



Machine Learning for Channel-Based User Scheduling in Ad Hoc Systems

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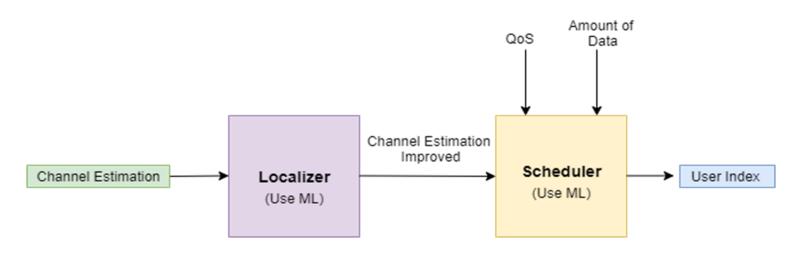
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BACKGROUND



- In 5G, massive number of users being served by cellular networks.
- Currently, machine learning (ML) algorithms are used to schedule users in centralized systems.
- Investigate ML algorithms for ad hoc networks to schedule users.





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MOTIVATION



Improve performance in applications:

- Internet of Things/Wireless Sensor Networks
- Machine-to-machine communication
- Vehicle-to-vehicle communication
- Healthcare systems
- Use machine learning to predict channel and other parameters



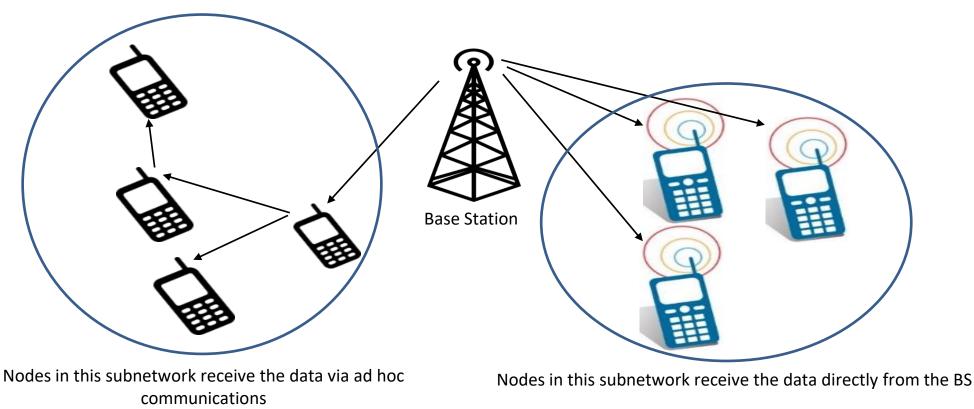




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Rely on ML in ad hoc systems to schedule users in order to reduce burden on base stations.

