SONG IDENTIFICATION USING THE NUMENTA PLATFORM FOR INTELLIGENT COMPUTING

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ABSTRACT

Hierarchical Temporal Memory (HTM) technology is a new computing paradigm based on the structure and function of the human neocortex [15]. HTM networks are the cornerstone technology in the Numenta Platform for Intelligent Computing (NuPIC), a new tool for artificial intelligence research developed by Numenta Incorporated. NuPIC provides researchers with a series of tools that they can use to train and test their HTM networks. Ultimately the developers of NuPIC believe that the long term applications will include image analysis, robotics, data mining, and intelligent systems for traffic monitoring and weather prediction [7]. However, up to this point HTM networks have only been used to develop a simple vision system that is limited to recognizing a small set of line drawings. Before researchers can claim to have realized the ultimate promise of NuPIC, they must utilize the technology to solve problems across wide range of subjects. The purpose of the research presented in this thesis is to provide an experience report of HTM technology and identify best practices for future HTM researchers. In order to facilitate this experience a solution to the non-trivial problem of song identification was developed. This problem is well-researched and hundreds of papers have been written that range from using signal processing techniques [13] to sampling an artist's work for unique features [16]. Several advanced solutions using existing technologies have been created and developing an equivalent solution to this problem using NuPIC helped identify several areas in need of more in-depth research.

In order to ensure that a successful song identification development experience was reached, several preparatory steps were taken. At the beginning of this research NuPIC was a relatively new artificial intelligence framework and there were no established processes for design, implementation, or testing. To remedy this shortcoming, NuPIC’s extensive training material was used to develop a more formal methodology for using the technology. One of the first steps in this newly created process was to develop an in-depth understanding of the data being used. In order gain this knowledge multiple digital music formats were researched. This analysis revealed that the Midi music format was the best candidate to produce data for HTM network consumption. The next step was then to use the Midi song data to run several song identification experiments using NuPIC in order to test different encoding schemes and diverse HTM network structures. A data encoding scheme based on melodic segmentation yielded an identification accuracy of 100% and supports the conclusion that NuPIC is a valid platform for further research in the area of song identification. The song identification development experience also identified several areas in need of more in-depth research. Many of the algorithms used in HTM networks are designed to work with very specific data encoding schemes. In order for HTM technology to gain more widespread use, these algorithms must be improved. HTM networks also require that input data follows a strict partition-based format. Switching to a XML-based data input format would allow researchers to quickly generate and validate data sets. Lastly, the development experience presented in this thesis shares many similarities with the development processes created by the data mining community. Researchers wishing to increase their likelihood of success should look for ways to incorporate the data mining community’s knowledge into their research.

ACKNOWLEDGMENTS

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TABLE OF CONTENTS

Chapters:

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

The Numenta Platform for Intelligent Computing (NuPIC) [1] is an emerging artificial intelligence framework which is based on the biological structure of the human brain. The creators of NuPIC believed that in order to simulate human intelligence using computers, one must first understand how the human brain worked. Their initial research culminated in an overarching theory for neuroscience that stated that human intelligence was centered in the neocortex and that a single, powerful algorithm is implemented by every region of the human neocortex [6]. This biological theory was then used to derive a computational theory for intelligence based upon the structure of the human brain called Hierarchical Temporal Memory (HTM). HTM networks replicate the structure and function of the human cortex, but are not limited by the same biological input constraints as humans. Since the cortical algorithm in the human brain is universal, almost any data stream can be input into a HTM network and expert systems can be developed across a wide range of topics [7]. For example, an intelligent traffic system could be developed by exposing the HTM network to data from traffic sensors, speed monitoring sensors, and traffic lights. This is possible because HTMs work by receiving arbitrary data streams and proceed to uncover the underlying temporal and spatial patterns in the data. These patterns are then compared those stored in memory and beliefs regarding the causes of sensory data are propagated throughout the hierarchy [7].

CHAPTER 2

PROBLEM FORMULATION

While HTMs are a new type of memory designed for modern computers, they cannot be programmed using traditional techniques such as writing C++ code. To enable researchers to build applications using HTMs, Numenta Incorporated released the Numenta Platform for Intelligent Computing (NuPIC). NuPIC is an extensible platform that implements a runtime engine designed for HTM network simulation and provides researchers with a series of tools that they can use to train and test their HTMs [1]. NuPIC is designed to solve problems that involve identifying patterns in large data sets. The range of applications NuPIC will be used to solve likely include image analysis, robotics, data mining, and intelligent systems such as traffic monitoring and weather prediction [7].

When one looks at the goals of NuPIC, it is difficult not to be skeptical. The developers of NuPIC have only used it to solve a simple problem that involves identifying several line drawings [14]. Before the promises of NuPIC can be realized, it must be used to solve several problems of significance. The purpose of the research presented in this thesis is to provide a NuPIC experience report by using it to develop a solution to the non-trivial problem of song identification. Before this research could take place, several topics had to be researched in order to gain the required base of knowledge for running song identification experiments using NuPIC. The first topic dealt with overcoming NuPIC's lack of best practices for HTM network development. In order to remedy this shortcoming, a development process had to be created that would allow researchers to iteratively train and test their HTM networks. However, the process could only succeed when coupled with an in-depth understanding of digital music formats. An investigation of digital music formats allowed several different encoding algorithms to be developed, which were then used to generate input data for HTM network experiments. After the preparatory steps were complete, song identification experiments using NuPIC could be carried out. The results of these experiments were then analyzed and they revealed several areas of NuPIC in need of more in-depth research.

CHAPTER 3

RELATED WORK

3.1. Hierarchical Temporal Memory

3.1.1. HTM Network Behavior

The structure of a HTM network is intended to mirror the nested hierarchical structure of real world objects [6]. This structure includes both spatial and temporal components. In order to illustrate this, imagine that one is attempting to build a HTM network to regulate and monitor freeway traffic. One approach might be to install sensors along the highway that can track cars passing by key junctions and road sensors to monitor distances between individual cars. A fundamental concept of HTMs is that the input data must contain both temporal and spatial components and an examination of the traffic data complies with this rule [15]. The temporal aspect of the traffic data is illustrated by the ‘ripple effect’ that one driver can cause by braking, inadvertently affecting traffic for miles. This phenomenon would be nearly impossible to detect using data from a single point in time and could only be found by observing changes in the data over time from a set of geographically diverse traffic sensors. The spatial component can be found by examining data on a micro level and monitoring the distances between individual cars. Unlike the ‘ripple effect’, it would be possible to examine a data snapshot from a small number of sensors and identify cars that were tailgating. This example also illustrates a fundamental trait of

HTM networks: Patterns emerge at multiple levels in the hierarchy [7]. A micro level effect like tailgating could be quickly identified using data from a limited number of traffic sensors to calculate the distance between two consecutive cars. A macro level pattern such as the ‘ripple effect’ would occur much higher in the hierarchy as traffic must be examined over a greater distance and time frame.

HTM networks are designed as a hierarchy of nodes, where each node has 2 phases of execution: training and inference [1]. Regardless of position within the hierarchy each node executes the same algorithm, but they operate at different levels of abstraction. When being trained, the network undergoes an iterative process where all nodes on a level are trained concurrently. Once a level is finished being trained, it is switched to inference mode and training is initiated on the next level. This pattern continues up the hierarchy until all nodes have been trained. During the training phase, HTM nodes on the bottom level receive direct sensory data and beliefs about the causes of the data propagate throughout the network [5]. Over time the HTM network uses these beliefs to build a model of its environment by observing how the beliefs behave over time [7]. Once a node is switched to inference mode the HTM refines its model by attempting to group the patterns it has learned. The model is further refined upon each iteration, until the top level category node is ready for training. The category node monitors the beliefs of its children and uses a category input file to perform supervised learning. Once the top level node is finished training, it is set to inference mode and the network is ready to be tested.

During inference novel data is presented to the bottom nodes and beliefs about the causes of sensory input propagate throughout the hierarchy. Data flows both ways in the hierarchy and a change in a high level node can affect the beliefs of a lower level node via a technique known as belief propagation [6]. As time progresses beliefs are formed by all nodes, but more complex and abstract beliefs occur higher in the hierarchy. These beliefs are then combined at the top level category node and the HTM outputs a belief vector, where each element in the vector contains the percentage likelihood that a specific type of input category is causing the current sensory data [1]. It is important to note that the structure of the HTM network does not have to be uniform and nodes can be connected to multiple parents. Figure 3.1 shows a possible HTM network structure and illustrates how beliefs about a single input vector propagate throughout the hierarchy.

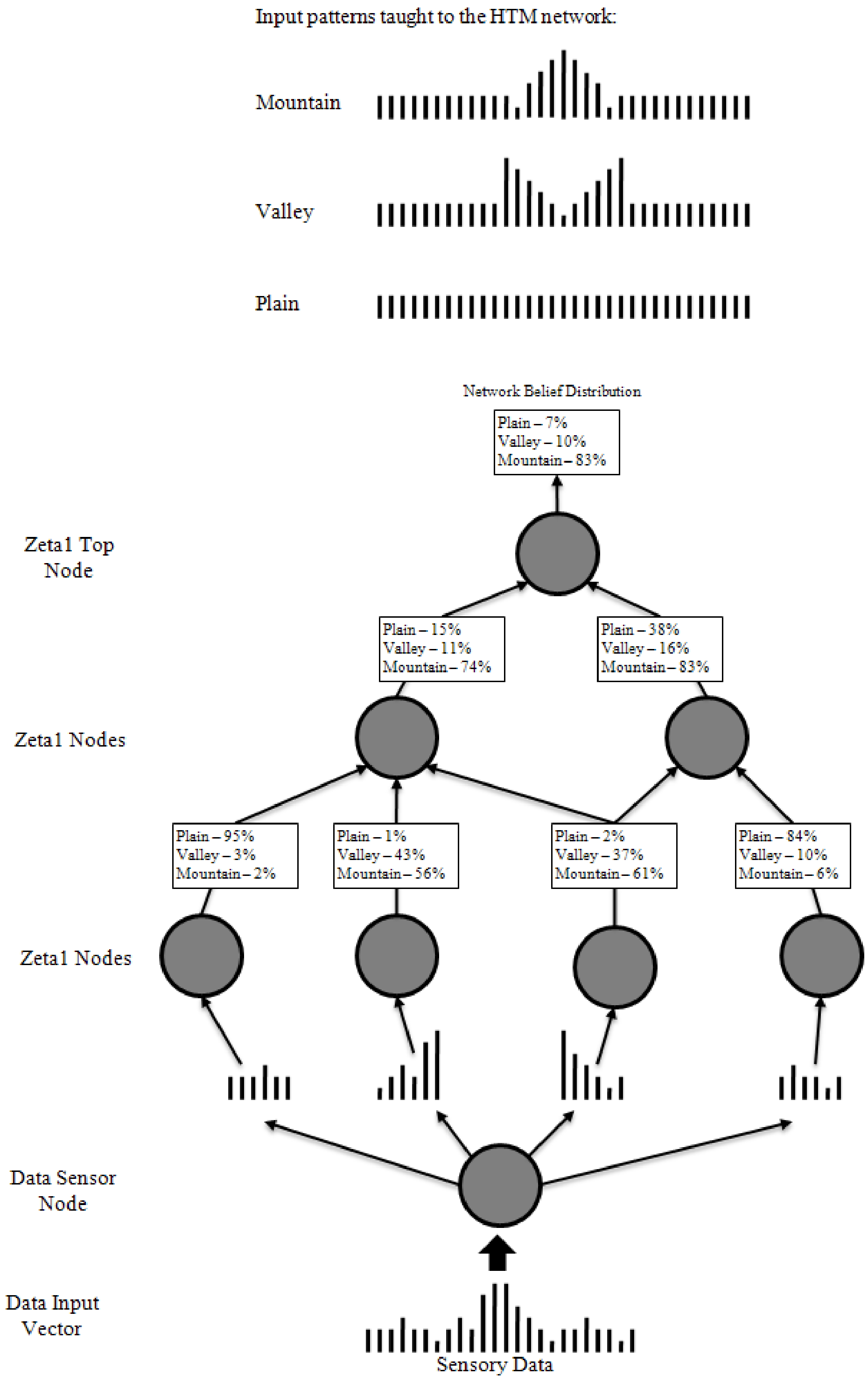


Figure 3.1: A sample HTM network.

