Wireless Broadband Service Quality Prediction App

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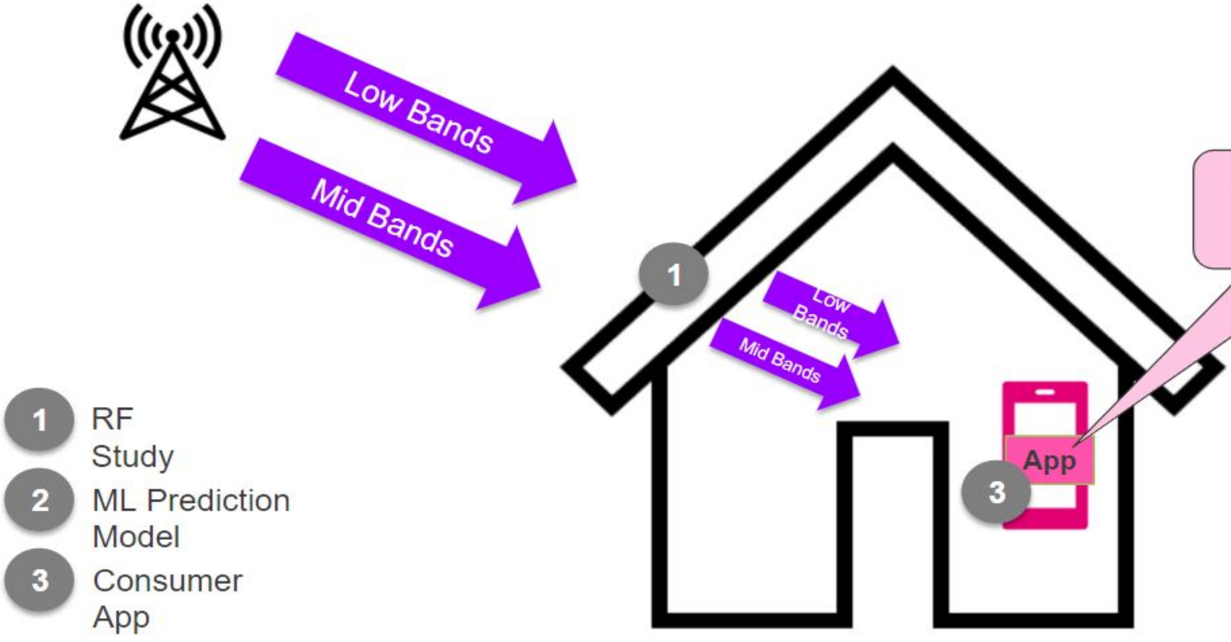
Problem Statement

- **Problem:**
  Some customers sign up for T-Mobile Home Internet but may experience poor service quality
  - Outdoor-to-indoor propagation complexities
    - Unreliable, inconsistent coverage
  - 5G bands may not be deployed in the customer's neighborhood
  - Results in unhappy customers and expensive churn

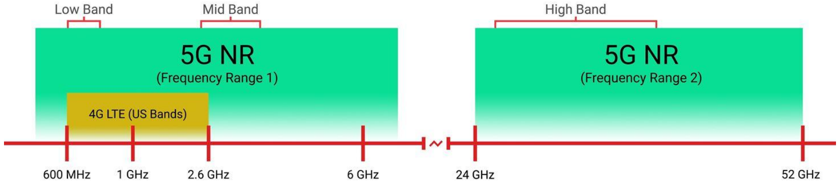
- **Solution:**
  Customers can use an app to predict service quality before signing up for T-Mobile Home Internet
  - Increases affordable internet access and ISP competition
  - Ensures customer satisfaction and reduces cost from churn
  - If the service is inadequate:
    - Will it improve with a new 5G band?
    - Provide T-Mobile with that data to inform deployment strategy

Requirements

1. Collect relevant RF data.
2. Train an ML model using the collected data to predict 5G internet speeds.
3. Build an app that will use this ML model to show the predicted T-Mobile Home Internet speed at a location.

