# Neural Network-based Blocking Prediction for Elastic Network Slicing

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## Overview

- This research is about **guaranteeing** the quality of **5G internet** connections
- **Elastic Network Slicing** can support various use cases (e.g., auto-driving vehicles and factory robots) while sharing the same internet infrastructure
- We use a **Machine Learning** algorithm to predict the potential performance degradation (blocking events) of such slices of a network so that users can enjoy uninterrupted internet connections

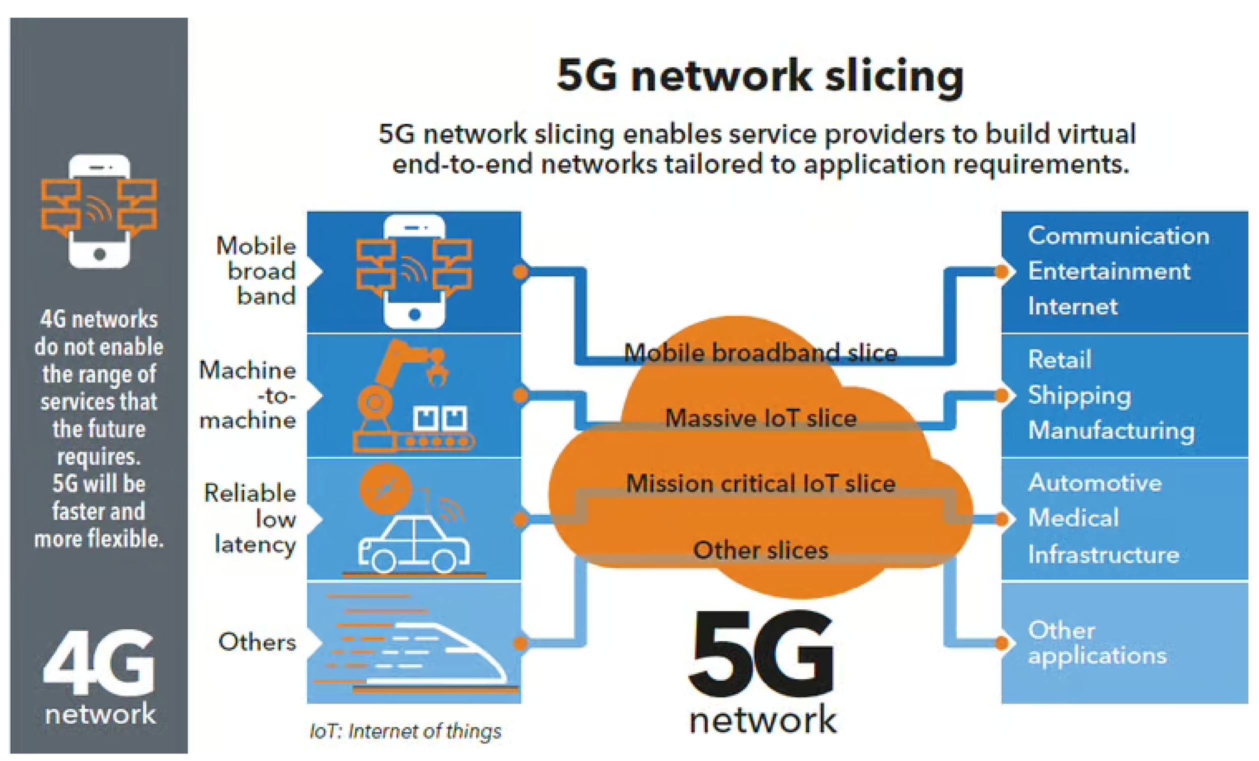


Figure 1. 5G Network Slicing [image from ITUNews]

## Introduction

Using **Network slicing**, many virtual networks can be built on top of the underlying infrastructure network, and each virtual network can be configured to its own distinct parameters such as bandwidth and latency.

**Elastic network slicing** can improve resource usage and cost efficiency by dynamically allocating resources to each slice; however, assessing the likelihood of blocking requests is a big data challenge that necessitates examining slice scaling history data.

## Problem

This paper addresses the issue of predicting an Elastic Network Slice Request's blockage in a single network.