3.1.2. Node Algorithms

The goal of each node in a HTM network is to form a model to describe the data it is encountering [5]. Each node contains a spatial pooler and a temporal pooler which work together to identify patterns over time (Figure 3.2). The input of the node is connected to the spatial pooler. The output of the spatial pooler then connected to the input of the temporal pooler, which is responsible for the output of the node. These pooling mechanisms are used to build a model of the data the node encounters and allow the node to perform inference on novel data.

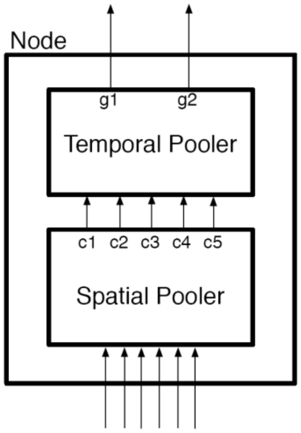


Figure 3.2: HTM Node Structure [5].

Once data enters a node, it is responsibility of the spatial pooler to quantize data inputs in an attempt to remove noise and group similar data input patterns. The spatial pooler accomplishes this task by using a Gaussian distance function to determine the distance between n-length data vectors. This distance is then compared to the quantization threshold and a decision is made as to how to quantize the vector. The sensitivity of the spatial pooler can be adjusted using node configuration parameters and will vary depending on the node’s position in the hierarchy

[1]. Figure 3.3 shows several sample data vectors and displays how the spatial pooler would quantize the data.

Distance between [1 1 1 1 1] and [1 1 0.99 1 1.02]

$$0.0224 = \sqrt{(1-1)^2 + (1-1)^2 + (1-0.99)^2 + (1-1)^2 + (1-1.02)^2}$$

Quantization Threshold = 0.1, vectors are equal

Distance between [1 1 1 1 1] and [1 3 1.5 1 0.1]

$$2.2494 = \sqrt{(1-1)^2 + (1-3)^2 + (1-1.5)^2 + (1-1)^2 + (1-0.1)^2}$$

Quantization Threshold = 0.1, vectors are different

Figure 3.3: Spatial Pooler quantization example.

The quantized data is then input into the temporal pooler, which attempts to pool together patterns based on their temporal proximity [5]. When a node is in learning mode, it records which patterns occur near each other in time and stores the data in a time adjacency matrix. Figure 3.4 displays how the matrix is structured and stores temporal proximity information.

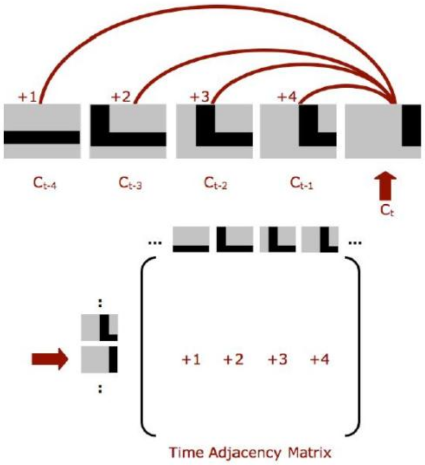


Figure 3.4: Time adjacency matrix operation [5].

After a node is switched to inference mode, it examines this matrix and attempts to group patterns with high temporal proximity. The temporal pooler accomplishes this by converting the time adjacency matrix into an undirected weighted graph [5]. Each quantization point represents a vertex and edge weights between quantization points depend on their temporal proximity. Temporal groups are identified by examining the graph for connected components and grouping together components based on edge strength. These groups are used when attempting to form beliefs about novel data and the output of a node is in terms of the temporal groups it has learned [5]. The memory and time adjacency edge strength threshold of the temporal pooler is configurable via node parameters and must be configured according to the data the node is encountering. Figure 3.5 displays several iterations of the temporal group formation process.

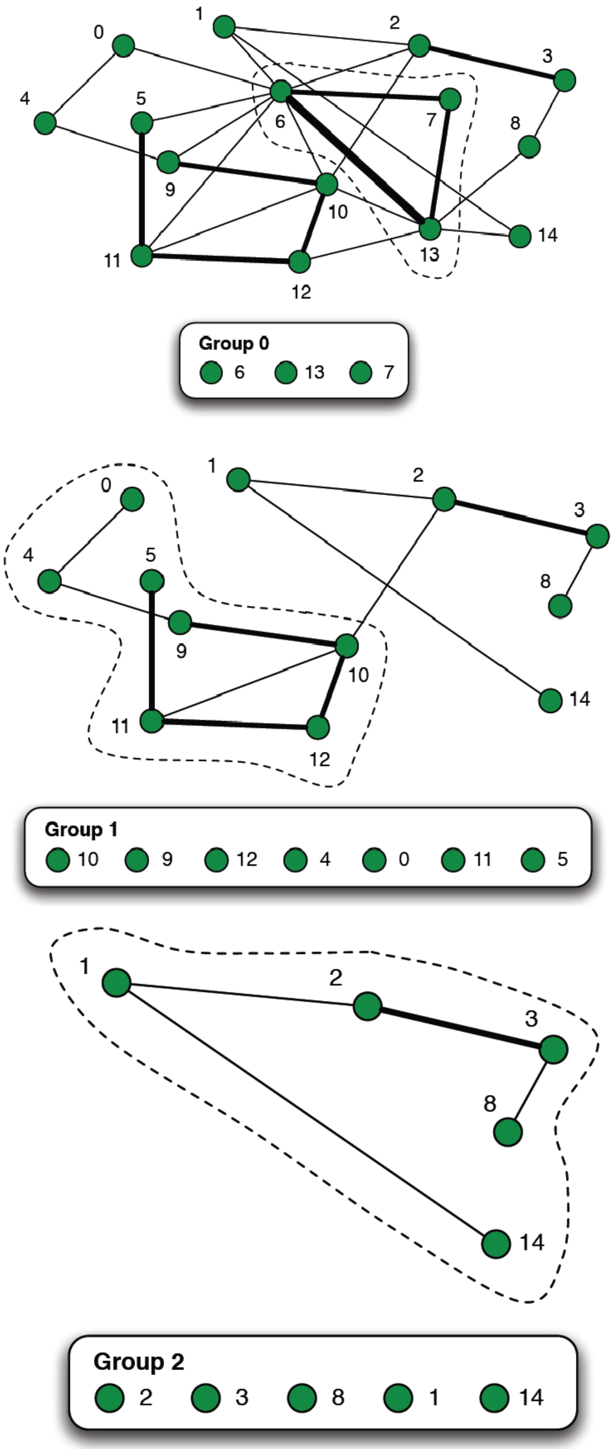


Figure 3.5: Temporal Pooler group formation [5].

3.2. Song Identification

The majority of music identification and classification research is conducted through the International Music information Retrieval Systems Evaluation Laboratory (IMIRSEL) Project. The organization holds yearly competitions in categories such as song identification and genre classification [9]. A large amount of the research is done using Midi music files, though some researchers are working with more complex sample based audio formats. Researchers involved with the IMIRSEL Project have had many years to refine traditional approaches and create hybrid artificial intelligence algorithms. Their research is now at a highly advanced stage and researchers are starting to combine multiple audio features to make their systems more robust [12, 16]. Unfortunately, due to the complexity of feature extraction and hybrid AI algorithms, this work is not accessible to entry level researchers.

Chapter 4

SONG IDENTIFICATION DEVELOPMENT EXPERIENCE

4.1. Research Process

NuPIC is a relative newcomer to the AI world and has no established set of best practices. The unique nature of HTM networks makes the traditional software development process of requirements analysis, design, implementation, and testing irrelevant. A major hurdle in this research was to come up with a scientific process that would allow for iterative development and experimentation with different HTM network configurations. An iterative process based on the NuPIC documentation was developed and revised throughout the research project. The final NuPIC development process is presented in Figure 4.1.

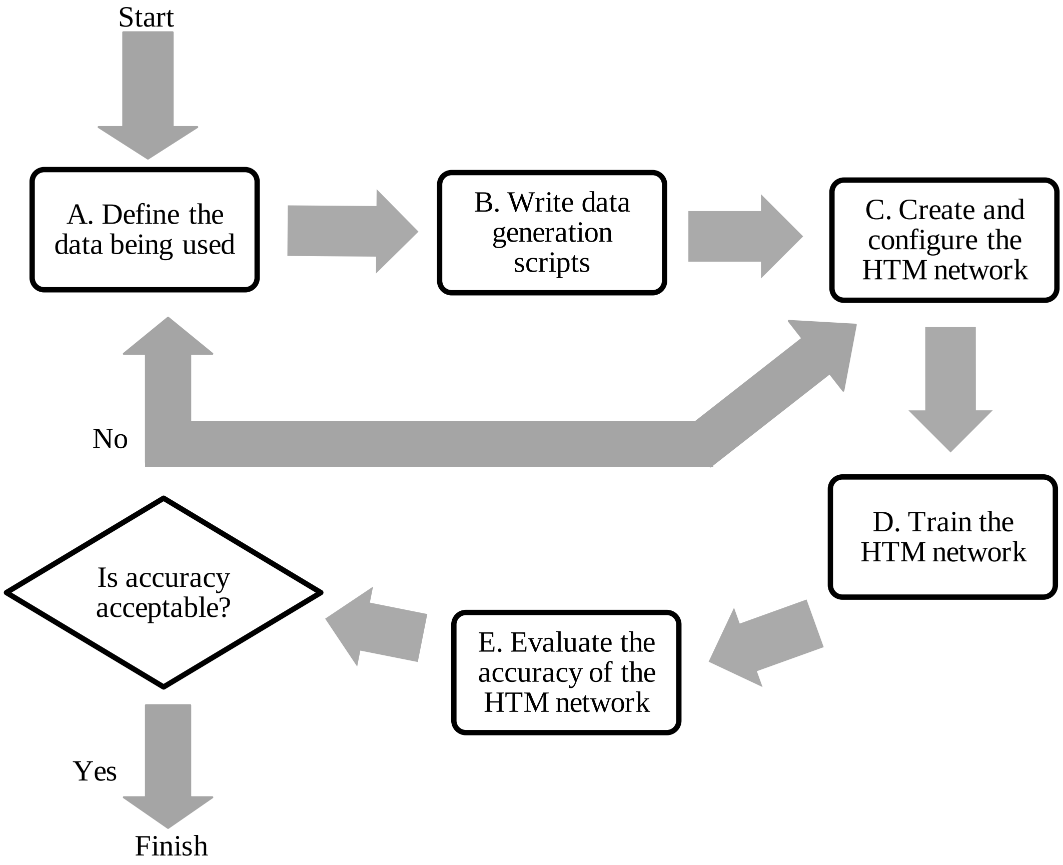

Start
A. Define the data being used
B. Write data generation scripts
C. Create and configure the HTM network
No
D. Train the HTM network
Is accuracy acceptable?
E. Evaluate the accuracy of the HTM network
Yes
Finish

Figure 4.1: The NuPIC development process.

