involved and q is the order of the moving average part, can be written as

$$(1-\phi_1 B-\cdots-\phi_p B^p)(1-B)^d y_t = c+(1+\theta_1 B+\cdots+\theta_q B^q)e_t, \tag{1}$$

where $(1-\phi_1 B-\cdots-\phi_p B^p)$ is the autoregressive part of order p AR(p), $(1-B)^d$ represents the d differences and $(1+\theta_1 B+\cdots+\theta_q B^q)$ is the moving average part of order q MA(q).

B. Seasonal ARIMA

Seasonal ARIMA model is formed by including additional seasonal terms in ARIMA models mentioned above. It is written as ARIMA$(p, d, q)(P, D, Q)_m$, where (p, d, q) is the non-seasonal part of the model, (P, D, Q) is the seasonal part of the model and m is the number of periods in each season.

The seasonal part of the model, consists of terms that are similar to non-seasonal part, but they use backshifts of the seasonal period (B^m instead of B). So, the general Seasonal ARIMA formula is similar to ARIMA formula showed in equation 1, but the non-seasonal terms are multiplied by seasonal terms as follows:

- Non-seasonal autoregressive part is multiplied by seasonal autoregressive part $(1-\Phi_1 B^m-\cdots-\Phi_p B^{mp})$.
- Non-seasonal difference is multiplied by seasonal difference $(1-B^m)^d$.
- Non-seasonal moving average part is multiplied by seasonal moving average part $(1+\theta_1 B^m+\cdots+\theta_q B^{mq})$.

C. Neural Networks

1) LSTM: LSTM (Long Short-Term Memory) is a type of recurrent neural network. That is, a network whose connections contain loops in order to keep information, passing it through the steps of the network. An LSTM-layer's special feature is that it can retain long-term information and learn when to get or not get it into account. The implementation of an LSTM unit consists of three gates: input gate, output gate and forget gate that are related according to the following equations:

$$c_t = i_t \circ tanh(W_c x_t + V_c y_{t-1} + b_c) + f_t \circ c_{t-1} \tag{2}$$

$$y_t = o_t \circ tanh(c_t), \tag{3}$$

where i_t, f_t, o_t are the respective activation functions of each gate:

$$g_t = sigmoid(W_g x_t + V_g y_{t-1} + b_g), \tag{4}$$

where g is the corresponding gate, W and V are weight matrices, b is a bias vector, x_t and y_t are input and output vectors of the step t, and $\circ$ corresponds to the entry-wise product between two matrices.

2) CNN-LSTM: CNN (Convolutional Neural Network) differs from a normal artificial neural network at its use of kernels to apply a convolutional operation over the input data in order to transform it and obtain specific information to focus on. The equation of a convolutional layer for a 2-dimensional input is described below:

$$X_{ij} * K_{ij} = \sum_{a=0}^{m-1}\sum_{b=0}^{n-1} w_{ab} X_{(i+a)(j+b)} \cdot K_{ab} + b \tag{5}$$

where X is the input and K is the $m \times n$ kernel. w and b are weight and bias respectively.

CNN-LSTM would be the combination of the two networks mentioned above. It will consist of a convolutional layer before an LSTM layer.

D. Naïve Model

The Naïve Model is defined as a forecasting model where the last observation will become the next forecast value, and it can be written as

$$y\prime_t = y_{t-m}, \tag{6}$$

when the data is seasonal with a period m.

With regard to the experiments of this paper, a Weekly Naïve Model, that repeats the last week of data as the forecast for the next week, is used as a trivial method to compare the performance of the other weekly forecast methods. This method has been chosen since mobile QoS and signal strength are affected by external factors with strong periodic components, such as weather [12] [13] or crowd movement [15] [16] according to human activities, so repeating previous values as forecast makes an acceptable model to set as initial baseline.