A Network Slice Request consists of **6 distinct** parameters:

- Source and target nodes $(s, t)$
- Regular and peak slice holding time in the network, $rh$ and $ph$
- Regular and peak bandwidth requested, $rb$ and $pb$

The Regular $(rh)$ and Peak $(ph)$ holding times denote the amount of time for which the slice tenant demands Regular $(rb)$ and Peak $(pb)$ bandwidth.

The network provider has access to the six parameters mentioned above; however, the problem lies in the fact that the timing during which Regular and Peak bandwidth is required is unknown.

## Multi-layer Perceptron Classifier

Multi-layer Perceptron Classifier (MLPClassifier) is a Neural Network-based Machine Learning Model in the Scikit-Learn library used to solve classification problems. In a neural network, data undergoes computations across hidden layers, with results passed through an activation function to the next layer. Upon reaching the final layer, a prediction is made - in our case, we classify a request as either blocked or unblocked.

## Experiment Setup

The experiment's dataset contains all permutations of Elastic Network Slice requests, each with a unique timestamp. Manually, a blockage can be determined by stacking requests on the same path, as shown below with two requests: *(s1, t1, 1, 1 , 1, 2)* and *(s2, t2, 1, 1, 1, 2)* in Figure 2.

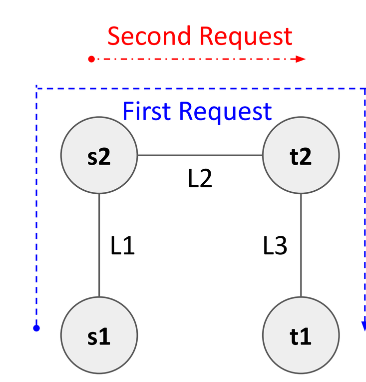


Figure 2. Simple example with 2 slice requests. Capacity of each link is 3

Table 1: 4 distinct scenarios

| Scenario | timeslot 1 | timeslot 2 |
|---|---|---|
| I | (r,p) | (p,r) |
| II | (p,r) | (r,p) |
| III | (r,r) | (p,p) |
| IV | (p,p) | (r,r) |

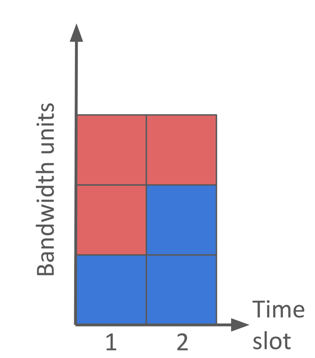


Figure 3. Scenario I (Symmetric to II) on L2: No Blocking

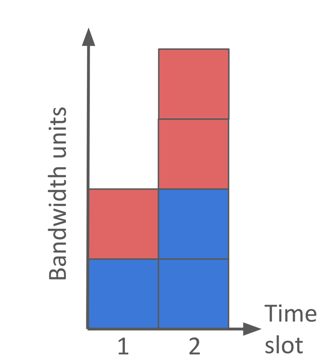


Figure 4. Scenario III on L2: capacity(L2) = 3 < 4. Blocked

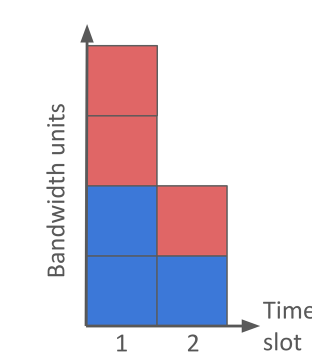


Figure 5. Scenario IV on L2: capacity(L2) = 3 < 4. Blocked

In this example, each link has a capacity of 3. Due to unknown timing requirements of bandwidth from slice tenants, we calculate all permutations of the request from Figure 2, listed in Table 1 as four scenarios for determining blockage. These permutations are illustrated in Figures 3, 4, and 5.

If a request **exceeds capacity restrictions** or **conflicts** with other requests, it is deemed **blocked**. Otherwise, it is **not** blocked.