A. Define the data being used

Before an HTM network can be developed, it is crucial to understand the type of data being used. Researchers need to develop a deep understanding of their data and create a representation scheme that highlights the data's spatial and temporal characteristics. Whatever scheme is used, HTM networks expect data to be presented as a series of vectors, meaning continuous data must be transformed into vector based samples. Lastly, HTM nodes use a Gaussian distance function to compute spatial distances and data may need to be scaled to ensure proper results [5]. There is rarely a simple answer to the multitude of questions presented in the data transformation stage and this step will be revisited many times throughout the HTM development process.

B. Write data generation scripts

Any programming language can be used to generate data sets for a HTM network. For a typical network, each data set contains two files: 1) A data file of input vectors where each vector is placed on a new line in the file 2) A category file where every row correctly categorizes the corresponding vector in the data file [1]. In order to properly train and test a network two distinct sets are used. Overall the format of the training and test data sets are very similar, but there is one crucial difference. Training data sets allow the researcher to insert specially formatted data vectors (a data vector of ‘0’s) to reset the temporal memory of the HTM [1]. This becomes important during supervised learning when the data vectors switch from one category to another because it prevents the temporal pooler from looking for patterns that do not exist. The following figure displays the format of a training data file:

```
0.7935 0.4761 0.0000 0.4761 0.0000 0.3053 0.3045 0.0000 0.0385 0.0362
0.0036 0.0000 0.4761 0.0000 0.1471 0.2013 0.3053 0.0000 0.7935 0.0000
0.0000 0.3526 0.0000 0.4761 0.0000 0.2013 0.0000 0.3053 0.0000 0.3322
0.0409 0.0000 0.7935 0.0000 0.4761 0.0000 0.4761 0.0000 0.3053 0.1768
0      0      0      0      0      0      0      0      0      0
0.0000 0.6448 0.5069 0.0000 0.5069 0.0000 0.1767 0.5069 0.0000 0.0000
0.2013 0.4240 0.5069 0.5675 0.5069 0.3543 0.0000 0.5069 0.5676 0.7567
```

Figure 4.2: Sample training data file.

C. Create and configure the HTM network

HTM networks are built and configured by writing Python scripts. While the majority of the script follows a standard pattern, each network requires customization. Researchers must leverage in-depth knowledge of their data to design and configure the hierarchy of nodes. Each node's algorithms need to be customized based on the input values it is encountering. Because of the large number of node parameters, node configuration values will most likely be tweaked each iteration in order to improve accuracy. Luckily the network structure will usually remain the same, reducing the amount of code that must be change. Figure 4.3 displays a sample network creation Python script.

```
#-------------------------------------------------------
# create the initial instance of the network
#-------------------------------------------------------
network = Network()

#-------------------------------------------------------
# Create data and category sensors
#-------------------------------------------------------
dataSensor = CreateNode("VectorFileSensor", phase=0, dataOut=80)
network.addElement("dataSensor", dataSensor)
category = CreateNode("VectorFileSensor", phase=2, dataOut=1)
network.addElement("categorySensor", category)

#-------------------------------------------------------
# Create and add Level 1 region, containing 4 nodes
#-------------------------------------------------------
level1 = Region(4,
           CreateNode("Zeta1Node",phase=1,bottomUpOut=200,symmetricTime=False,
                     spatialPoolerAlgorithm="gaussian",maxDistance=0.001,
                     sigma=0.01,transitionMemory=4,topNeighbors=1,maxGroupSize=20,
                     temporalPoolerAlgorithm="sumProp",detectBlanks=1
             )
)
network.addElement("level1", level1)

#-------------------------------------------------------
# Create and add Level 2 region, containing 2 nodes
#-------------------------------------------------------
level2 = Region(2,
           CreateNode("Zeta1Node",phase=2,bottomUpOut=100,symmetricTime=False,
                      spatialPoolerAlgorithm="Gaussian”,maxDistance=0.001,
                      sigma=0.01,transitionMemory=4,topNeighbors=1,
                      maxGroupSize=10,temporalPoolerAlgorithm="sumProp",
                      detectBlanks=1
                  )
)
```

```
network.addElement("level2", level2)

#-------------------------------------------------------
# Create supervised node at the top level
#-------------------------------------------------------
topLevel = CreateNode("Zeta1TopNode", phase=3, categoriesOut=5,
                      spatialPoolerAlgorithm="product", mapperAlgorithm="sumProp")
network.addElement("topLevel", topLevel)

#-------------------------------------------------------
# Create file effector to write outputs of top level node to a text file
#-------------------------------------------------------
output = CreateNode("VectorFileEffector", phase=4)
network.addElement("fileOutput", output)

#-------------------------------------------------------
# Link the HTM network together
#-------------------------------------------------------
network.link("dataSensor", "level1", SimpleSensorLink())
network.link("level1", "level2", SimpleFanIn())
network.link("level2", "topLevel", SimpleFanIn())
network.link(source="categorySensor", sourceOutputName="dataOut",
             destination="topLevel", destinationInputName="categoryIn")
network.link(source="topLevel", sourceOutputName="categoriesOut",
             destination="fileOutput", destinationInputName="dataIn")

#-------------------------------------------------------
# save the network to disk
#-------------------------------------------------------
network.writeXML(“HTMNetwork.xml”)
```

Figure 4.3: Sample HTM network creation script.

D. Train the HTM Network

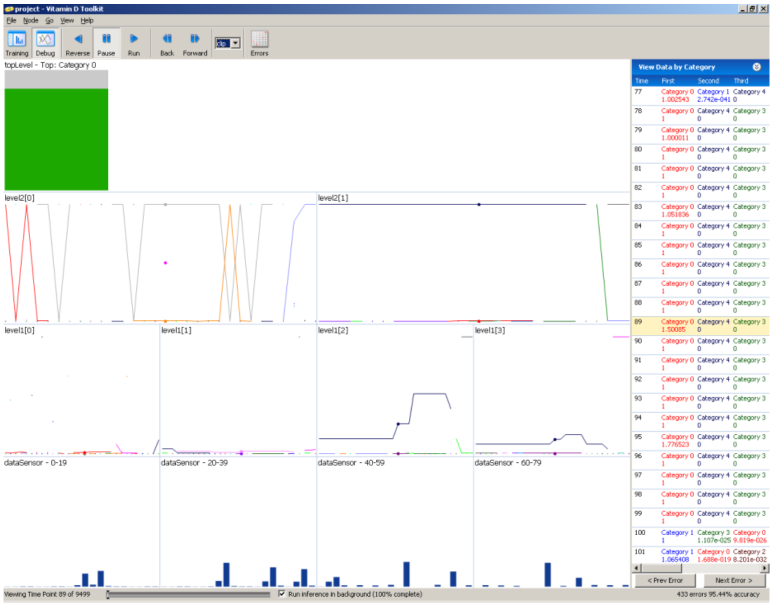
Training the HTM network is one of the easier steps in the process due to a simple API to automate training. The automation API allows researchers to quickly write a training script even though it may take a long time to execute. Training scripts must be written in Python and enable researchers to save the results after each level in the network is trained, minimizing the impact of a runtime failure. Figure 4.4 displays a typical training script.

```
#--------------------------------------------------------
# Load network and prepare data files we will use.
#--------------------------------------------------------
runtimeNet = CreateRuntimeNetwork(untrainedNetworkFile, files=[trainDataFile,
trainCategoryFile])
dataSensor = runtimeNet.getElement("dataSensor")
categorySensor = runtimeNet.getElement("categorySensor")
dataSensor.execute("loadFile", trainDataFile)
categorySensor.execute("loadFile", trainCategoryFile)
rows = 5000


#--------------------------------------------------------
# Train Level 1
#--------------------------------------------------------
runtimeNet.run(Zeta1Train("level1", rows), ["dataSensor", "level1"])
runtimeNet.writeXML(“PostLevel1.xml”)

#--------------------------------------------------------
# Train Level 2
#--------------------------------------------------------
dataSensor.setParameter("position", "0")
categorySensor.setParameter("position", "0")
runtimeNet.run(Zeta1Train("level2", rows), ["dataSensor", "level1", "level2"])
runtimeNet.writeXML(“PostLevel2.xml”)



#--------------------------------------------------------
# Train Top Level Category Node
#--------------------------------------------------------
dataSensor.setParameter("position", "0")
categorySensor.setParameter("position", "0")
runtimeNet.run(Zeta1Train("topLevel", rows), exclusion=["fileOutput"])

#--------------------------------------------------------
# Save the network and retrieve trained network file from bundle
#--------------------------------------------------------
runtimeNet.writeXML(“TrainedNetwork.xml”)
runtimeNet.cleanupBundleWhenDone()
```

Figure 4.4: Sample HTM network training script.

E. Evaluate the Accuracy of the HTM Network

Once the training script has finished executing, the Vitamin D Toolkit can be used to load the network and interactively step through the test data set (Figure 4.5). The toolkit allows developers to assess the network accuracy as a whole, as well as investigate how the beliefs of individual nodes affect the network. This is especially helpful when trying to isolate the source of incorrect inferences. If the results of the test are not satisfactory, the researcher has two options. When the low accuracy is due to a poor data representation scheme, the researcher can attempt to redefine the data and develop a new representation scheme. If the researcher simply needs a slight increase in accuracy, HTM node parameters can be modified and the network can be re-trained.



