# Decoding User Experience On Mobile Broadband in Challenged Networks: An Empirical Analysis

**CS 293 PROJECT** 

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# Challenged Networks...?

- Resource constrained
- Inaccessibility to broadband
- ☐ 60% rural vs 4% urban

Possible reasons:

- ☐ Lack of economic feasibility/interest
- □ Lack of Federal initiatives
- □ Vintage FCC policies

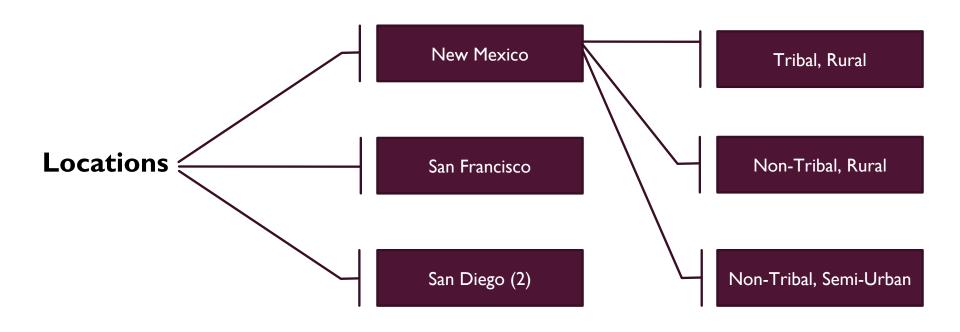


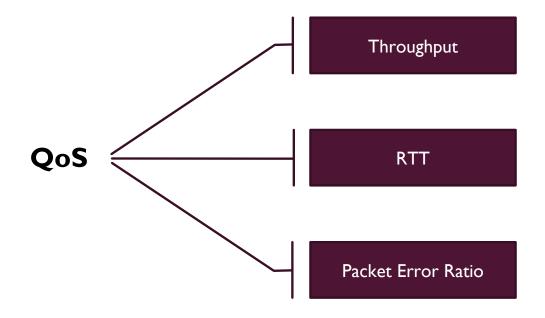
#### WHY IS THIS IMPORTANT?

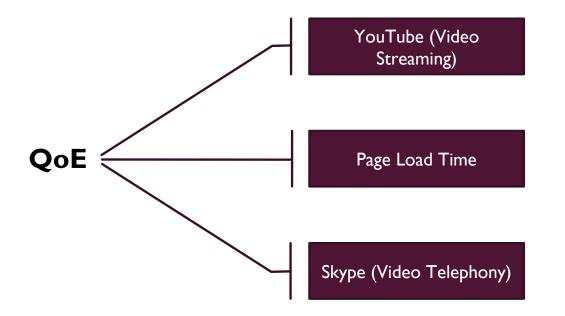
- Network disparity
- Learning about performance differences
- Findings' impact on FCC policies
- Social impact

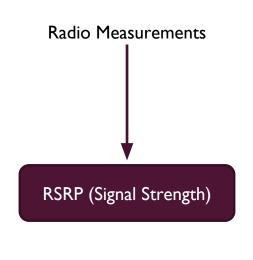
#### **RESEARCH QUESTIONS**

- How do radio measurements affect QoE/QoS?
- Can we estimate QoE metrics for given radio measurements?
- How do predictive models differ across different geo/socio-economic locations?





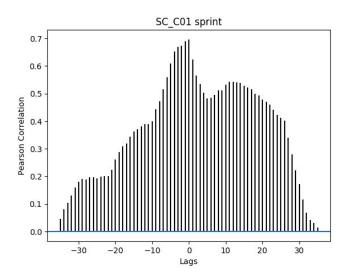




#### Network Quality Metrics - QoS/QoE

- Network Quality Metrics
  - Rsrp, thput, buffer\_size, avg\_res
  - Radio and Network Level measurements
- 15,000+ samples
- Temporally varying data points
- Goal: Determine contribution of metrics on Quality of Experience

