Neural Audio: Music Information Retrieval Using Deep Neural Networks

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Introduction

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Music is rich in information - from things like what key and time signature are being played in up to the sociocultural context in which the lyrics were written.

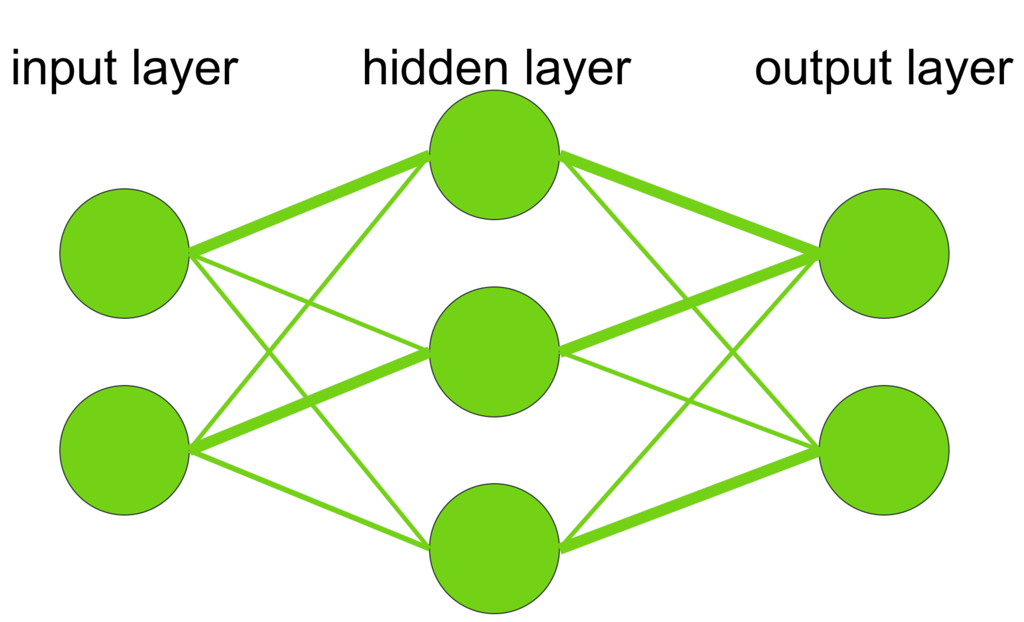
The field of music information retrieval exists to provide musicologists with automated tools. Complex tasks like genre recognition remain out of reach. Neural networks offer a solution to this problem: a form of machine learning that consist of nodes connected by weighted edges. Input is propagated through the network from node to node along those edges.

Neural Networks

structure | Neural networks are based on the structure of the human mind: nodes serve as neurons, and weighted lines between them alter the input values as they flow through the network.

A deep neural network is one with several hidden layers. (Any layer other than the input and output layers is considered 'hidden.')

training | Neural networks are an alternative to traditional programming. Instead of writing an algorithm by hand, simply provide training data - inputs, and the output expected: `([0, 821, 1643,...],"art")`

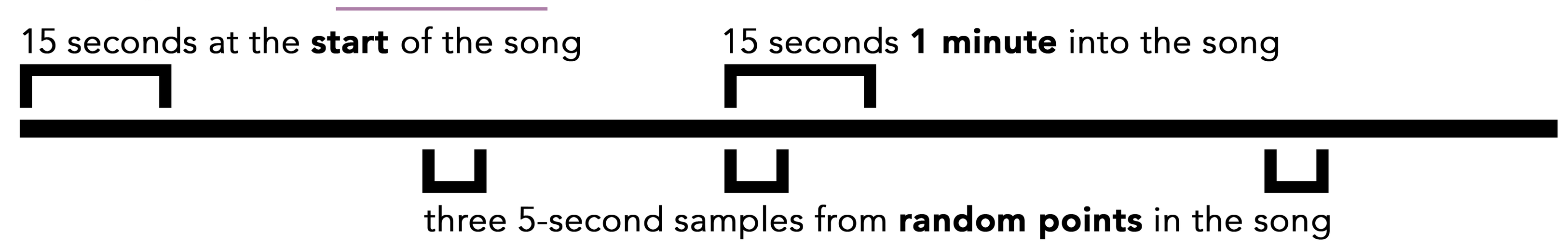


The software uses stochastic gradient descent to minimize the cross-entropy of the correct versus the calculated answers.

output | The output can be either a direct categorization or a softmax (weighted probability distribution). Softmax results were used throughout, as they provide more information.