Time	First	Second	Third
77	Category 0 1.002543	Category 1 2.742e-041	Category 4 0
78	Category 0 1	Category 4 0	Category 3 0
79	Category 0 1.000011	Category 4 0	Category 3 0
80	Category 0 1	Category 4 0	Category 3 0
81	Category 0 1	Category 4 0	Category 3 0
82	Category 0 1	Category 4 0	Category 3 0
83	Category 0 1.051836	Category 4 0	Category 3 0
84	Category 0 1	Category 4 0	Category 3 0
85	Category 0 1	Category 4 0	Category 3 0
86	Category 0 1	Category 4 0	Category 3 0
87	Category 0 1	Category 4 0	Category 3 0
88	Category 0 1	Category 4 0	Category 3 0
89	Category 0 1.50085	Category 4 0	Category 3 0
90	Category 0 1	Category 4 0	Category 3 0
91	Category 0 1	Category 4 0	Category 3 0
92	Category 0 1	Category 4 0	Category 3 0
93	Category 0 1	Category 4 0	Category 3 0
94	Category 0 1	Category 4 0	Category 3 0
95	Category 0 1.776523	Category 4 0	Category 3 0
96	Category 0 1	Category 4 0	Category 3 0
97	Category 0 1	Category 4 0	Category 3 0
98	Category 0 1	Category 4 0	Category 3 0
99	Category 0 1	Category 4 0	Category 3 0
100	Category 1 1	Category 3 1.107e-025	Category 0 9.819e-026
101	Category 1 1.065408	Category 0 1.688e-019	Category 2 8.201e-032

Viewing Time Point 89 of 9499

☑ Run inference in background (100% complete)

433 errors 95.44% accuracy

Figure 4.5: HTM network analysis using the Vitamin D Toolkit.

4.2. Exploration of Representation Schemes

In order for a HTM network to be successful at song identification, the data representation scheme must include several key characteristics. Well formed data sets are evenly distributed because outliers and clustered data can introduce errors into the spatial pooler. Patterns within the data must also slowly emerge over time because the temporal pooler has difficultly identifying patterns that quickly appear and disappear. However, patterns that span hundreds of data vectors will be difficult for the temporal pooler to identify because of its limited temporal memory. Lastly, each category that the HTM is trying to learn should have its own set of unique patterns. This will allow the HTM to discover which patterns can be used to correctly identify a category.

4.2.1. Sample Based Audio Files

Modern day digital music is stored electronically via an extremely complicated and accurate data format. Researchers in the field must be educated in both audio theory and computer science to fully comprehend music encoding methodologies. Popular formats such as wav, mp3, ogg, or wma are all built on the same fundamental concept of sampling and differ only in their strategy for compression. Of these formats, the wav format was chosen for deeper analysis due to its relatively uncompressed and straightforward encoding format [18]. Compression makes it difficult to extract the wave samples from the music file and an uncompressed format requires less preprocessing of the audio waveform. Figure 4.6 shows a typical audio waveform using a 10 second sampling period and Figure 4.7 displays a subsection of the same waveform over a 1 second sample period.

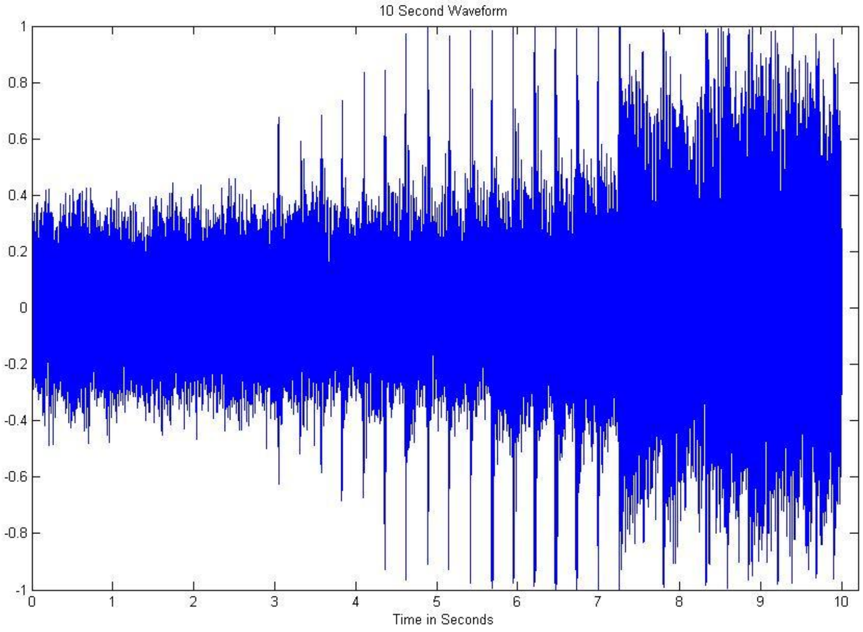


Figure 4.6: Audio waveform using 10 second sample period.

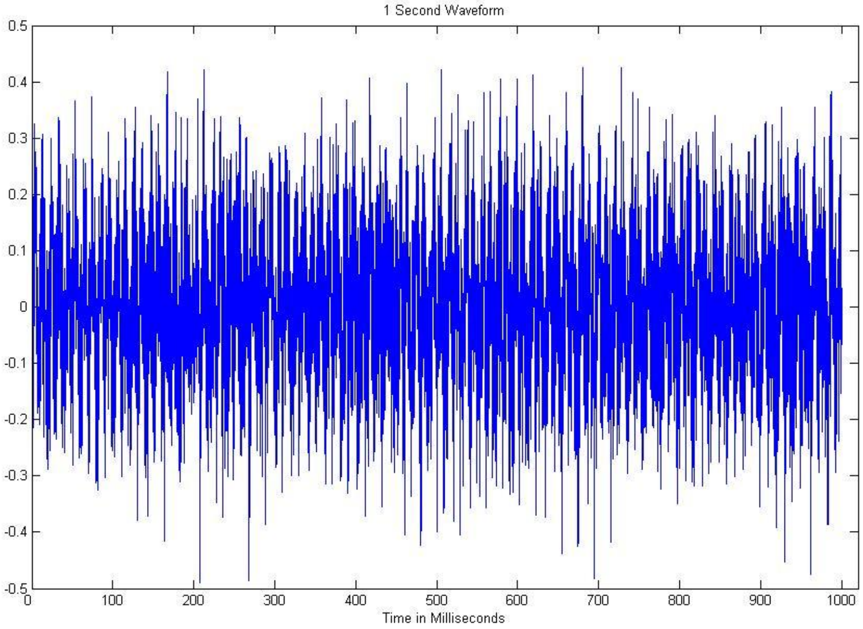
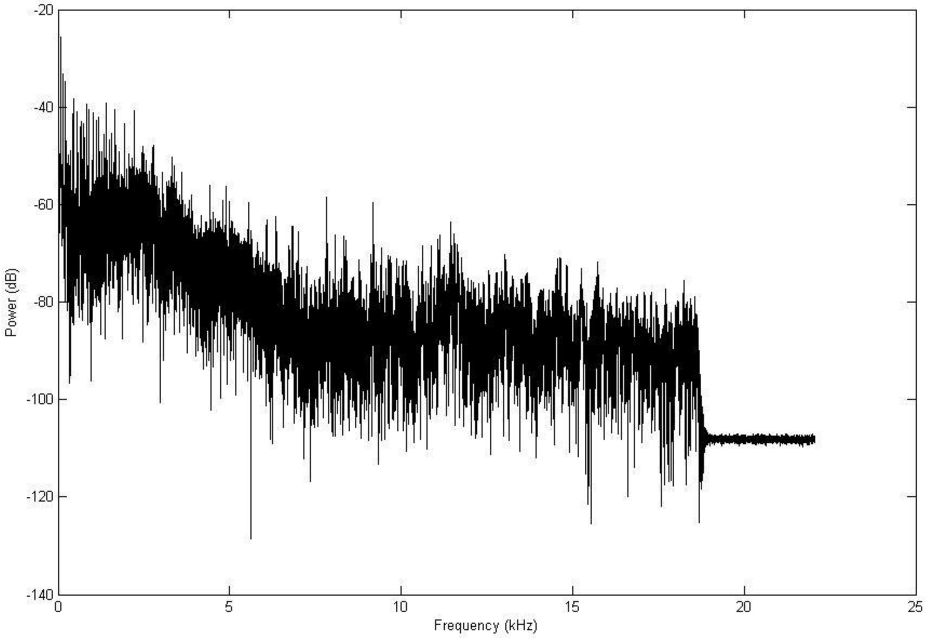


Figure 4.7: Audio waveform using 1 second sample period.

Standard wav files sample the audio waveform at a rate of 44,100 samples per second. This creates a large, rapidly changing data set that is difficult to use when training HTM networks. The large amount of variance makes it challenging for the spatial pooler to quantize the data vectors, which in turn overwhelms the temporal pooler with a large amount of unique data vectors. This results in a time adjacency graph with a large amount of low-weight edges. The high connectedness of the graph makes it very difficult for the temporal pooler to identify distinct groups within the graph. A popular data processing technique used to summarize a waveform involves building a Discrete Fourier Transform over a predetermined segment of data. This transform can be used to determine the power of the wave over the human audible frequency spectrum [10]. Since the Fourier transform provides a plot of frequency versus power, it is often possible to identify specific frequencies being played within the waveform. Therefore the Fourier Transform data has the potential to identify chords and uncover melodic patterns by examining consecutive segments. Figure 4.8 shows a Fourier Transform created using 1 second segments from two different points in the song.



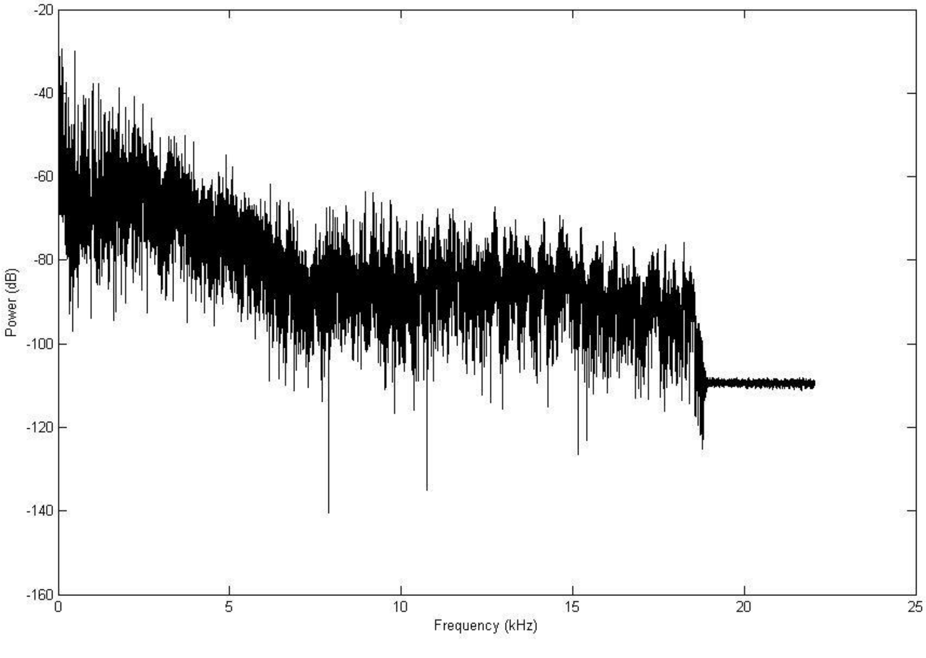


Figure 4.8: Sample Fourier Transform plots.