V. Experimental Results

The goal of the experiments is to forecast an entire week of data (received signal strength) from user devices in a reduced area from the center of the capital city of Chile (Santiago), based on the information given by the eight immediately previous weeks. The input for the forecast methods are eight weeks of median values of aggregated data over two hours of signal strength reported by the users connected to cellular antennas near the weather station of the Ministry of Public Works of Chile. The input data also contains eight weeks of information given by the weather station about air temperature, humidity and precipitations.

The experiments perform predictions of signal strength received for 3G UMTS and 4G LTE users separately. These two (UMTS and LTE) were chosen because, according to the data set, they are the most used network types by mobile devices in Santiago, Chile. Each of the forecast models presented before, perform separate predictions of three consecutively weeks as of December 12, 2016, in order to get more generalized results, reporting their forecast errors.

Figures 3 and 4 compare forecast values of 3G UMTS and 4G LTE signal strength with real data, using the four selected models. These Figures show the results of forecast with and without including weather information. Next, results of forecast considering weather information are described (red lines).

For 3G UMTS forecasts in Figure 3, ARIMA and SARIMA models with weather information seems to capture correctly the general pattern of real signal strength data, but their smoothed curves fails at forecasting sudden signal strength changes. In the other hand, Neural Network forecasts with weather information can also capture real data pattern, but in a riskier way, giving the chance of predict sudden changes in signal strength values, getting in the case of LSTM model a more fitted forecast curve.

4G LTE forecasts in Figure 4 show a similar behavior to UMTS forecasts described above, in which ARIMA and SARIMA models with weather conditions seem to forecast a very similar smoothed pattern, and Neural Networks again make riskier predictions, which benefits to capture some patterns better. It is important to say that LTE time series is more scattered than UMTS time series, what causes that

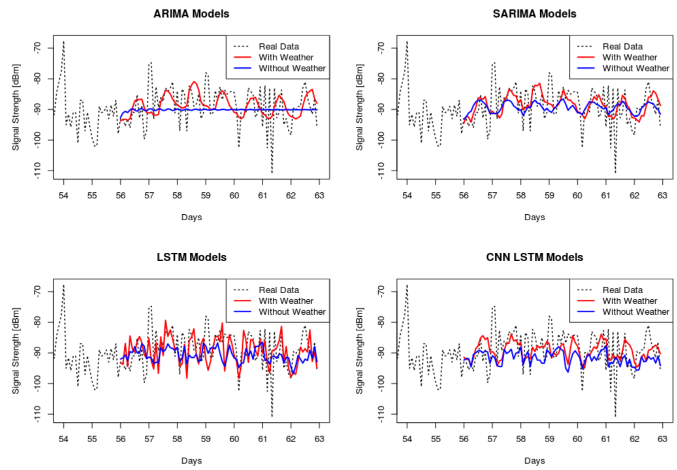

Fig. 3. UMTS Signal Strength Forecast Models.

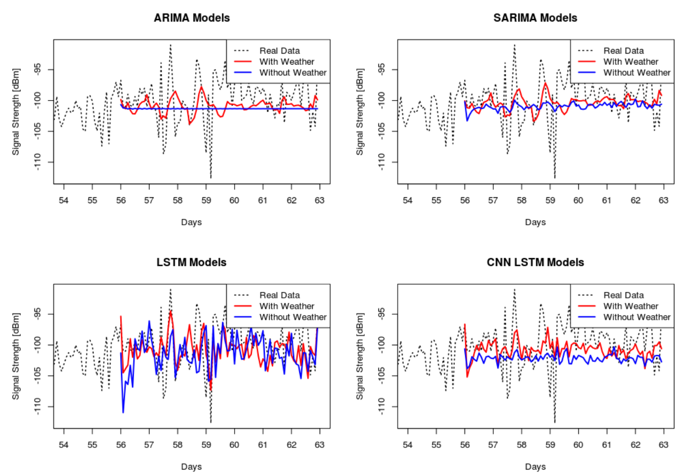

Fig. 4. LTE Signal Strength Forecast Models.