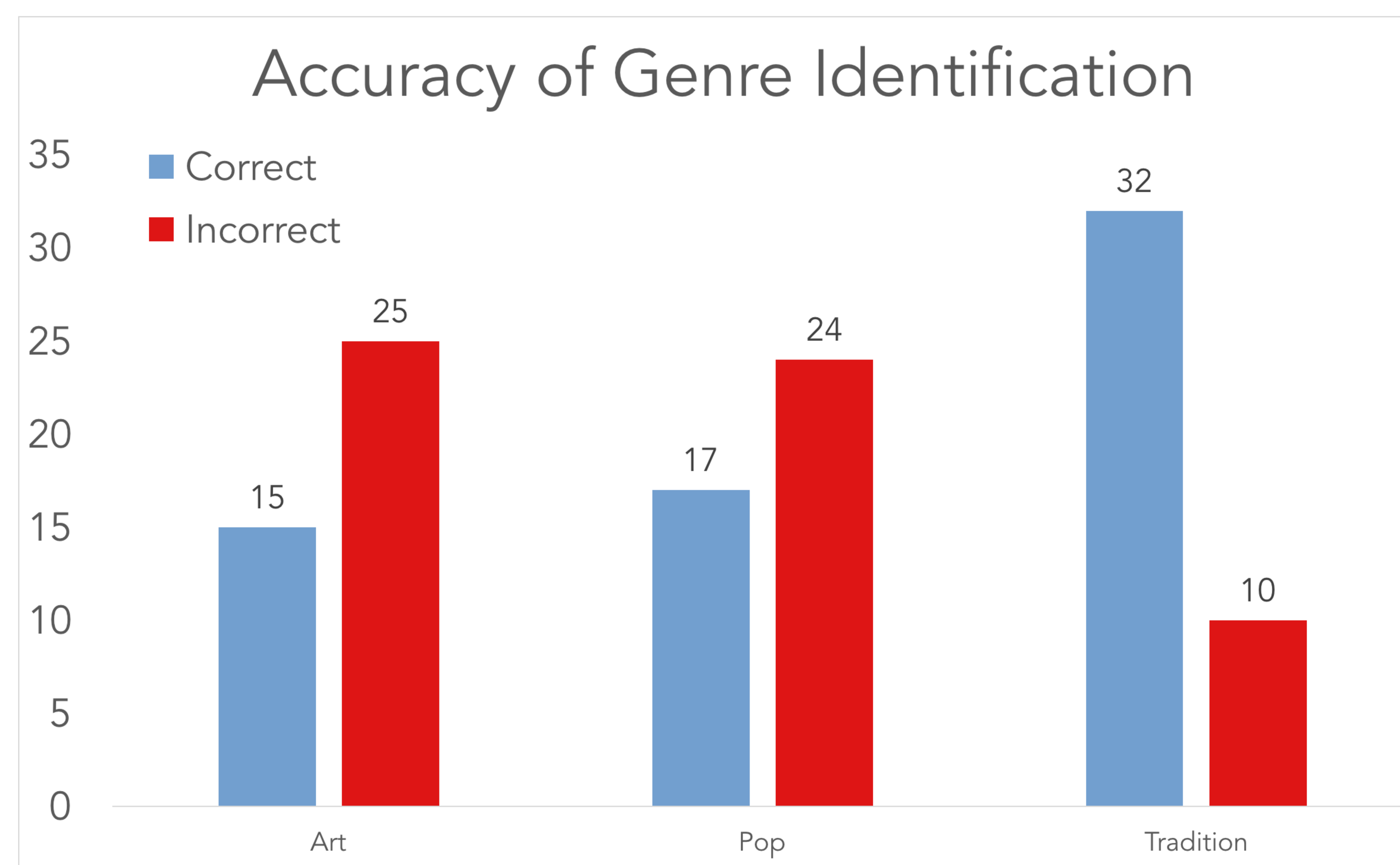
Genre Identification

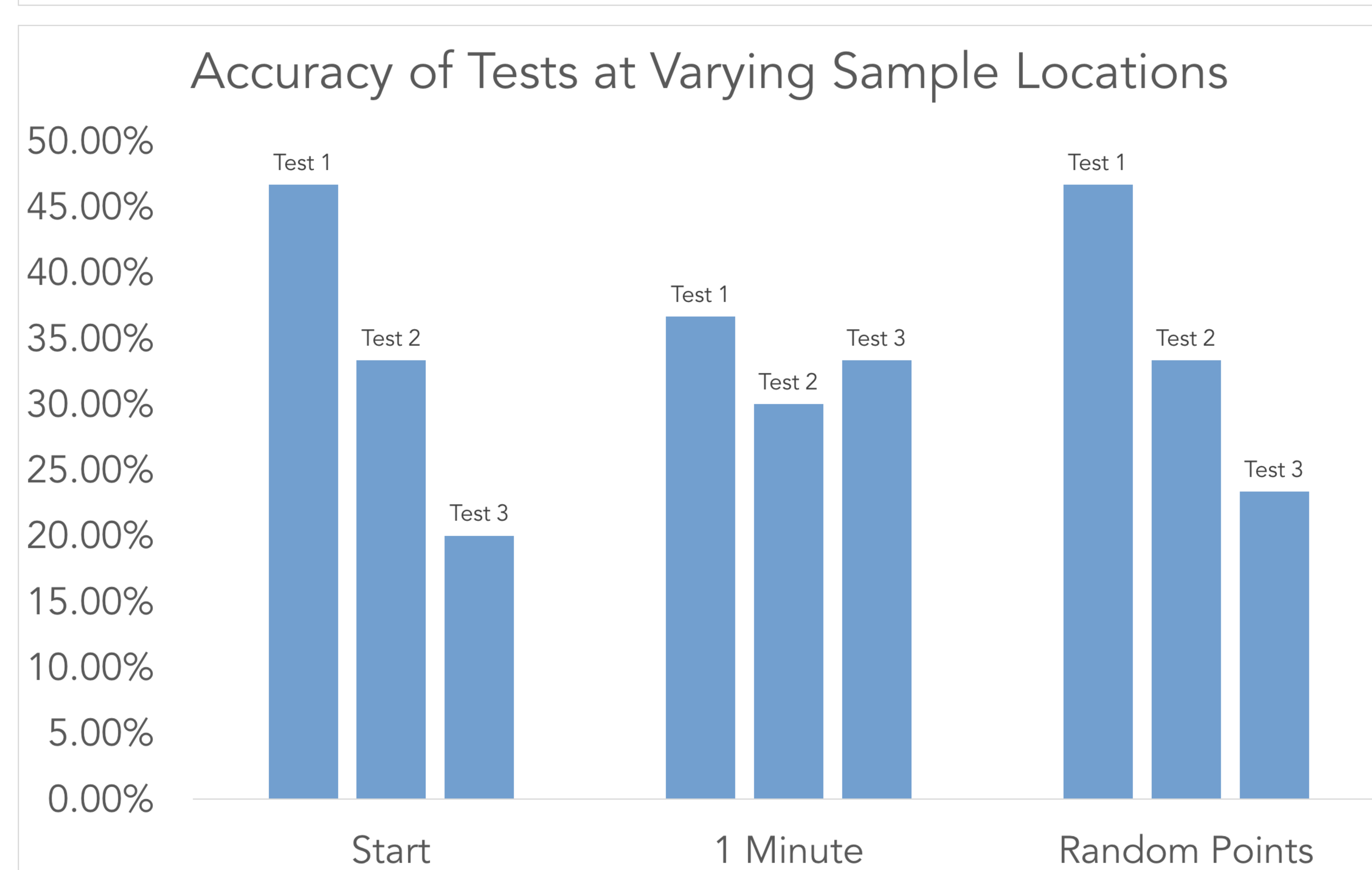
methods | Input was split into three categories: art, popular, and traditional. For reading in a song from the library, three windows were used:



Each window of samples was fed into the neural network, which attempted to categorize it into one of the three genres; all inputs were annotated with 'correct' answers, used for training.

results | Overfitting proved to be a problem: most of the miscategorizations were filed into 'tradition.' Reading 1 minute into the song was most precise, if not most accurate.