Even though the transforms shown in Figure 4.8 are taken from different sections of the song, they are difficult to differentiate. Fourier Transforms created using 1 second segments are too generic and the segment size needs to be reduced in order to isolate the notes being played by each instrument. However, this approach is problematic due to the fact that the number of samples in the segment affects the accuracy of the Fourier Transform. For example, using a segment size of 44,100 samples (1 second) results in 22,050 data points to describe the frequency spectrum. While this large amount of data points is sufficient to characterize the frequency spectrum, it is too large a time frame to isolate the unique melodic elements of a song. A smaller sample size such as 10 milliseconds would be better suited to isolate melodic elements, but results in just 220 data points. This lack of data resolution becomes a problem when dealing with lower pitch notes, where single octaves can span as little as 25Hz. Figure 4.9 shows a Fourier Transform created using a segment size of 10 milliseconds. Upon close examination of Figure 4.9 it is possible to see linear interpolation between the data points, inaccurately summarizing important data in the process. This figure illustrates the segment size and data resolution problem with the Fourier Transform, making it a poor candidate to produce data for a HTM network.

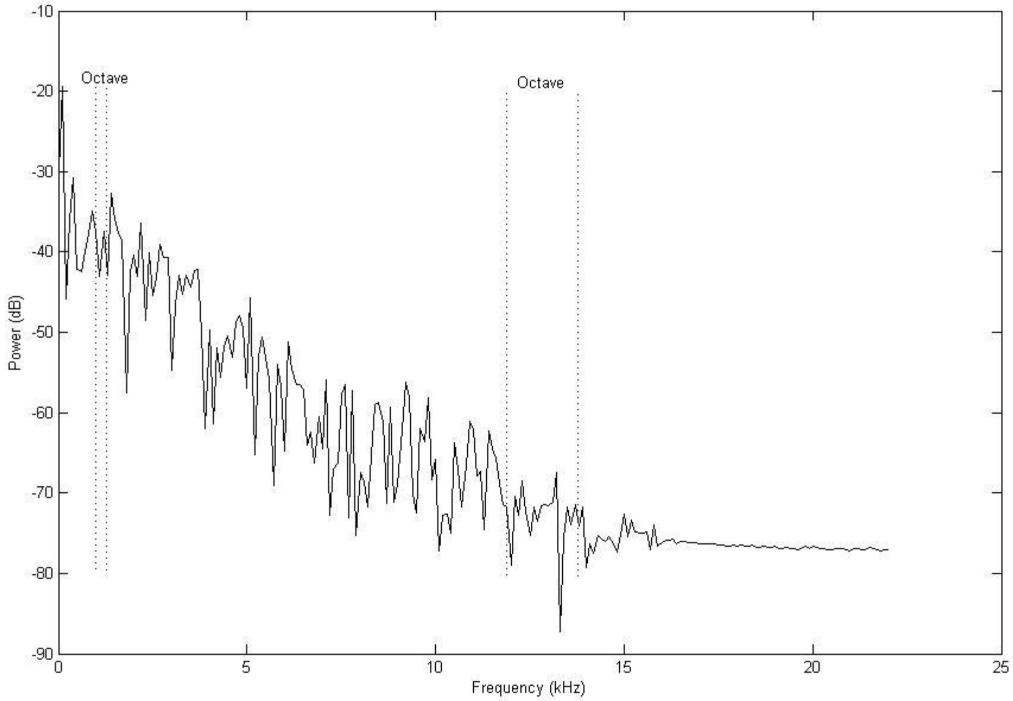


Figure 4.9: Fourier Transform taken over 10 millisecond song clip.

A technique often used to overcome the Fourier Transform data accuracy and time tradeoff is to compute a set of Mel Frequency Cepstral Coefficients (MFCCs) for the segment. These coefficients are calculated using the Mel Scale, which more closely resembles human auditory recognition because it is based on a logarithmic scale (Figure 4.10) [11]. While the MFCCs are promising, the initial step of this technique requires that a Fourier Transform be computed on the segment. For a large segment size, the MFCCs effectively summarize the data points created by the Fourier Transform. The problem comes when trying to identify melodic components of the song. In order to do this effectively, one must decrease the segment size. Hence this approach also confronts the data accuracy and time tradeoff issue associated with Fourier Transforms. Other researchers are attempting to overcome the pitfalls of the Fourier

Transform by incorporating other types of data into their identification algorithms. Instead of relying solely on transform based data, researchers are moving to a feature based approach [12]. Features attempt to characterize the song according to the building blocks of music theory. Typical features include tracking the beats of the song, isolating different instruments, or identifying the tempo of the song. Regardless of the feature, complex extraction algorithms are required to preprocess the data and have spawned an entire community of researchers. This community has matured rapidly over the last few years and feature based song identification techniques are starting to see more widespread success [13, 16].

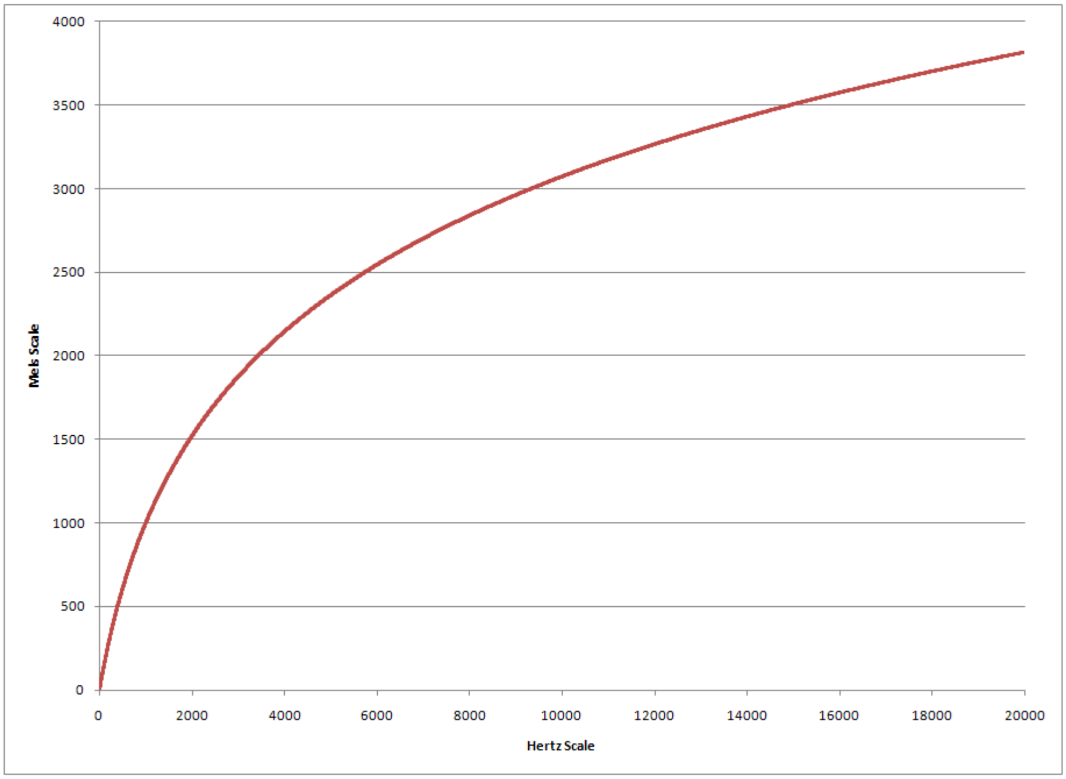


Figure 4.10: Mels Scale versus Hertz Scale plot.

4.2.2. Midi Audio Files

Due to the difficulties of sample based audio formats, many researchers in the field of song identification have shifted their focus to Midi files. Musical Instrument Digital Interface (Midi) is a standard for saving and transmitting musical information, similar to sheet music. Instead of sampling an audio waveform thousands of times per second, Midi files format music as a series of on and off events for a fixed set of pitches. The file structure allows for 128 notes and assigns every note a unique identification number. Note events are then created by recording the note start time, duration, and velocity of the note strike [4]. These events are compiled into a data structure called a note matrix, displayed in Table 4.1. Since Midi files do not record the audio signal of a song, the complexity of the format is greatly reduced and it is possible to store the data in a format easily understood by humans.

Onset (Beats)	Duration (Beats)	Midi Pitch	Velocity	Onset (Sec)	Duration (Sec)
4.0000	1.5000	55	82.0000	2.3812	0.8929
4.5000	3.0990	67	59.0000	2.6788	1.8448
5.0000	0.5000	79	74.0000	2.9765	0.2976
5.5000	2.0990	79	75.0000	3.2741	1.2495
5.5000	1.5000	55	83.0000	3.2741	0.8929
6.5000	1.0990	71	72.0000	3.8694	0.6542
7.0000	0.5990	55	87.0000	4.1671	0.3566
7.5000	0.9792	72	85.0000	4.4647	0.5829
8.0000	1.5000	60	66.0000	4.7624	0.8929
8.5000	2.8333	67	68.0000	5.0600	1.6867
9.0000	1.0000	72	67.0000	5.3577	0.5953
9.5000	1.8333	71	66.0000	5.6553	1.0914
9.5000	1.5000	60	73.0000	5.6553	0.8929
10.0000	1.3333	72	76.0000	5.9530	0.7937

Table 4.1: Sample Midi note matrix data structure.

4.2.3. Local Boundary Detection Model

Regardless of the music file format chosen, the goal is to encode the music for playback at a future date. These goals create more work for the HTM network because it must discover melodic and chordic patterns. The Local Boundary Detection Model (LBDM) attempts to analyze the melody of a song and is based on the hypothesis that the completion of a melodic phrase is marked by an increase in note length [3]. The LBDM calculates boundary strength values for each melodic interval using local grouping analysis, accentuation, and metrical structures. The underlying principals of the LBDM are based on Gestalt principles, which assert that objects that are close together or similar tend to be perceived as groups [3]. Identity-change and proximity rules derived from Gestalt principles are used to detect points of maximum change and enable the algorithm to identify local boundaries in a melody. The identity-change rule examines consecutive intervals and attempts to determine the degree of change between them, assigning a boundary strength value based on the degree of change [3]. If both intervals are identical then no melodic boundary is suggested. The proximity rule examines consecutive intervals and assigns a boundary strength based on the strength of change [3]. These two rules are then used to build a graph of the boundary strength profile, which can be used to identify local melodic boundaries by examining the graph for peaks. Figure 4.11 displays a sample boundary strength plot.