ARIMA, SARIMA and CNN-LSTM tend to give most forecast values near the median value, in order to decrease forecast errors. However, LSTM model shows a more fitted curve, capturing in a very good way some abrupt changes in signal strength.

The forecast errors obtained for all these forecast methods considering weather information, in addition to Naïve Model, are presented in Tables I and II for information about 3G UMTS and 4G LTE signal strength forecasts, respectively.

In order to show the benefit of including weather conditions as external regressors of forecast models, Figures 3 and 4 also compare the results of predicting UMTS and LTE signal strength using the four selected models between considering or not considering weather conditions as external regressors. It is evident that without including weather conditions for ARIMA models, the forecast do not capture the periodicity in real data values, and all their forecast values are very close to

TABLE I
UMTS SIGNAL STRENGTH FORECAST ERRORS

	1^{st} Week			2^{nd} Week			3^{rd} Week			Total		
Method	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE
Naïve Model	8.64	6.49	1147.24	10.43	7.88	803.71	10.41	7.95	3850.82	9.86	7.44	1933.92
ARIMA	5.99	4.70	**235.93**	**7.96**	5.78	**152.39**	7.18	5.60	**319.71**	7.09	5.36	**236.01**
SARIMA	**5.91**	**4.63**	237.31	8.02	5.83	163.61	**7.16**	**5.46**	331.58	**7.08**	**5.31**	244.17
LSTM	6.45	4.89	308.17	9.36	7.01	437.23	8.34	6.57	399.82	8.14	6.16	381.74
CNN-LSTM	6.23	4.87	252.75	8.20	**5.76**	295.73	7.61	5.71	337.38	7.39	5.45	295.29

TABLE II
LTE SIGNAL STRENGTH FORECAST ERRORS

	1^{st} Week			2^{nd} Week			3^{rd} Week			Total		
Method	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE	RMSE	MAE	*Watt* MAPE
Naïve Model	5.49	4.28	105.93	5.58	4.16	88.16	7.50	5.33	896.19	6.26	4.59	363.43
ARIMA	4.11	3.16	84.77	**4.56**	**3.48**	69.27	**5.33**	**4.18**	**178.24**	**4.68**	3.59	**109.49**
SARIMA	3.93	**2.94**	88.40	4.60	3.49	67.57	5.49	4.29	218.82	4.72	**3.57**	124.93
LSTM	**3.86**	3.14	**74.37**	5.43	4.20	66.93	6.08	4.96	222.67	5.21	4.10	121.33
CNN-LSTM	3.94	3.11	80.80	4.93	3.86	**66.07**	5.45	4.22	220.26	4.82	3.73	122.38

median value, reducing in this way forecast errors, but without capturing real data patterns. This can be explained since ARIMA models are not good at forecasting periodic data if a periodic component is not given as an external regressor. So including weather conditions gives to the model the periodicity information implicitly, because both temperature and humidity have a strong periodic component and have a significant effect on signal strength. With regard to SARIMA model, since it is a specialized model to forecast periodic time series, it captures the periodic pattern in UMTS and LTE data anyway without needing weather conditions, but when including these as external regressors, the forecast curves gets more fitted to real data values, being more accurate in UMTS prediction. LSTM models have a similar behavior to SARIMA models at forecasting UMTS signal strength data, since the fact of considering weather conditions in the models makes predictions more fitted to real data values. However, at forecasting LTE data values, the difference between considering or not weather information is not so clear. In the case of CNN LSTM models, both UMTS and LTE predictions capture real data patterns in a better way, showing again the benefit of considering weather conditions to obtain better forecasts.

