Spectrum Sensing for Cognitive Radio Applications

By Lars Vonk (336028)

Introduction

Since the internet has become popular and smartphones have become more widespread the amount of radio signals that are constantly being transmitted has increased greatly. Especially in crowded areas in cities this has led to finding available bandwidths for Wi-Fi and other use cases can be difficult.

The current approach to find available bandwidths is to scan passively or actively. This is done by sensing the already present radio signals on pre-defined channels.

In an ever-digitalising world where the number of smart devices and IoT devices transmitting radio signals is every increasing, preventing interference is increasingly more important.

Literature review

The topic of spectrum sensing to find low interference channels is a well-researched topic. Different approaches have been put forward to effectively achieve this goal like [1]

- Matched filtering
- Cyclostationary-based sensing
- Waveform-based sensing
- Wavelet-based sensing
- Eigenvalue-based sensing
- Energy detection sensing

These methods all seek to solve the problem of finding the occupancy of a frequency by mathematical analysis. Using methods like generative AI is not discussed. Which with the current development of this technology could be a good fit in predicting the occupancy of a frequency based on prior data.

With the appearance of large language models like ChatGPT the technology behind generative AI has improved greatly. ChatGPT uses generative AI to generate text responses based on prior knowledge [2], which then forms a coherent answer to a question. This technology can also be used to generate images using tools like Midjourney [3]. This technology could also be useful in sensing radio signals and predicting the occupancy of a specific frequency at a specified location and time.

Generative AI works by being able to recognise patterns in data and from these patterns based on an input, be able to generate an output. These generative AI's have become more and more powerful with the introduction of improved processing power introduced by companies like Nvidia [3].

Challenges that may arise in predicting spectrum occupancy using generative AI can be that the model that is trained on specific data from one location and time. It will need to differ based on different locations and time. Since the traffic on different frequencies differs by time of day and location. For instance, at noon in a large city like Warsaw there will be a lot of traffic, while at night in a small town it would be negligible low. This problem gets exacerbated by a generative AI model needing a lot of training data to get an accurate prediction. This means that a lot of data must be gathered, or a method must be found to get accurate predictions on less data [4].

One way I think this could be possible is to integrate a way to measure occupancy of the spectrum by devices using the final model (edge devices) and sending this data to a central server which will use this data to constantly update the model, this will not only give a lot of access to data but also keep the data up to date. Another added bonus is

that differences in time of year for instance a cold winter versus a hot summer will also be included in the dataset.

Methodology

This project will use generative AI for spectrum sensing in Wi-Fi frequencies. To this end Python will be using with libraries like:

- PyTorch
- NumPy
- SciPy
- Matplotlib
- Seaborn
- Scikit-learn

Data will be collected using custom hardware provided by the Warsaw University of Technology. Initial training data will be collected from an open-source data platform.

This data will be pre-processed by removing missing values and normalising the data to ensure that all features are on the same scale as to not exaggerate certain features which will overshadow other potential interesting features.

Some feature exploration will occur with the processed data to find which information provides the best indicator for the wanted results. This step will take the most time in creating the model since it will require a lot of experimentation to get an accurate but still lightweight model that can be used on edge devices.

The quality of the model will be measured by the accuracy of the prediction over the spectrum. The predictions for a frequency at a specified time and location will be compared to the actual occupancy of the frequency.

The trained model will be able to predict which frequency is most likely to have low occupancy based on input of a specific time range which is yet to be determined.

A final implementation will work by sensing the spectrum using edge devices and providing this data to a central processing server which will use the data from multiple devices to make predictions of occupancy in the shared location of these devices (e.g. the centre of Warsaw). To account for the potential differences in occupancy during different hours of the day, parts of the day will be used like morning, noon, evening and night. These will be enough to proof that the concept works or not.

Below is a diagram of how the data will flow in this implementation.
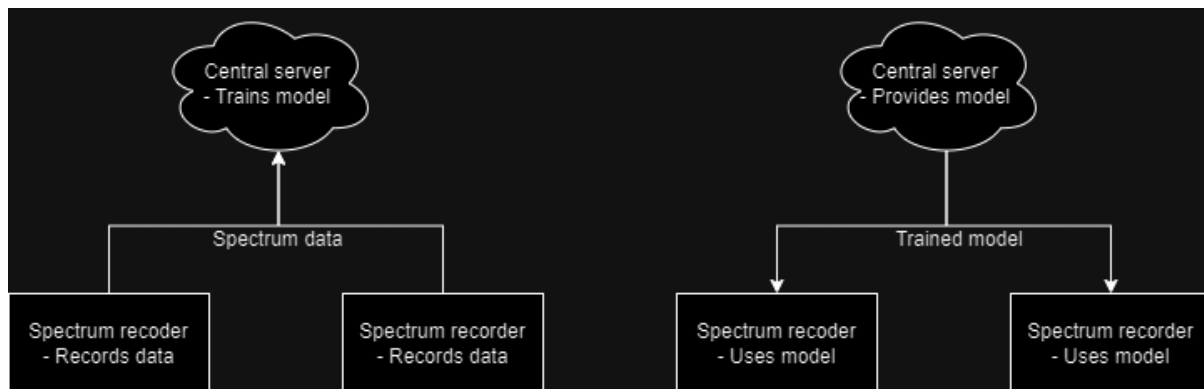
If the concept works, the dataset and training parameters can be more detailed with specific time of the day instead of part of the day and even smaller regions of a specific radius. This is however not in the scope of this research.

Sources

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3. What is a Large Language Model? | A Comprehensive LLMs Guide. (n.d.). Elastic. https://www.elastic.co/what-is/large-language-models#what-is-the-difference-between-large-language-models-and-generative-ai
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