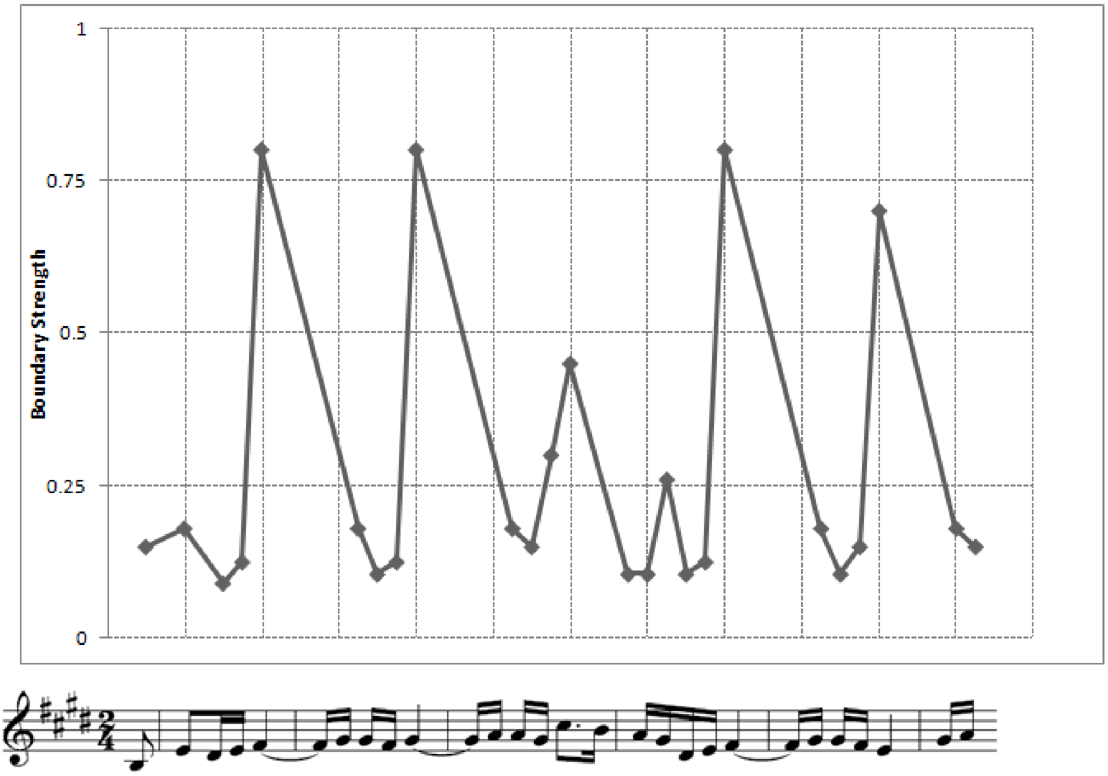


Figure 4.11: LBDM melodic analysis [3].

4.3. Software Tools Used

4.3.1. HTM Tools

Even though Hierarchical Temporal Memory (HTM) is relatively new technology, several advanced tools are available to researchers. The Numenta Platform for Intelligent Computing (NuPIC) is a computer program designed to allow researchers to develop, train, and test their HTM networks [1]. The software is still in the beta release stage and is freely available to the academic community. During the period of this research new versions of NuPIC were being released and this research is based on release 1.4 of NuPIC.

Interaction with NuPIC is primarily text based, although it does offer some basic visualization and reporting modules [1]. In practice these modules are difficult to use because they either incorrectly summarize important data or overwhelm the client with large data sets. To overcome these shortcomings, The Vitamin D Toolkit can be used. The toolkit is a robust application which seamlessly interacts with NuPIC for graphical debugging of HTM networks [17]. Vitamin D allows developers to examine training results of individual nodes and step through HTM networks as data vectors are read in. The toolkit is in the early stages of development and is freely available for download [17].

4.3.2. Data Preparation Tools

The data preparation step is highly dependent on the data being used and requires experimentation with several different techniques. In order to prepare data for Midi based HTM networks the Midi Toolbox was used, which is built on top of the Matlab scripting framework [4]. The toolbox offers a combination of analytical and graphing capabilities and is well documented. The software is freely available for academic use and can be installed by adding it to Matlab's include directory list. The main advantage of using Matlab to process Midi files is that it allows developers to visually debug programs, reducing the time needed to isolate and eliminate bugs.

4.4. Piano Roll HTM Network

4.4.1. Data Representation Scheme

The first song identification experiment was based on the piano roll graph (Figure 4.12) provided by the Midi Toolbox. The graph leverages the fact that Midi files are structured as a series of on and off key events and builds a graph similar to the sheet music rolls of the nineteenth century player piano [4]. The piano roll is a two-dimensional graph where each value on the y-axis represents one of the 128 piano keys Midi files can play and the x-axis of the graph represents time. The Midi file structure allows researchers to take samples of the frequency spectrum at specific points in time, making it an ideal choice for creating HTM network data sets.

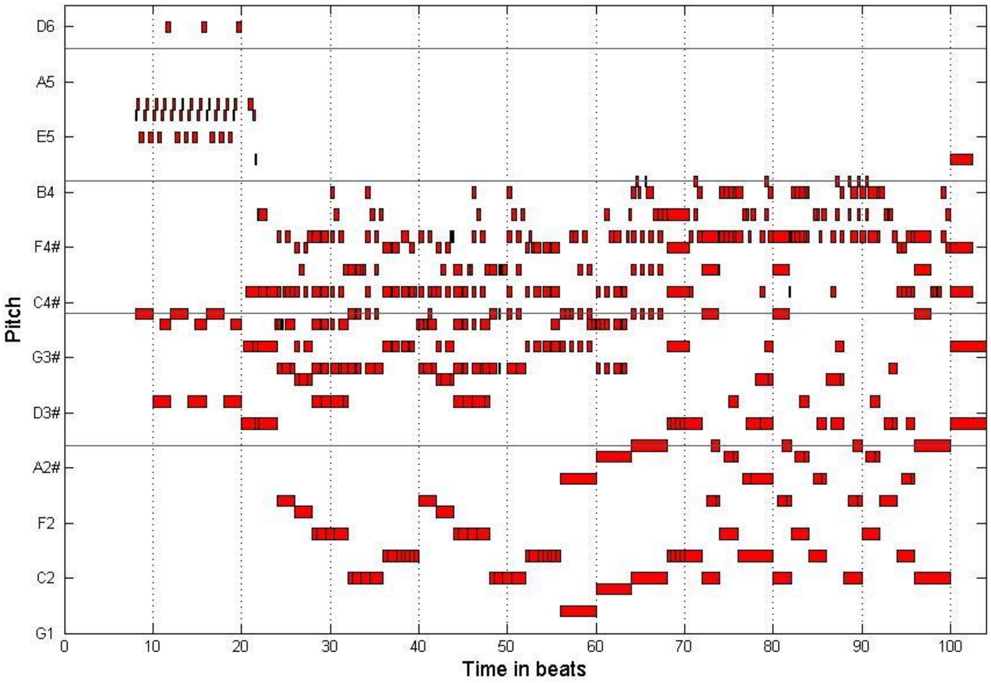


Figure 4.12: Midi Toolbox piano roll graph.

An equivalent data structure based on the Midi event data was created, with the note start and stop times quantized to line up with a quarter beat sample rate. This was done using a special function in the Midi Toolbox. Notes shorter than a quarter beat were removed and the remaining notes were snapped to the nearest quarter beat. Once the data was quantized, a two dimensional array was created to store note information similar to the piano roll graph. The rows of the array corresponded to the y-axis of the graph and each row represented 1 of the 128 possible Midi notes. The array columns were used to represent samples of the note matrix every 0.25 beats, assigning a ‘0’ if a note was off and a ‘1’ if a note was on. The following sample illustrates the structure of the array using sample Midi event data:

Abbreviated Midi Event Data:

Onset (Beats)	Duration (Beats)	Midi Pitch
0.00	1.00	2
0.50	0.50	3
1.00	0.25	1

Piano Roll 2-D Array:

		Time (Columns)					
		0.00	0.25	0.50	0.75	1.00	1.25
Pitch (Rows)	1	0	0	0	0	1	0
	2	1	1	1	1	0	0
	3	0	0	1	1	0	0

Table 4.2: Piano roll 2-D array structure.

This encoding scheme was used to create the input vector file for the HTM network. Due to the design of the data structure, each column of the 2-D array described the frequency spectrum at a specific point in time. This allowed a loop to iterate though every column vector and write the inverse of the column vector to the data file. For example, the piano roll array in Table 4.2 would result in the following data vectors: [0, 1, 0], [0, 1, 0], [0, 1, 1], [0, 1, 1], [1, 0, 0], and [0, 0, 0].

Data sets were then generated using the piano roll matrix transformation algorithm. A data set consisting of five Midi files from various music genres was used in order to ensure song distinction. The algorithm was run on each song and the vectors were concatenated to create a single training data file. As data was being written to the training data file, the corresponding song number was written to the training category file used for supervised learning. The test data was generated by selecting 20-30 beat song clips and alternating songs until each one had reached its end.

4.4.2. HTM Network Design

The HTM network structure was modeled after the Bitworm tutorial provided with NuPIC. The tutorial provided a good model because it was designed to handle binary encoded input vectors, which allowed many of the same parameter values to be used when configuring nodes in the piano roll HTM network [1]. The Bitworm tutorial also made use of a simple one level network hierarchy. This lack of complexity made the network easy to debug and was replicated in the piano roll HTM network. The final layout of the HTM network is shown in Figure 4.13.

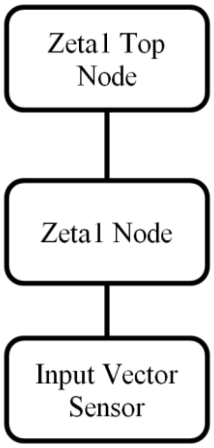


Figure 4.13: Piano roll HTM network layout.

4.4.3. Evaluating HTM Network Results

A Python script was written to sequentially train all nodes in the HTM network. Upon completion, the network was ready to be tested. The overall testing concept was to model the way that humans recognize music. Short 20-30 beat song clips were collected from the Midi files used to train the network. These clips were input into the network and the song belief of every data vector within the clip was recorded. Once the clip was finished, the belief data was examined and the song with the highest belief count was chosen. For example, suppose the following array summarizes the beliefs of each sample over a 25 beat (100 samples) clip: [0 11 63 12 14]. In this example the third song would be identified as the clip being played. After compiling the results, the HTM network had a disappointingly low accuracy rate of 47%. The confusion matrix in Table 4.3 displays the test results in more detail.

		Correct Song				
		Song 1	Song 2	Song 3	Song 4	Song 5
Predicted Song	Song 1	0	0	0	0	0
	Song 2	1	0	0	0	0
	Song 3	0	0	8	0	0
	Song 4	16	17	9	17	2
	Song 5	0	0	0	0	15

Table 4.3: Piano roll confusion matrix.

Experiments were run using several different node configurations without improving accuracy. These results indicated that the low accuracy was not the fault of the HTM network, but rather due to a poor choice of data set. Upon analysis, it was realized that the binary encoding scheme prevented the spatial pooler from forming good quantization points. The spatial pooler is designed to quantize data by consolidating values that are very close to each other, such as 0.999999 and 0.999998 [5]. While the pooler performs well for continuously distributed data sets, it has difficulty correctly quantizing binary data sets. The pooler determines what vectors to quantize using a Gaussian distance function, which sees no difference between the arrays 0011000000 and 1000000001, even though the former represents two consecutive notes and the latter spans an entire octave. The data set is also flawed because multiple songs often share the same note patterns. A careful examination of the data revealed that on average only 2 to 4 notes are ‘on’ per sample and often formed a musical chord. Chords are a fundamental building block in music and chances are high that many songs will reuse popular chords many times over. This fundamental flaw revealed that the data representation scheme needed to be modified and other analysis algorithms in the Midi Toolbox had to be explored.

