Applying Machine Learning to Jet Noise Prediction

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Acoustics Technical Working Group Meeting
NASA Glenn Research Center
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About me

- Intern at NASA Glenn Research Center
  - Scientific Computing and Visualization Team
- Student at Michigan State University
  - B.S. Computer Science
  - Pursuing M.S. Computer Science
- Two years experience in data science and machine learning
Objectives

Predictive modeling
Can we use machine learning to create accurate predictive models for sound modeling?

Data Insight
Can we learn more about the domain?
Do we need to modify our experiments?

Requirements
Hardware requirements?
Time requirements?
Machine Learning:

A crash course.
Linear Model

Output value is weighted sum of inputs (or features)
Output can be a vector (multiple values). Each feature will have a different weight, or parameter, for every predicted output value.
Often output cannot easily be modeled by a linear combination of features.
Add hidden layer which applies some non-linear function (activation) to the output of the first linear system.

Many options for non-linear activation.
Output is now the weighted sum of the hidden layer activations.
Each hidden layer abstracts things a little more.
Input shape is defined by your data.
Neural Network

Output shape is defined by your data.
Neural Network

Hidden layers..?

Up to you. Typical to start with something in between your input and output sizes.
Hidden layers...?

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Neural Network

Hidden layers..?

Up to you. Typical to start with something in between your input and output sizes.
Initialize random weights.
Training

Feed network an observed sample input, compute a predicted output.
Training

Compute some error (or loss) between the predicted output and the observed sample output.

Many options for loss functions.
Update weights such that the error will be less when we predict this sample again.
Training vs. Validation

Training data
- Samples used to fit your parameters to your data.
- Learn the parameters which minimize loss for training set.

Validation data
- Samples used to measure your model’s performance
Validation

Good  Poor

Training

Poor  Good
Validation

Good

Poor

Underfitting

Training

Poor

Good
The Experiment
The Approach
1 hidden layer
64 hidden units

15 features

ReLU activation

87 frequencies
(1/12 Octave)
<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>NozzleArea</td>
<td>3.141590</td>
</tr>
<tr>
<td>xE</td>
<td>1.300000</td>
</tr>
<tr>
<td>hE</td>
<td>0.000000</td>
</tr>
<tr>
<td>Ma</td>
<td>0.699508</td>
</tr>
<tr>
<td>Mj</td>
<td>0.734632</td>
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<tr>
<td>NPR</td>
<td>1.431810</td>
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<td>1.004820</td>
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<tr>
<td>TSR</td>
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</tr>
<tr>
<td>Tamb</td>
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</tr>
<tr>
<td>Pamb</td>
<td>14.257300</td>
</tr>
<tr>
<td>RelHumidity</td>
<td>57.931600</td>
</tr>
<tr>
<td>SSS_Beta</td>
<td>5.120000</td>
</tr>
<tr>
<td>angle</td>
<td>115.000000</td>
</tr>
<tr>
<td>shield/reflect</td>
<td>1.000000</td>
</tr>
<tr>
<td>AspectRatio</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

Network Outputs:
- 668.3 Hz
- 707.9 Hz
- 749.9 Hz
- 89130.0 Hz
- 94410.0 Hz
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![Graph showing PSD (db) vs Frequency (Hz)](image)
Results
Round Nozzle

Mean Absolute Error: 0.412

PSD (db)

Frequency (Hz)

Observed
Predicted
Mean Absolute Error: 0.32

Round Nozzle
Rectangular Nozzle

Mean Absolute Error: 1.292

PSD (db)

Frequency (Hz)
Error

Round Nozzle Model

# Validation Samples: 4272
Average: +/- 0.575 dB
Worst sample: +/- 2.23 dB

Rectangular Nozzle Model

# Validation Samples: 12594
Average: +/- 0.599 dB
Worst sample: +/- 3.47 dB
Error

Round Nozzle Model

Rectangular Nozzle Model
Live Demo

I move the sliders and the plot changes.
Go deeper?

No, *go shallower*

Modeling the data looks promising.

Rapidly *prototype small models*, turn knobs, flip switches, see what happens.
Error: 2.60
Error: 2.60

- nozzle area
- surface length
- surface standoff distance
- nozzle pressure ratio
- observer angle
- nozzle aspect ratio
- jet potential core length
- static temperature ratio
- total temperature ratio
- acoustic mach number
- ambient pressure
- shielding or reflecting
- nozzle pressure ratio
Error: 2.60

- nozzle area
- surface length
- surface standoff distance
- nozzle pressure ratio
- observer angle
- shielding or reflecting
- nozzle aspect ratio
- static temperature ratio
- ambient pressure
- total temperature ratio
- acoustic mach number
Error: 2.60

- shielding or reflecting
- nozzle aspect ratio
- ambient pressure
- static temperature ratio
- total temperature ratio
- acoustic mach number
- observer angle
- surface standoff distance
- surface length
- nozzle area
Error: 2.61

- nozzle area
- surface length
- surface standoff distance
- shielding or reflecting
- nozzle aspect ratio
- static temperature ratio
- total temperature ratio
- acoustic mach number
- observer angle
- nozzle area
Error: 2.62

- shielding or reflecting
- nozzle aspect ratio
- static temperature ratio
- total temperature ratio
- acoustic mach number
- observer angle
- surface standoff distance
- surface length
Error: 2.66

- shielding or reflecting
- nozzle aspect ratio
- static temperature ratio
- observer angle
- acoustic mach number
- surface standoff distance
- surface length
Error: 2.67

shielding or reflecting
nozzle aspect ratio
observer angle
acoustic mach number
surface standoff distance
surface length
Error: 2.72

- shielding or reflecting
- observer angle
- surface standoff distance
- surface length
- acoustic mach number
Reduce the feature space

Simplify experiments

Collect more data
How do we do it?
1. Python 3.6 (free)
2. Keras + TensorFlow (free)

```python
from keras.layers import Input, Dense
from keras.models import Model

input_layer = Input(shape=(INPUT_SIZE,))
hidden_layer = Dense(NUM_HIDDEN_UNITS, activation='relu')(input_layer)
output_layer = Dense(OUTPUT_SIZE)(hidden_layer)
model = Model(input_layer, output_layer)
model.compile(optimizer='adadelta', loss='mse')
```
Training Time: <1 hr
DISCLAIMER:
Results may vary...
Neural network
short, thin, and simple

- Only 15 input features
- 7,000 trainable parameters
Consider...

- 224x224 color image over 150,000 features
- Good classifiers contain millions to hundreds of millions of trainable parameters
Data

~20mb

- 1700 experiments \( \times \) 24 microphones
- 42,000 total data points
This is a good application of machine learning.
What’s next? Try holding out certain ranges of features, test extrapolation ability.
What’s next?

Add another dimension to observer position.
What’s next?

Modify loss function to incentivize close fit on frequencies of annoyance.
What’s next?

Investigate poor predictions, identify weak points in data acquisition or feature range.
Acknowledgements

Cliff Brown (NASA) – Data Acquisition & Research Advisor

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Lauren McIntyre (NASA) – Technical Mentor
Questions?