VI. DISCUSSION

The results obtained show a positive performance for all forecast methods at predicting signal strength values using weather conditions as external regressors. All the tested methods consistently obtained lower prediction errors than Naïve Model at forecasting UMTS and LTE signal strength for each of the three experimental weeks, as showed in Tables I and II, achieving a high increase in accuracy, especially when comparing signal strength in *Watts* scale. ARIMA and SARIMA models obtained the lowest forecast errors in most of the occasions, which supports the fact that in literature, they are the most used models to forecast similar time series. However, Neural Network models also obtained satisfactory results, getting forecast values closely fitted to real data and sometimes obtaining even better forecast errors than ARIMA and SARIMA models. This is relevant since the use of Neural Networks to forecast similar time series has not been highly exploited and, as this paper showed, they demonstrate a strong potential to this purpose. This fact leaves open the possibility of developing new more complex and specialized Deep Neural Networks architectures to keep improving the results.

Some ARIMA and SARIMA models' forecasts that obtained good results show a more restrained behavior than solutions generated by Neural Network models, as showed in Figures 3 and 4, so each forecast value has always a low forecast error. However, this makes it less capable of predicting sudden signal strength changes correctly. Instead, Neural Networks capture periodic pattern of data without smoothing their values, which enhances forecasting on abrupt changes, that ARIMA and SARIMA lack. This is especially important at forecasting LTE signal strength, where LSTM model is the only one with an easily observable forecast curve closely adjusted to real data curve (Figure 4).

It is important to mention that even when the decrease of RMSE and MAE indicators of forecast methods over Naïve Model could seem low, it is mainly because RMSE and MAE are calculated for signal strength in *dBm* scale, which is a logarithmic scale for *Watts*. That explains that what appears to be a little or insignificant increase in accuracy is really a great improvement, as can be confirmed by analyzing *Watt* MAPE values.

The fact that, for all forecasts done, the Weekly Naïve Method had worse results than all the other methods, and especially bad results at comparing *Watt* scale MAPE, is a proof that even when consecutive weeks could present similar signal strength patterns between them, there are another things to consider at forecasting signal strength values, hence the forecast task presented is not trivial.

The experimental results show the improvement that weather information causes to signal strength forecasting, supporting the fact that weather conditions impact on mobile phone quality of service, and specifically on mobile phone signal strength. Since the measurements used in this paper come from multiple smartphones devices performing a crowd measurement process and not from specialized hardware as in other studies, weather conditions can impact signal strength measured in other ways besides degradation of signal due to physical events as scattering or absorption by raindrops. For example, when there is low temperature and high humidity levels, people usually prefer to be indoors with windows and doors closed and wear more layers of clothes, generating more interference in the signal received by their mobile devices, causing that measured signal strength values to be lower.

VII. Conclusion and Future Work

This paper shows the feasibility to forecast mobile Internet QoS in a specific geographic area, performing weekly forecasts of signal strength received by users and using weather conditions as external regressors, showing the benefit of including this external information in forecast models. The obtained results show that all proposed forecast methods have good performance, being ARIMA and SARIMA the best models at comparing their forecast error values, and LSTM the best model at recognizing sudden changes in the data.

Given the good results at forecasting weekly values, it is proposed as future work the implementation of daily forecast using the same methods described for weekly predictions. Daily forecasts should have lower forecast errors in comparison with weekly forecast, because it is easier to predict closer values, in part by cause of when forecasting signal strength, the models need forecast weather conditions, and daily weather forecasts have better accuracy than weekly weather forecasts.

There is a possibility to perform forecast methods to other QoS indicators. Another QoS indicator to be similarly forecast is the Internet connectivity status, which refers to the probability to experience an Internet outage, since the correlation between Internet outages and weather conditions have been studied before [12] and connectivity information is also present in *Adkintun Mobile* data.

It is important to study carefully the existence of other external factors that may interfere with mobile Internet QoS. Recent investigations have taken the first steps to determine the effect on the performance of the mobile phone network against mass groupings of people at large events, using both active measurements as passive measurements [15] [16]. These studies have left open problems for future work, such as carrying out a greater analysis to relate large groups of people with the intensity of the signal received. Consequently, information about mass grouping in reduced areas as in sport events, musical concerts or street protests, could be used in order to perform more accurate signal strength predictions, using this information as another external regressor in forecast models.

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