Implement and evaluate ML methods for parameter estimation



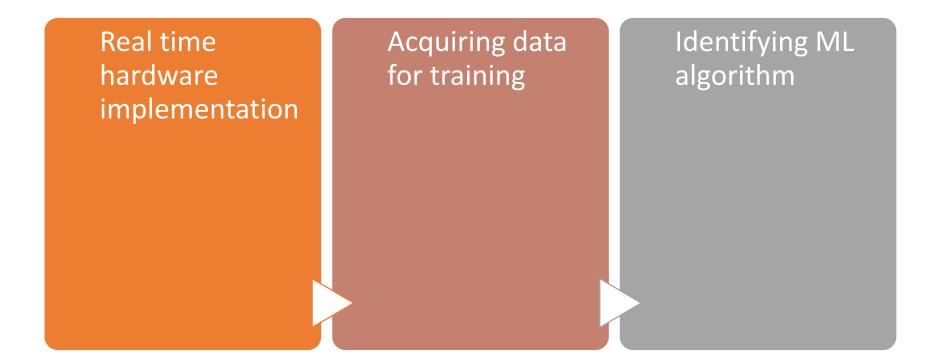


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CHALLENGES







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EXPERIMENTAL METHODS



Use GNU Radio Companion to operate USRP kits

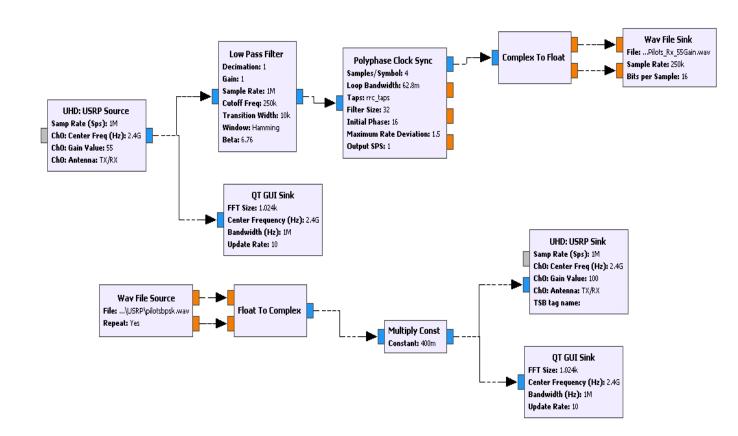


Figure 1: Depicted is a receiver (Rx) and transmitter (Tx) block in GNU Radio software used in the USRP kits.



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Figure 2: The USRP B200 Radio with an antenna attached at the Tx/Rx port.



EXPERIMENTAL METHODS

Received Signal (GNU Radio Software)

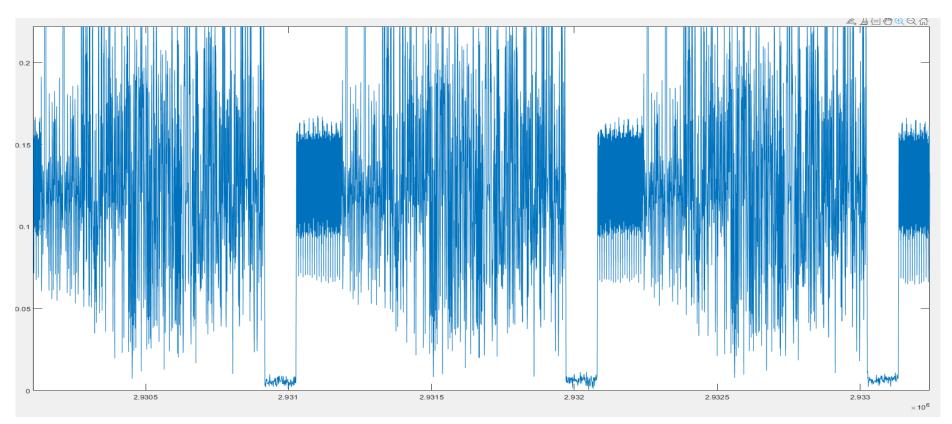


Figure 3: A MATLAB plot displaying the received signal obtained by the .wav file located at the Rx block in GNU Radio software development.



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Channel Estimation vs. Subcarriers (MATLAB) using kits

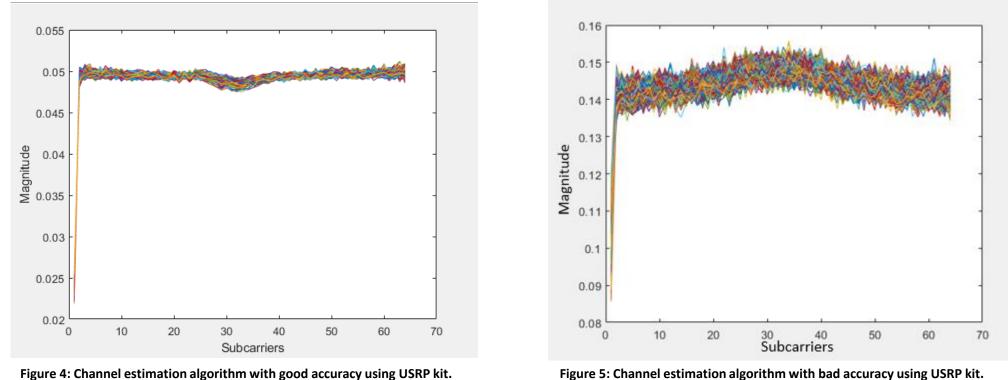


Figure 5: Channel estimation algorithm with bad accuracy using USRP kit.



