Machine Learning based Spectrum Detection for Cognitive Radio

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OUR OBJECTIVES

- **We aim to understand the cognitive network and its methodology, the techniques that have been perfected and the grey areas which need further improvement especially concerning machine learning**
- **We wish to pick up the machine learning algorithm used for cognitive radios, and understand the regression model that the data is fit into**
- **We’d like to draw up a test and training dataset and fit our own regression model into each, comparing the similarities and accuracy of the model fitted through our function**
- **Through the process we aim to find parameters which help to increase/decrease the accuracy of the model.**

Cognitive Radio

What is it all about?

Cognitive Radio is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communications to run concurrently and also improve radio operating behavior.

Primary User

A licensed user is a primary user. The user has been allocated fixed spectrum for communication and may choose to use it at his/her own will, as er its need

Secondary User

An unlicensed user is a secondary user called a cognitive radio. It does not have any allocated spectrum of its own but searches for available spectrum from the dormant primary users to make use of it

OPERATIONS OF COGNITIVE RADIOS

1. **Spectrum sensing :**

   aims to determine which spectrum is available and to detect the presence of the licensed users when a user operates in a licensed band.

2. **Spectrum management :**

   to predict how long the spectrum holes are likely to remain available for use to the unlicensed users .

3. **Spectrum sharing :**

   to distribute the spectrum holes fairly among the secondary users, bearing in mind usage costs.

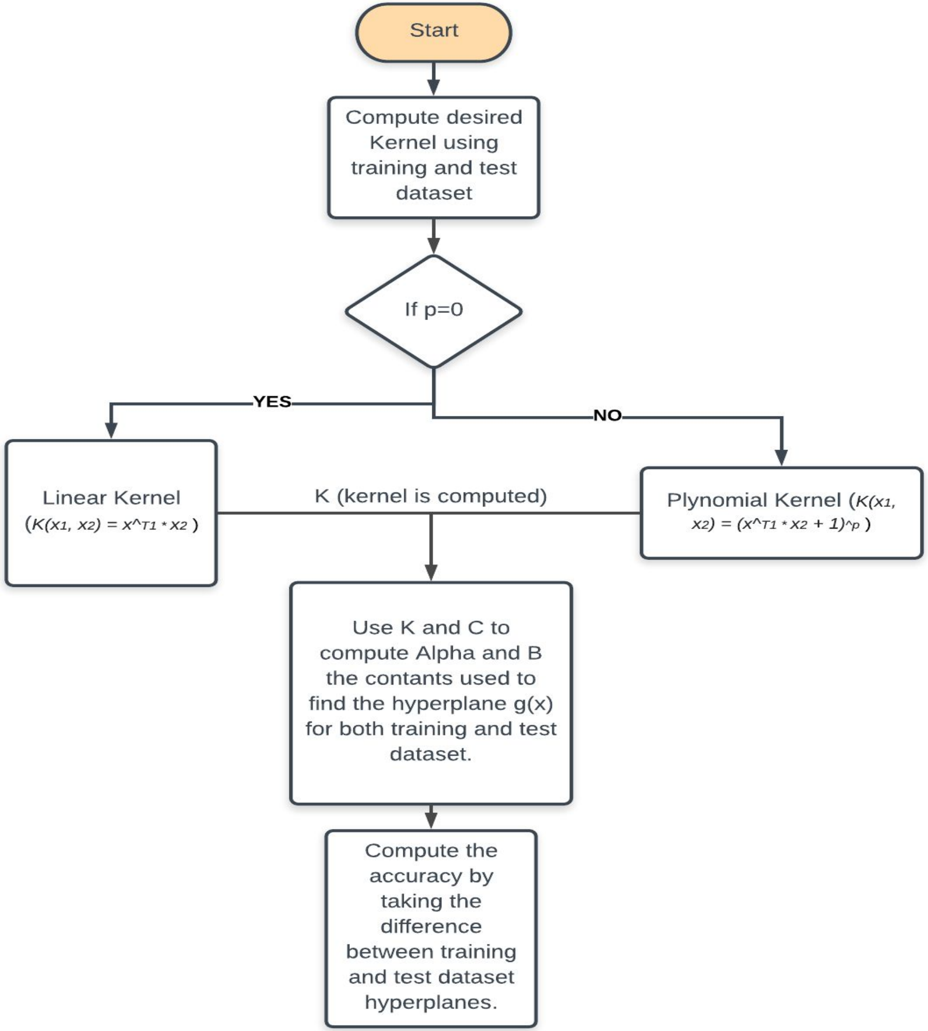
4. **Spectrum mobility :**

   to maintain seamless communication requirements during the transition to better spectrum.