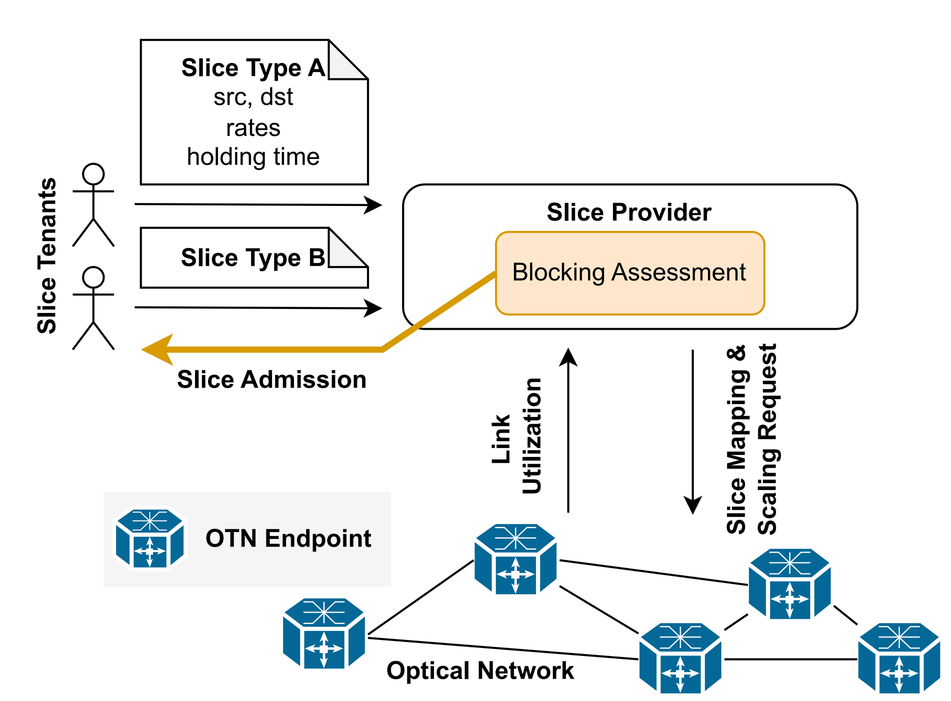


Figure 6. Network Framework

## Evaluation Results

We make use of algorithms MLPClassifier, GradientBoostingClassifier (GB), and RandomForestClassfier (RF) from the Scikit-Learn library to solve the problem at hand.

The machine learning models' performance has been evaluated using 2 metrics: Accuracy and F1 score in relationship to the link utilization - as shown in Figure 7 and Figure 8.

Formulas: **Accuracy** $= \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$, **F1** $= \left(\frac{\text{precision}^{-1} + \text{recall}^{-1}}{2}\right)^{-1}$

**MLP exceeds** the accuracy of GB and RF at each step in the link utilization.

The accuracy and F1 scores of all three models decrease when link utilization is between 0.8 and 0.9, due to the increasing difficulty in predicting blockage at these points, where probabilities of being blocked or unblocked growing closer.