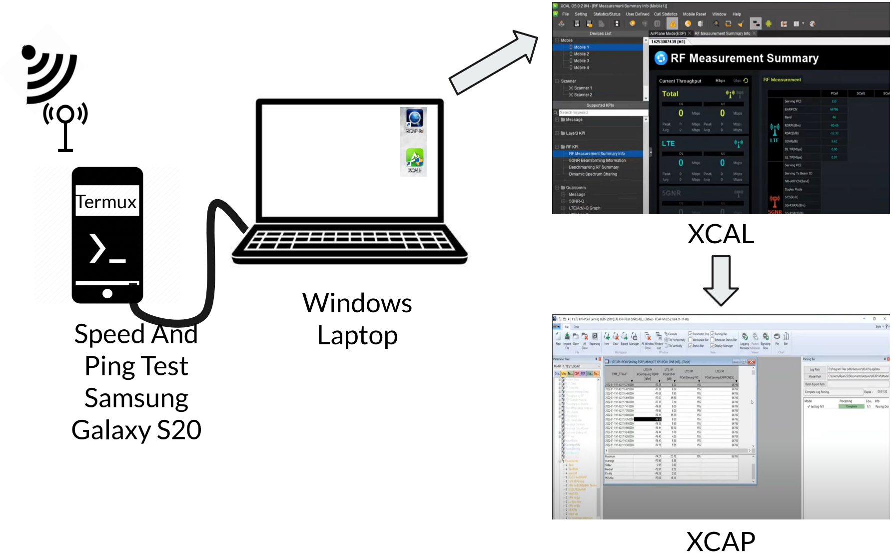


Stage-1: RF Study



Investigate outdoor-to-indoor RF propagation for low and mid frequency bands

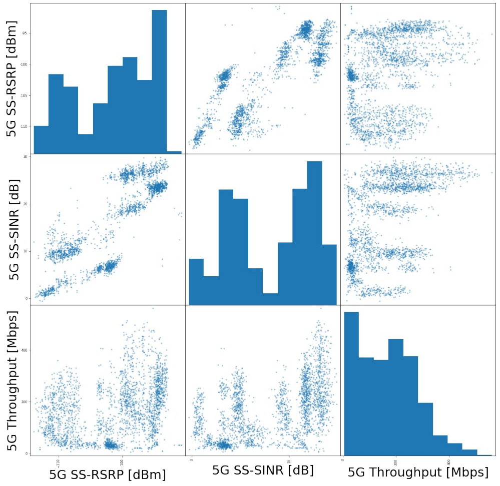
RF Data Collection Workflow



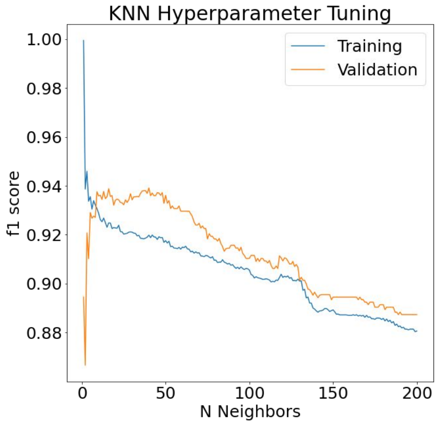
- # Data Points Collected: **117,580**
- # of homes: **5**
- # of rooms/sites: **27**

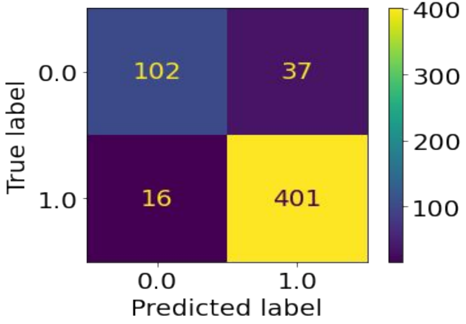
Stage-2: ML Prediction Model

- Data prepped for machine learning
  - Raw data is first cleaned so that completed rows of datasets could be extracted
  - Clean data are then sieved to drop out the columns we do not need
- Features correlations are checked using a scatter matrix to verify the dependencies of the chosen columns
- Then models will be chosen among the state-of-the-art machine learning models



	train accuacy	validation accuracy	validation f1 score
logistic regression	0.798	0.785	0.858
decision tree	0.837	0.86	0.911
random forest	0.837	0.835	0.895
k-nearest neighbors	0.903	0.897	0.933
KNN tuned	0.877	0.905	0.938