SPECTRUM SENSING TECHNIQUES

One of the key technologies of CR is spectrum sensing. Traditional techniques for the same are :

1. Energy based spectrum sensing techniques .
2. Waveform based spectrum sensing techniques.
3. Cyclostationary based spectrum sensing techniques.
4. Multitaper spectral estimation.
5. Covariance based spectrum sensing techniques.
6. Wavelet based spectrum sensing techniques.



The learning engine is responsible for augmenting the list of actions available to the radio that allow it to adapt to a changing environment.

Nearly every learning technique involves the use of an objective function to determine the value of the learned data.

In a cognitive radio, these objective functions reflect the overall goal of the application.

The data that is to be segregated can follow two types of margins:

1. **Hard margin**: There is no scope for error, i.e. samples are stictly on either side of the hyperplane
2. **Soft margin**: There is some scope for error and a small percentage of devaiations are allowed in samples from the hyperplane

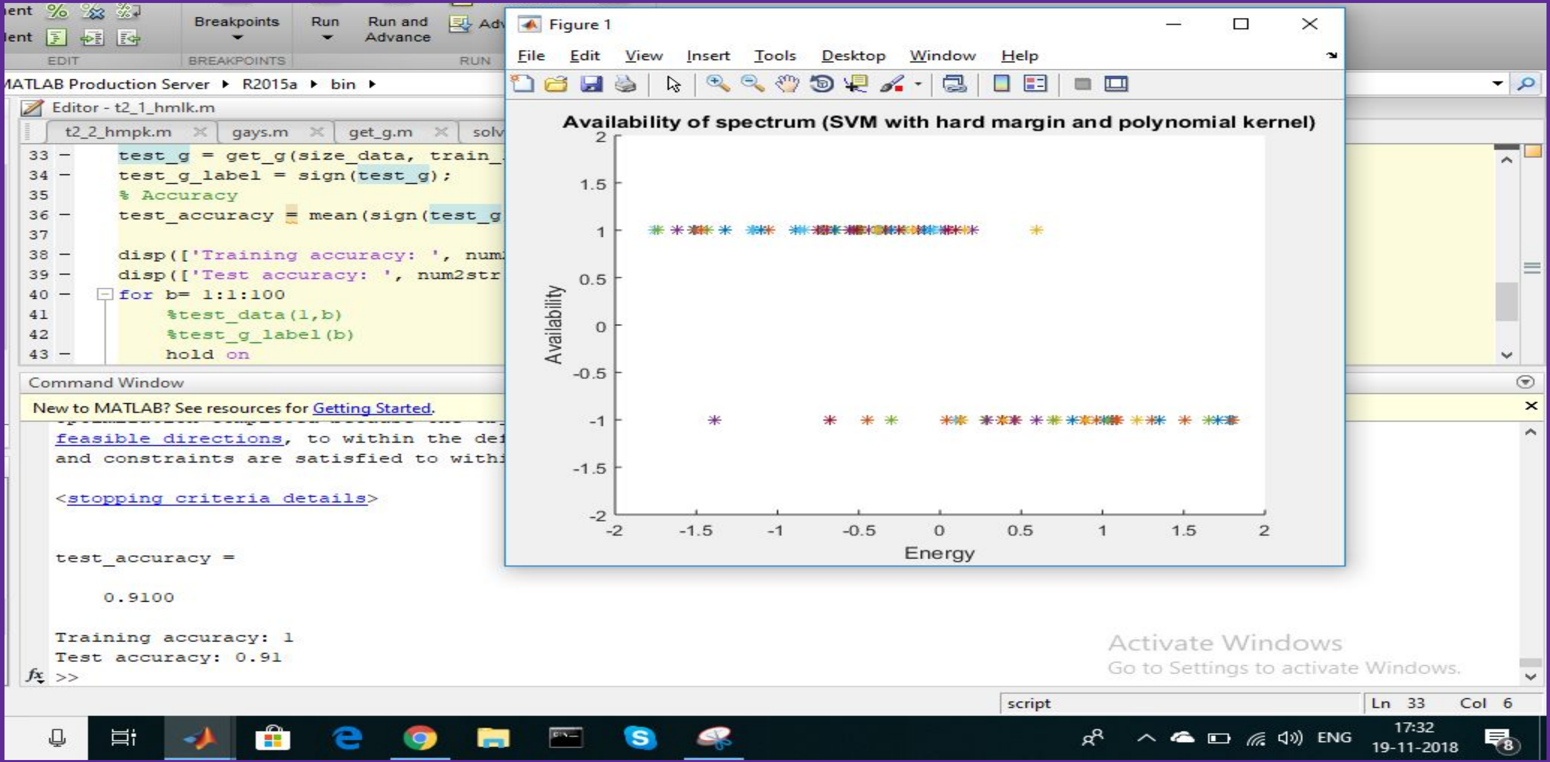
Types of Kernels for SVM model :-

1. A hard-margin SVM with a linear kernel - $K(x_1, x_2) = x^T{}_1x_2$
2. A hard-margin SVM with a polynomial kernel - $K(x_1, x_2) = (x^T{}_1x_2 + 1)^p$
3. A soft-margin SVM with a polynomial kernel - $K(x_1, x_2) = (x^T{}_1x_2 + 1)^p$

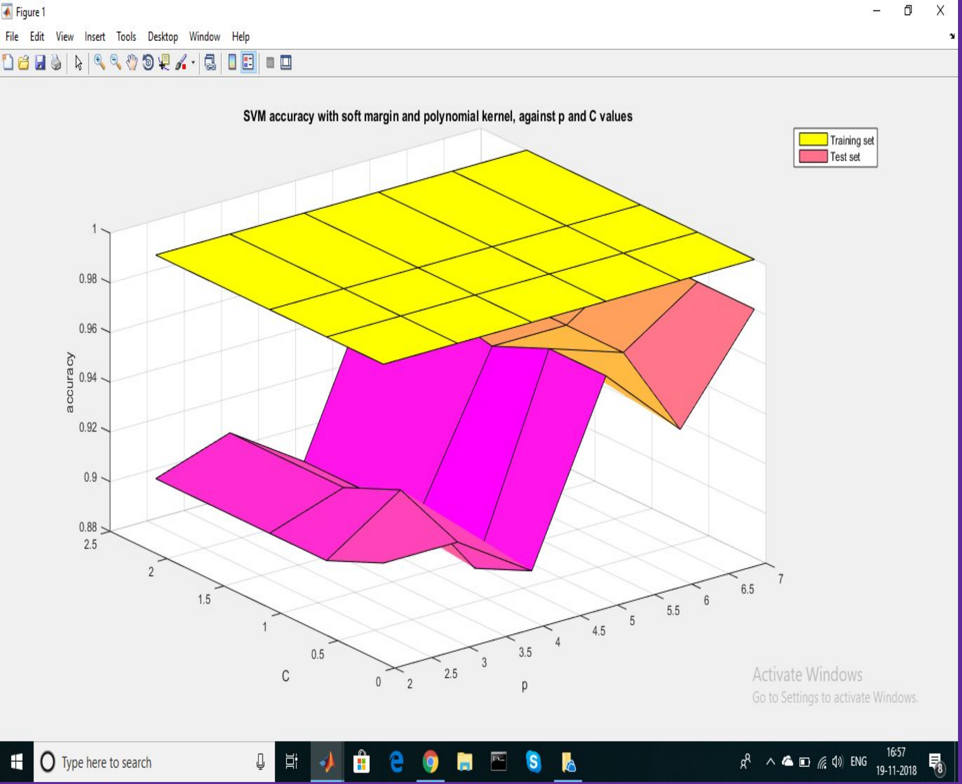
Results:

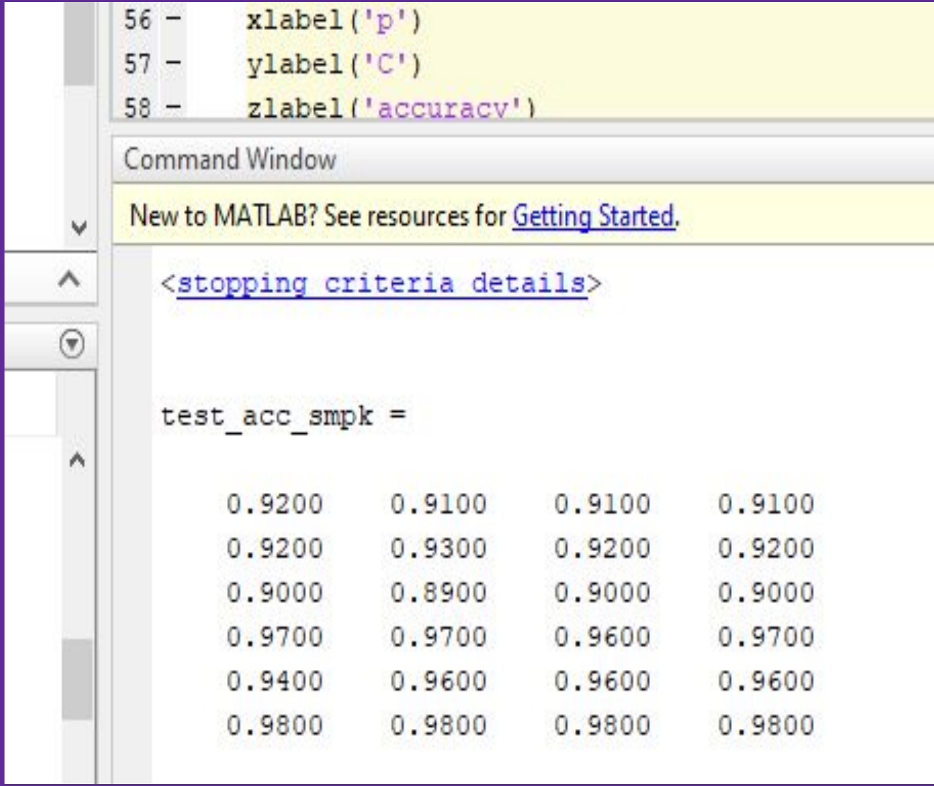
(Accuracy Plots for different kernels)

