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 consists of nodes connected by weighted edges. Input is propagated through the network from node to node along those edges.

Neural Networks

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'.)

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.

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

Genre Identification

methods

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

- 15 seconds at the start of the song
- 15 seconds 1 minute into the song
- three 5-second samples from random points in the song

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 was a problem: below, most of the incorrect were misfiled into 'tradition.' Reading 1 minute into the song was most precise, though not the 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.

Accuracy of FFT vs. Sample Input

Accuracy of Genre Identification

```
<table>
<thead>
<tr>
<th>Samples read 1 minute into the song</th>
</tr>
</thead>
<tbody>
<tr>
<td>Art</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>15</td>
</tr>
<tr>
<td>24</td>
</tr>
</tbody>
</table>
```

References

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. This material is based upon work supported by the National Science Foundation under award OCI-1560410 with additional support from the Center for Computation & Technology at Louisiana State University.