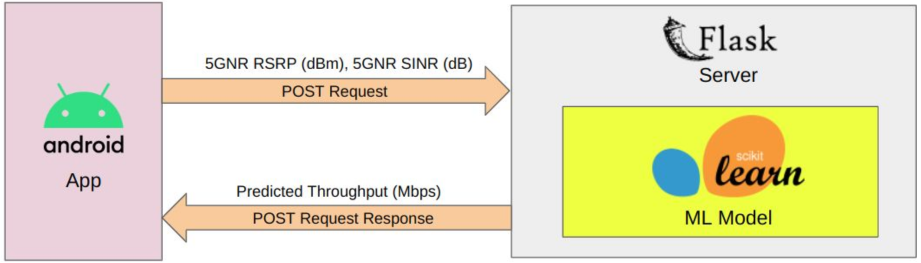
Stage-3: Consumer App

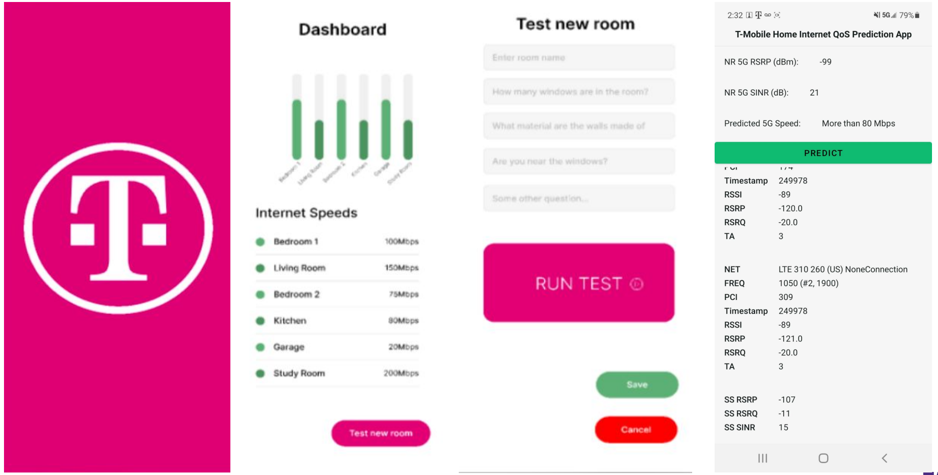
1. The android app collects RF metrics available to the smartphone using the Android Telephony APIs.

2. Out of all the collected RF metrics, 5GNR RSRP (dBm) and 5GNR SINR (dB) are taken and using POST request is sent to the backend server, where the ML model is hosted.

3. Upon receiving the 5GNR values, the server feeds them as input to the ML model and the model spits out the prediction which is sent back to the app in JSON format as a response to the POST request.

Server URL:
https://tmobile-uw-capstone-server.herokuapp.com/





Working Demo

Video URL: https://youtu.be/2giW8nwzv5E

Conclusion/ Future works

- App predictions were validated using the T-Mobile Home Internet device.

- Create a 5G NR RF prediction model from 4G LTE RF data
- Implement behavior for 5G low band waves
- Create user authentication and allow them to store data
- Improve UI/UX and conduct user testing
- Integrate a feedback loop to collect large scale train data and verify model
- Expand dataset to more RF conditions
- Numerical models for ML

References

[1] **T-Mobile ENGINE Project Kickoff Google Slides** by *Nick Lambert, Alexander Ryan, Ryan Colter, Timur Kochiev, Alan MacDonald and Ahmad Armand*

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[3] **Android.telephony; android developers. Android Developers. (n.d.).**, from *https://developer.android.com/reference/android/telephony/package-summary*

[4] **Mroczis. (n.d.). Mroczis/netmonster-core: Android Telephony SDK Bridge with some additional features**. GitHub., from *https://github.com/mroczis/netmonster-core*

[5] **Flask Documentation (2.1.x). (n.d.).**, from *https://flask.palletsprojects.com/en/2.1.x/*