4.5. Melodic Segmentation HTM Network

4.5.1. Data Representation Scheme

The second experiment explored the use of the melodic segmentation algorithms implemented within the Midi Toolbox. These algorithms analyze songs to find melodic components based on how fast the similarity of notes change and how strong the change is [4]. The results of these algorithms are data sets which have melodic patterns encoded in the data, unlike the piano roll data. HTMs using this data may focus on pattern recognition, instead of melodic discovery. The Midi Toolbox offers several different melodic segmentation algorithms from which the Local Boundary Detection Model (LBDM) by Cambouropoulos was chosen [4]. As discussed earlier, the LBDM attempts to identify the points of maximum melodic change and produces a well-distributed data set. Figure 4.14 shows a sample graph of the local boundary detection algorithm produced by the Midi Toolbox.

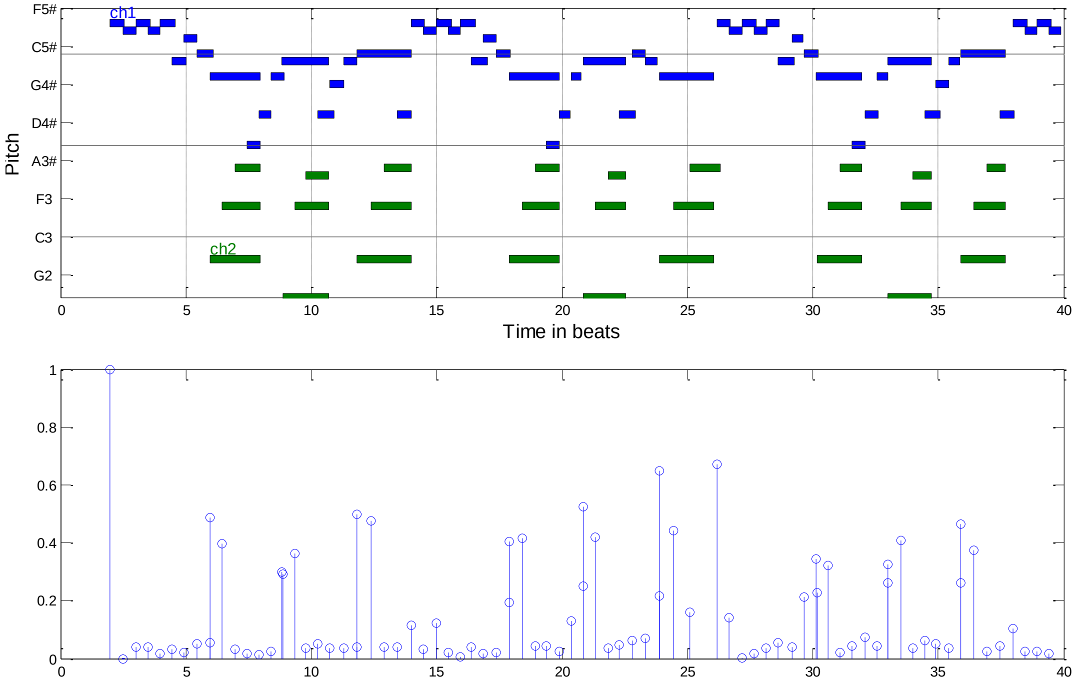


Figure 4.14: Graph of the local boundary detection algorithm.

An examination of the local boundary detection data indicates sufficient variance and hence appropriateness for use in a HTM network. However, before a data set could be created, a transformation algorithm to convert a continuous graph along the time axis into a series of data vectors needed to be developed. To perform this translation a window based approach was used. Imagine a window of size 20 was placed on the graph which only allows one to see data from time 1 to 20. As time continues to increase, the window slowly moves from left to right across the graph. During each iteration, the data values within the window were recorded and placed in a 20 element wide data vector. Figure 4.15 illustrates this algorithm graphically. This algorithm was chosen because it encoded time into the data set, making up for NuPIC's lack of time-based pattern inference. Five songs were chosen for the initial data set and the data from each window was concatenated to create a single file for the training data. The test data was generated by selecting 20-30 beat clips of songs and alternating songs until each one had reached its end.

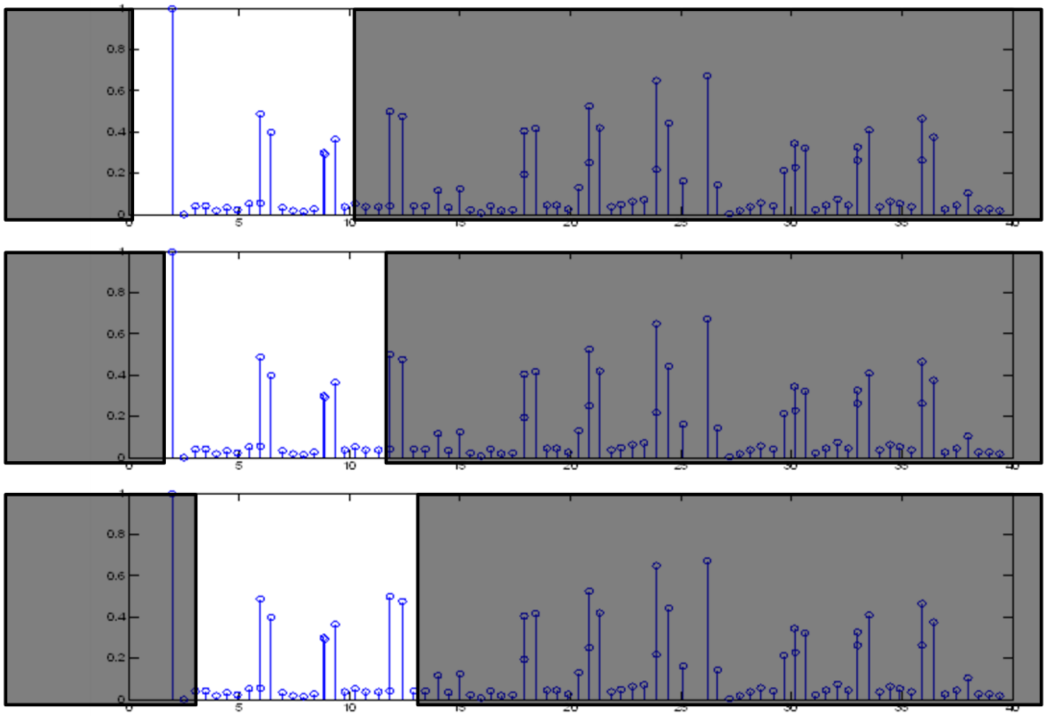


Figure 4.15: Window based data generation algorithm.

4.5.2. HTM Network Design

A multi-level hierarchy was used to create the melodic segmentation HTM network (Figure 4.16). The bottom level of the network contains 20 element-wide data sensors which were combined into a 4 sensor-wide bank, resulting in a total input array length of 80 elements. The goal of utilizing a wider bottom level was to make the network more robust. HTM networks with a single data sensor are highly dependent on the beliefs of the sensor. An incorrectly classified input vector causes the entire network to be incorrect. These vectors make the network volatile and cause the top level belief to rapidly change. HTM networks with a wide base minimize the impact of an incorrect bottom node belief because the remaining nodes are able to override the incorrect node using belief propagation. Increasing the height of the HTM also improves network stability. One of the underlying principles of HTMs is that low level nodes encounter rapidly changing data and will quickly change beliefs, while higher level nodes have more stable beliefs [7]. Increasing the height of the network takes advantage of this principle and increases the likelihood of network stability.

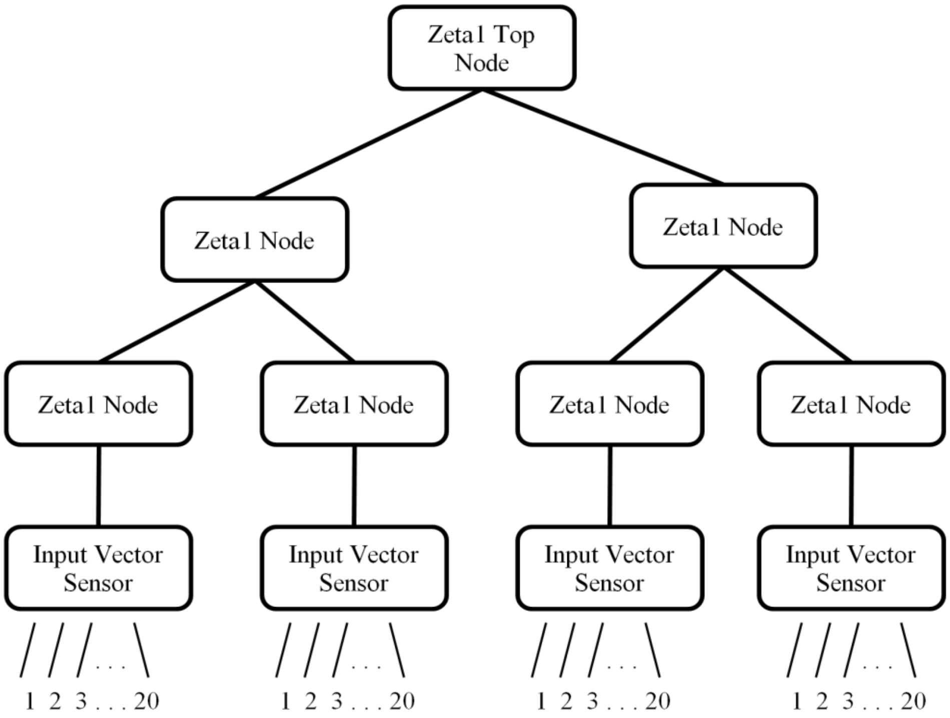


Figure 4.16: Melodic segmentation HTM network structure.

4.5.3. Evaluating HTM Network Results

The test data set for the melodic segmentation HTM consisted of the same 5 songs used to evaluate the piano roll HTM. The network was evaluated using 20-30 beat long song clips and achieved a successful identification rate of 100%, as shown in Table 4.4. These results were a 53% improvement over the piano roll HTM and validated the melodic segmentation data representation scheme. While these results were encouraging, it was important to verify that the network maintained this high success rate as the size of the data set increased. A data set of 40 songs was chosen and modifications were made to the HTM to make sure its memory was capable of handling the larger data set. Even though the data set grew to 8 times its original size, the HTM still achieved a success rate of 100%. The high identification rate using these two data sets can be attributed to unique melodic phrases in each song and the HTM network's ability to identify and group these phrases together. Encoding time into the data set also helped make up for the temporal pooler's inability to perform time-based inference. Lastly, the data set's even distribution over the range 0 to 1 allowed the spatial pooler to be configured based on the data values, instead of simply tweaking the parameters to minimize the error of the spatial pooler as had been done in the piano roll HTM network.