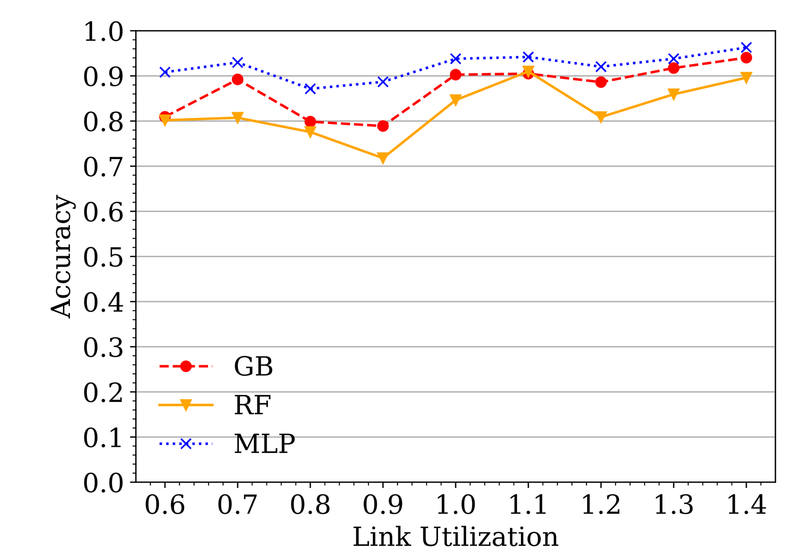


Figure 7. Accuracy vs. Util

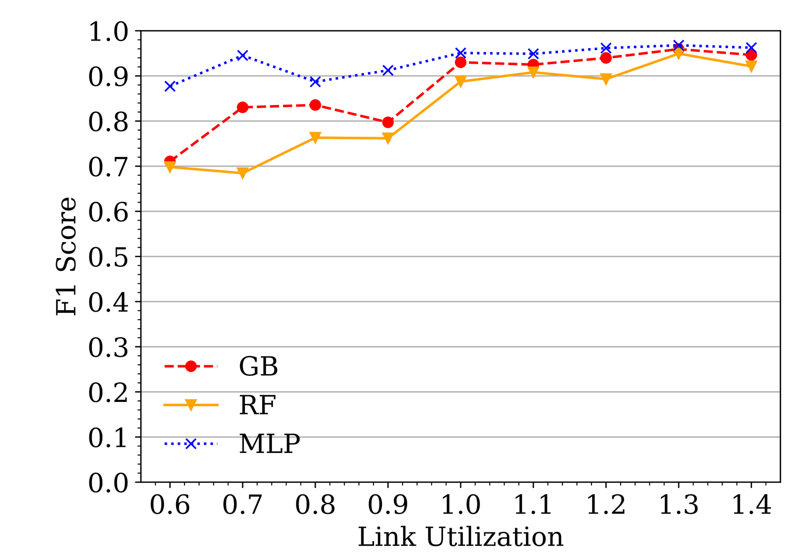


Figure 8. F1 score vs. Util

In Figure 9, we can notice that the Accuracy and F1 score are unaffected by the number of permutations.

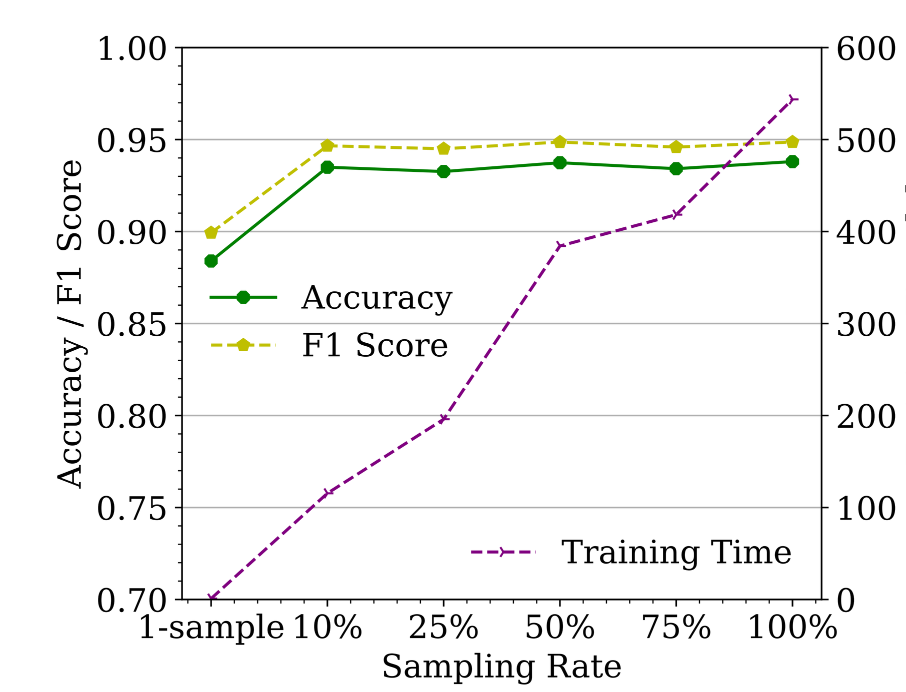


Figure 9. Accuracy and F1 vs. Sampling Rate

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https://sjsu-interconnect.github.io/

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