SVM with hard margin and linear kernel

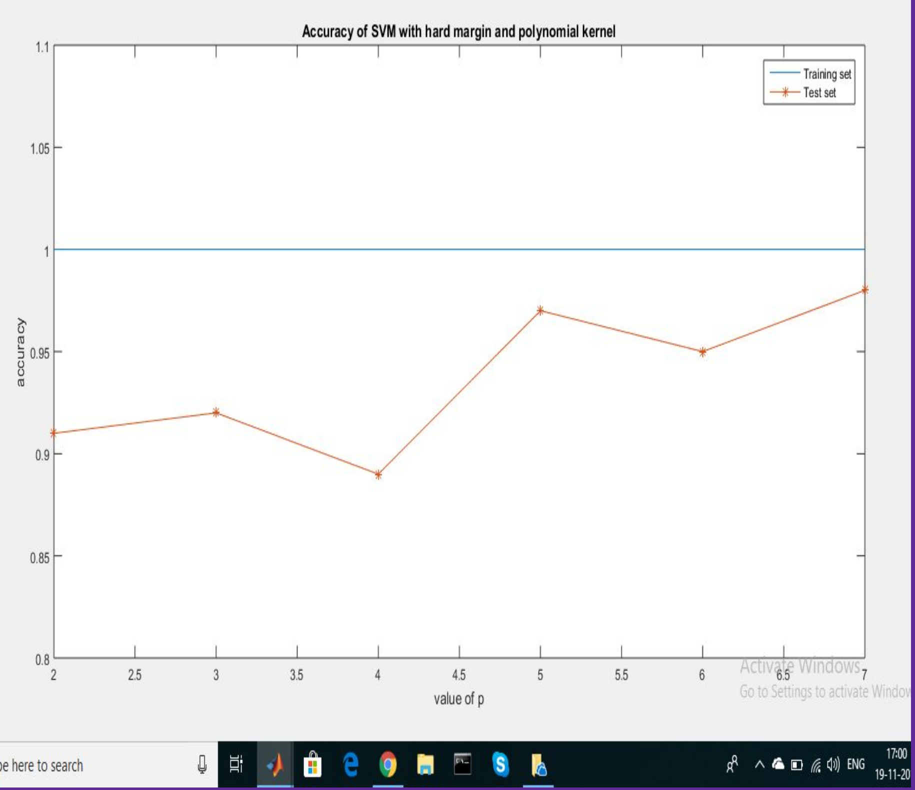


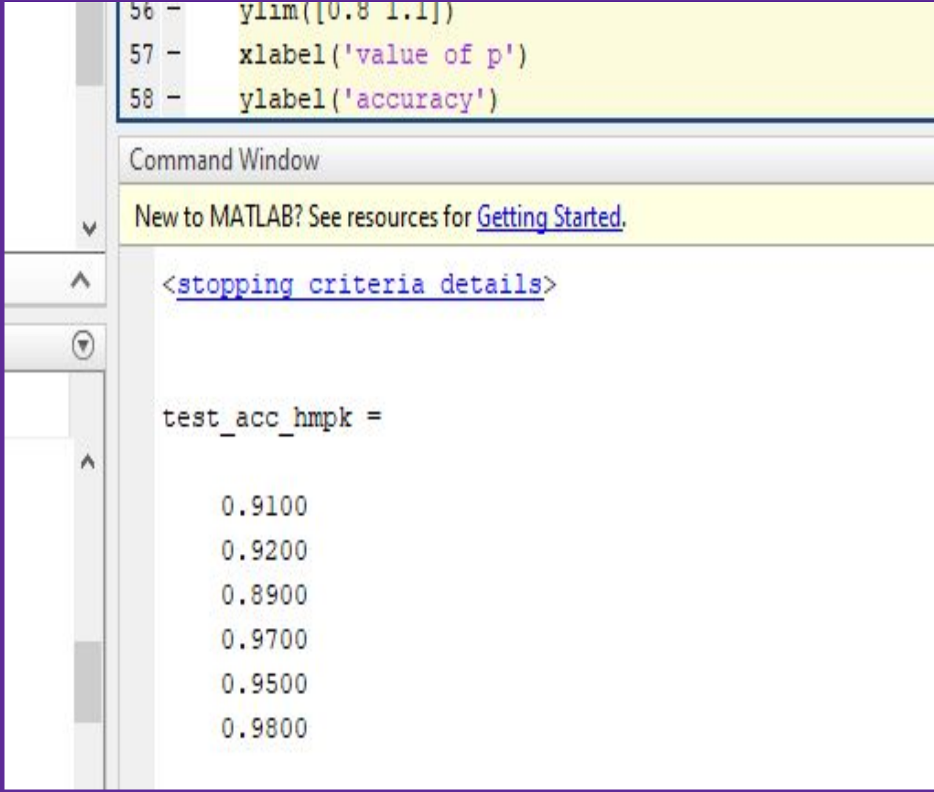
SVM with soft margin and polynomial kernel





SVM with hard margin and polynomial kernel





Types of SVM	training accuracy				Test accuracy			
Hard margin with linear kernel	1				.91			
Hard margin with polynomial kernel	p=2	p=3	p=4	p=5	p=2	p=3	p=4	p=5
	1	1	1	1	.91	.92	.89	.97
Soft margin with polynomial kernel	c=0.1	c=0.6	c=1.1	c=2.1	c=0.1	c=0.6	c=1.1	c=2.1
p=2	1	1	1	1	.92	.91	.91	.91
p=3	1	1	1	1	.92	.93	.92	.92
p=4	1	1	1	1	.90	.89	.90	.90
P=5	1	1	1	1	.97	.97	.96	.97