		Correct Song				
		Song 1	Song 2	Song 3	Song 4	Song 5
Predicted Song	Song 1	19	0	0	0	0
	Song 2	0	19	0	0	0
	Song 3	0	0	19	0	0
	Song 4	0	0	0	19	0
	Song 5	0	0	0	0	18

Table 4.4: Five song melodic segmentation HTM confusion matrix.

Chapter 5

DISCUSSION

5.1. Analysis of HTM Node Algorithms

While the melodic segmentation HTM network has proven that NuPIC can be used to solve a traditional artificial intelligence problem, several limitations of HTM networks were discovered along the way. The first experiment exposed a weakness in the spatial pooler's Gaussian distance function when data is represented in a binary format. The function does not take an element's position within the data vector into account and thus is unable to distinguish between inputs such as 100001 and 000110, as shown below:

Distance between 100001 and 000000

$$1.4142 = \sqrt{(1-0)^2 + (0-0)^2 + (0-0)^2 + (0-0)^2 + (0-0)^2 + (1-0)^2}$$

Distance between 000110 and 000000

$$1.4142 = \sqrt{(0-0)^2 + (0-0)^2 + (0-0)^2 + (1-0)^2 + (1-0)^2 + (0-0)^2}$$

Figure 5.1: Position error in the spatial pooler.

Even though the Bitworm tutorial provided by NuPIC used a similar binary encoding scheme, the weakness was not exposed because the HTM was trained to identify a limited amount of vastly different patterns. The piano roll data set was more complex and had a large amount of subtle patterns. In order to overcome this error in the spatial pooler, a more complex distance function that takes element position into account needs to be developed. NuPIC already allows developers to configure the spatial pooler when creating the network and it would be relatively simple to allow developers to specify a special purpose distance function based on their data set. Researchers would then be able to examine their data set and decide which distance function is applicable.

Although NuPIC has a temporal pooler for time dependent patterns, it is only used when training the network. During training the temporal pooler creates temporal groups based on which quantization points occur near each other in time. Once the network is switched to inference mode the HTM outputs the temporal group that contains the quantization point produced by the spatial pooler, which allows for no time based inference [1]. Time based inference allows a network to remember what it has previously seen and improves recognition results [1]. As Figure 5.2 displays, time is essential to recognize certain types of patterns, especially when there is a large amount of noise in the data. The melodic segmentation data set overcame this shortcoming by using data that contained very little noise and encoding time into the data set via sliding windows. However, in order for HTMs to be effective with more complicated data, an algorithm for time based inference must be developed.

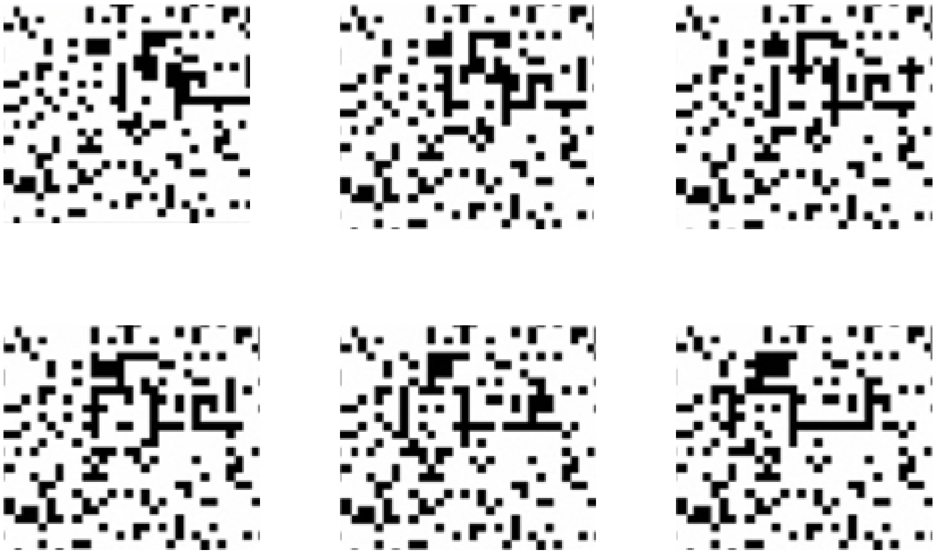


Figure 5.2: Difficultly of recognizing patterns in noisy data [1].

5.2. Development Process

A significant portion of this research was spent studying and pre-processing data sets before they could be fed into HTM networks. Due to the project's focus on developing song identification experiments, it wasn't until the end of the research that the importance of this step in the NuPIC development process was realized. Upon investigation into the topic it was discovered that the field of data mining also spends a large amount of time developing and refining data. A brief survey of data mining literature revealed robust processes for refining data and training data mining systems [2]. A large amount of the processes were also iterative due to the uncertain nature of data mining. Figure 5.3 displays a popular data mining process developed by Berry and Linoff [2]. After comparing the informal process created for HTM network development to several popular data mining processes, a surprising amount of similarities were found. Both processes require researchers to understand and pre-process data in order to eliminate any problems with the learning algorithms. If HTM researchers wish to increase their likelihood of success, they should look for ways to incorporate the data mining community's knowledge into their research.

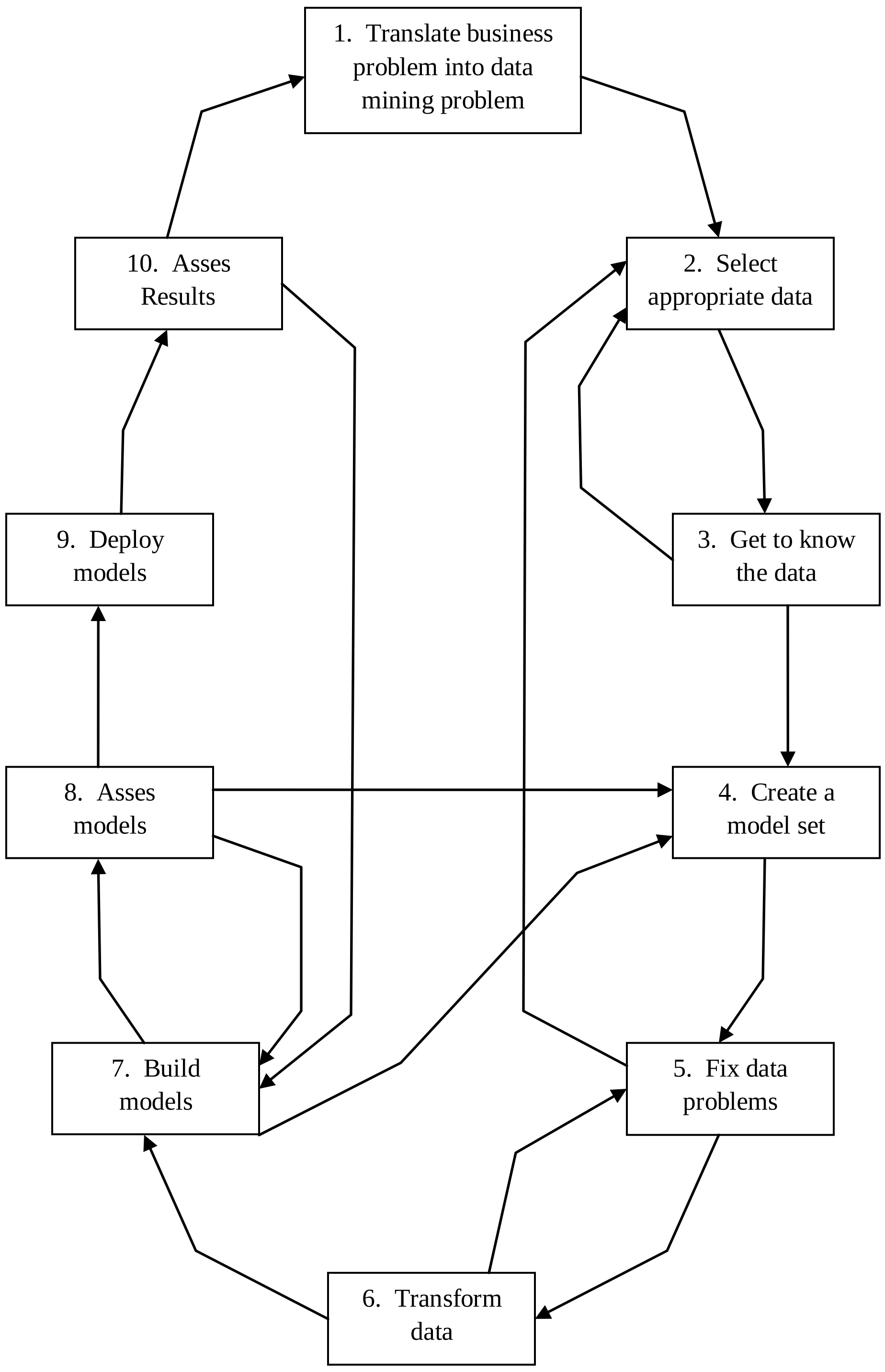


Figure 5.3: Sample iterative data mining process developed by Berry and Linoff.

5.3. Data Set Format

NuPIC has a partition-based data format for files read into HTM networks. The current specification calls for input vectors to be placed into the data file one line at a time, with elements separated by a single space [1]. If a category file is being used, a separate file must be used where a single category number is placed on each line, corresponding to the line number in the data file [1]. Maintaining data across two separate files and making sure line numbers match is a cumbersome process, forcing large amounts of formatting code to be written in the data generation scripts. It is also difficult for multiple data files to be read and combined. In order to fix these problems NuPIC needs to switch to a XML based data input scheme, enabling freely available XML toolkits to be used when writing data generation scripts. This format would allow input vectors and category data to be combined into one file, hence making the data set easier to maintain. A XML based data format would also enable researchers to develop schemas and validate their data before the HTM is executed. Validation would reduce overall development time by reducing data formatting errors, which are currently found only at run time.

5.4. Future Work

When evaluating NuPIC it is important to remember the software is still in its infancy. As this research illustrates, NuPIC can be used to tackle more complex problems and researchers need to continue to push NuPIC to its limits. The majority of current research is focused on extending existing NuPIC tutorials to solve very detailed problems. While this is important, researchers also need to focus on widening the number of problems NuPIC can be used to solve. A crucial tool in increasing the scope of HTM research is time based inference. Late in this research NuPIC version 1.5 was released which includes a time based inference algorithm [1]. Now that NuPIC has delivered this important feature, researchers need to make sure that their data set gives them the ability to test the algorithm. It would also be interesting to see how this algorithm would perform if the amount of temporal information encoded in the melodic segmentation data set was minimized.

While this research indicates that NuPIC is not ready to handle a complex sample based audio file format, it would be worthwhile to see how HTMs perform using multiple features. While attempting to find a Midi file analysis toolkit, a tool for Midi file feature extraction tool called JSymbolic was discovered [13]. This tool allows developers to extract a wide range of features from the Midi files and is highly configurable. Data produced from this tool could then be used to train a HTM designed for song identification. Combining multiple features could also enable HTM researchers to move beyond the song identification problem and focus on a more complex problem like genre classification.

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