Motivation

• The applications of satellite imagery in deep learning are widespread (crop yield prediction, poverty prediction, etc.)
• Precise AQI readings are sparse (especially in remote areas).
• **Goal:** train a deep neural network to predict difference in AQI given two satellite images from the same location but different times.

Model

• **Siamese Network:** Two parallel, pre-trained image vector representations. This neural network contains 8 convolutional layers
• **Customized Prediction Head:** Three untrained layers with single output unit

Evaluation (Baseline)

• **Intuition** hails from human performance
• **Rationale:** Humans guess random based on their knowledge about the outcome distribution.
• **Baseline MSE:** 1231.53.

Optimizing the Learning Process

• **Learning Speed:** Parallelization and freezing pre-trained layers made training faster (>10x speedup)
• **Improving Val. Predictions:** Using a deeper network, scaled sigmoid activation, and “skewed” training data yielded meaningful predictions faster.
• **Countering Overfitting:** Adding dropout layers, re-sampling the training data, and leveraging image augmentation (i.e. 50% flipped or rotated)

Results

<table>
<thead>
<tr>
<th>Error Rates</th>
<th>Non Aug</th>
<th>Aug</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>985.9</td>
<td>441.5</td>
</tr>
<tr>
<td>Val</td>
<td>1093.8</td>
<td>635.4</td>
</tr>
<tr>
<td>Test</td>
<td>1234.1</td>
<td>753.9</td>
</tr>
</tbody>
</table>

Future Work

• **Insight from error analysis:** high validation error can be attributed to wide variety of contextual image conditions, for instance
• **Countering Overfitting:** Adding dropout layers, re-sampling the training data, and leveraging image augmentation (i.e. 50% flipped or rotated)

References