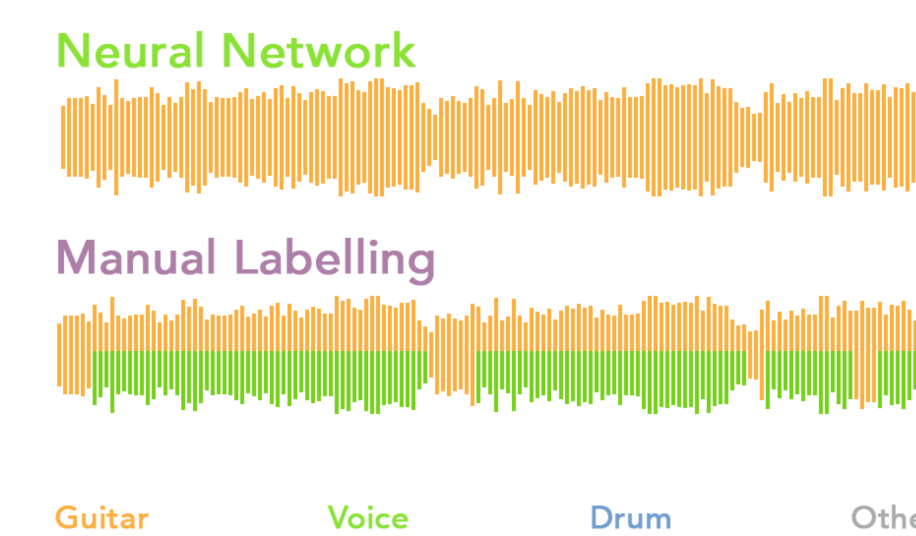




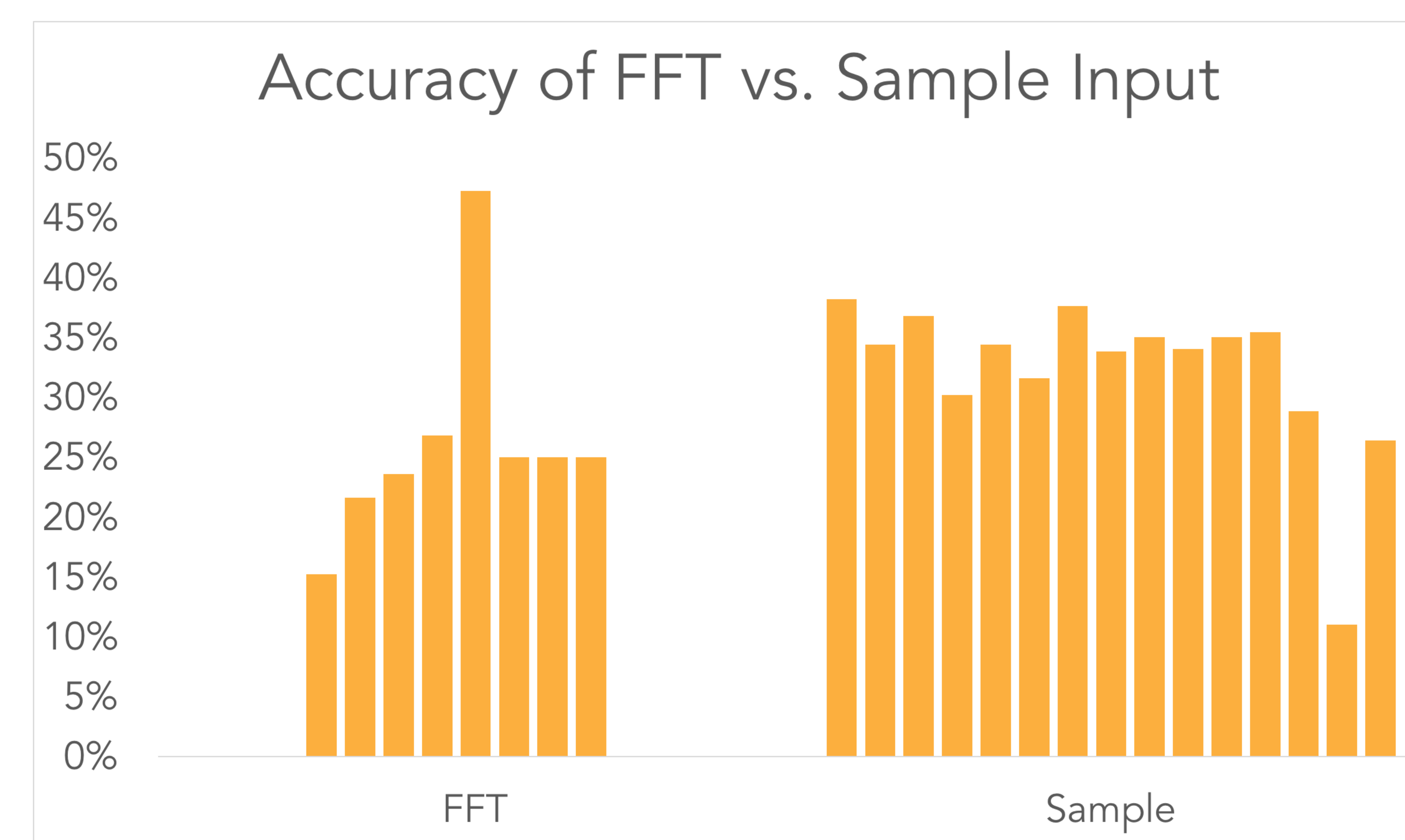
Instrument Identification

methods | Song stems and mixes were broken into four categories: vocal solo, guitar solo, drum solo, and ensemble 'other.'

Each song was broken into windows of 1-3 seconds, with .5-1.5 seconds of overlap. In training, four files (one from each category) were read in concurrently, shuffling the input to avoid overfitting. In evaluation, an entire song can be fed through sequentially, getting an array of categorization results. That was then converted into an array of category start/stop times. The graph above is a visual representation of this, showing the problem of overfitting.



results | Using raw samples, rather than FFT data, appears to yield higher overall accuracy.



References

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R. Bittner, J. Salamon, M. Tierney, M. Mauch, C. Cannam and J. P. Bello, *"MedleyDB: A Multitrack Dataset for Annotation-Intensive MIR Research"*, in 15th International Society for Music Information Retrieval Conference, Taipei, Taiwan, Oct. 2014.

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