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Artificially generated dataset of channels (MATLAB)

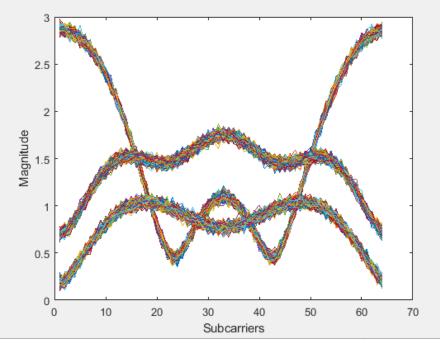


Figure 6: Artificially generated channel estimations with an SNR value of 30 dB at 3 different data points.

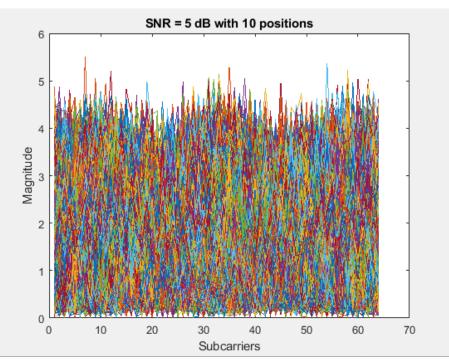


Figure 7: Artificially generated channel estimations with an SNR value of 5 dB at 10 different data points.



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EXPERIMENTAL METHODS

Supervised learning classification algorithms:

- Logistic Regression (LG)
- Support Vector Machine (SVM)



https://www.dominodatalab.com/data-science-dictionary/sklearn/



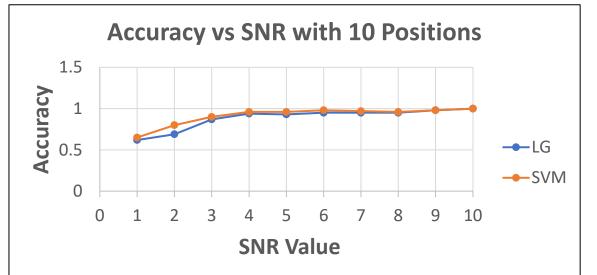
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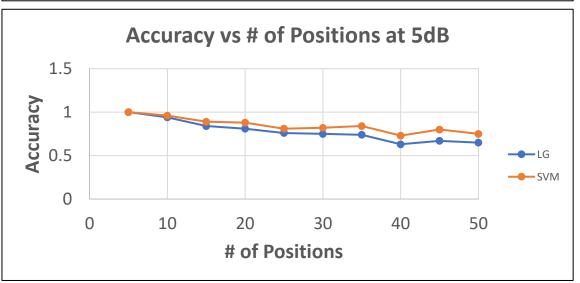
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PRELIMINARY RESULTS





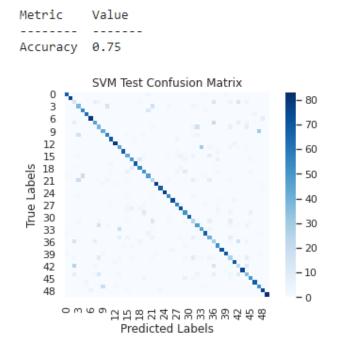


Figure 8: Confusion matrix using 50 different positions at a SNR value of 5dB. The accuracy represents the SVM algorithm correctly predicting the location of each curve (channel estimation magnitude).



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- Attempted real time implementation with USRPs
- Demonstrated the ability of ML to predict the location of users which could then be used to estimate their channels
- Initial results work better with the SVM algorithm than LG algorithm
- Method to use hardware kits to represent real world environment
- Explore other classification algorithms





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