#### Cross-correlation between RSRP and buffer size (YouTube)



Using rsrp to predict buffer size

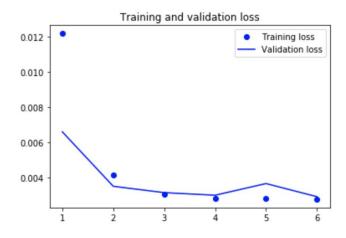
Property	Result
Layers	4
Cells per Layer	30
Parameters	18,631
Optimizer	Adam
Loss Function	Mean Square Error

Layer (type)	Output Shape	Param #		
lstm_1 (LSTM)	(None, 50, 30)	3960		
lstm_2 (LSTM)	(None, 50, 30)	7320		
lstm_3 (LSTM)	(None, 30)	7320		
dense_1 (Dense)	(None, 1)	31		

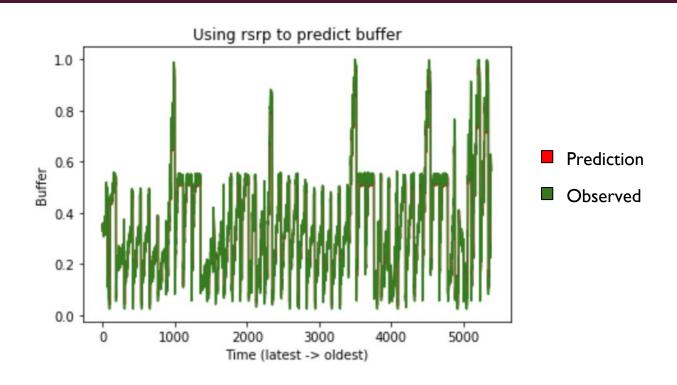
Total params: 18,631 Trainable params: 18,631 Non-trainable params: 0

Using rsrp to predict buffer size

Metric	Result
Batch Size	32
Time per Epoch	130 sec.
Loss	Too low?
MSE	Too low?



Using rsrp to predict buffer size



#### Quantile and Uniform Binning

Metric	Quantile Binning	Uniform Binning	
Accuracy	0.780468	0.805859	
Precision	0.780514	0.805612	
Recall	0.780468	0.805859	
MAE	2.089936955	-	
MSE	28.92972955	-	
RMSE	5.378636403	-	

# Random Forest Quantile and Uniform Binning

Metric	Quantile Binning	Uniform Binning
Accuracy	0.4981219	0.87633631
Precision	0.5370021	0.88293638
Recall	0.4981219	0.87633631

#### **ARIMA**

#### Quantile and Uniform Binning

Metric	Quantile Binning				
MAE	2.459093				
MSE	43.44281				
RMSE	6.591119				

Model	Accuracy	Precision	Recall	MAE	MSE	RMSE	Training Time	Prediction time
Random Forest (Quantile Binning)	0.49	0.53	0.49				46.565	1.920
Random Forest (Uniform Binning)	0.87	0.88	0.87				44.44	2.05
ARIMA				2.45	43.44	6.59		
LSTM (Quantile Binning)	0.78	0.78	0.78				92.233	0.170
LSTM (Uniform Binning)	0.8	0.8	0.8				76.12	0.17
ADA Boost	0.35	0.21	0.35				1.587	0.135
ADA Boost Regression				3.89	25.46	5.04	0.21	0.001
Extra Randomized Tree	0.76	0.76	0.76				0.008	0.005
Extra Randomized Tree Regression				2.64	30.92	5.56	0.022	0.0006
Bagging	0.87	0.87	0.87				0.603	0.006
Bagging Regression				2.38	18.03	4.24	0.618	0.006
Boosting	0.88	0.88	0.88				29.14	0.025
Boosting Regression				2.22	14.81	3.85	2.001	0.002
Naïve Bayes	0.31	0.18	0.31				0.003	0.002
KNN	0.15	0.13	0.15				0.013	0.094
KNN Regression				22.37	718.47	26.8	0.012	0.271
SVM	0.17	0.05	0.17				10.09	1.383

8.0

2.59

29.99

5.47

0.0004

0.0006

0.104

0.102

Decision Trees

Decision Trees Regression

8.0

8.0

# Thank you!