



Computer Vision: Using Satellite images to infer AQI in California

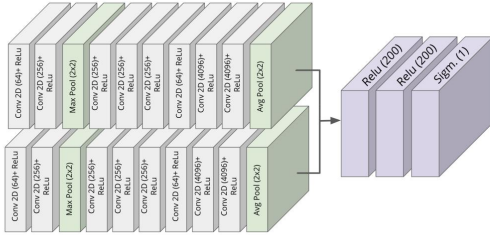
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Motivation

- The applications of satellite imagery in deep learning are widespread (crop yield prediction, poverty prediction, etc.)
- Precise AQI¹ 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.

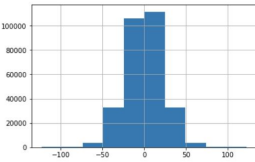
Model

- Siamese Network:** Two parallel, pre-trained image vector representations². This neural network contains 8 convolutional layers
- Customized Prediction Head:** Three untrained layers with single output unit



Evaluation (Baseline)

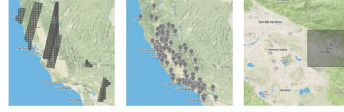
- Intuition** hails from human performance
- Rationale:** Humans guess random based on their knowledge about the outcome distribution.
- Baseline MSE:** 1231.53.



Daily AQI Readings

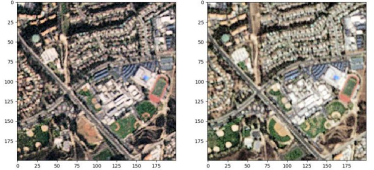
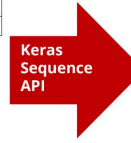
| Date | Daily AQI | ... | SITE_LAT | SITE_LONG |
|----------|-----------|-----|-----------|-------------|
| 01/01/19 | 40 | ... | 37.687526 | -121.784217 |
| 01/02/19 | 32 | ... | 37.687526 | -121.784217 |

Monthly Satellite Imagery

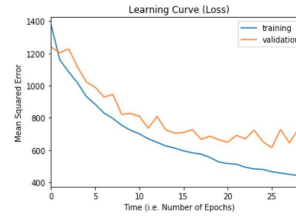


Data

- Training set:** approx. 300,000 image pairs
- Test set:** 18,900 image pairs



Results



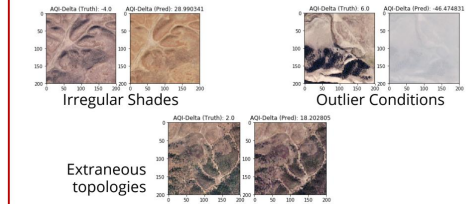
Train MSE:
421.13

Val. MSE:
615.21

Test MSE:
1041.38

Future Work

- Insight from error analysis:** high validation error can be attributed to wide variety of contextual image conditions, for instance



Optimizing the Learning Process

- Learning Speed:** Parallelization and freezing pre-trained layers made training faster (>10x speedup)
- Countering Overfitting:** Adding dropout layers and re-sampling the training data kept training and validation error close
- Improving Predictions:** Using a deeper network, scaled sigmoid activation, and "skewed" training data yielded meaningful predictions faster.

References

- [1] United States Environmental Protect Agency, "Air Quality Index (AQI) Basics." <https://www.airnow.gov/index.cfm?action=aqibasics.aqi>. [Online; accessed 30-April-2019].
- [2] N. Jean, M. Burke, M. Xie, W. M. Davis, D. B. Lobell, and S. Ermon, "Combining satellite imagery and machine learning to predict poverty," *Science*, vol. 353, no. 6301, pp. 790-794, 2016.
- [3] M. Kubat, R. C. Holte, and S. Matwin, "Machine learning for the detection of oil spills in satellite radar images" *Machine learning*, vol. 30, no. 2-3, pp. 195-215, 1998.
- [4] X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton, and A. M. Mouazen, "Wheat yield prediction using machine learning and advanced sensing techniques," *Computers and Electronics in Agriculture*, vol. 121, pp. 57-65, 2016.