Climate Classification Using Landscape Images

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Introduction

Given an photo of a natural landscape we trained models to predict the Koppen-Geiger climate type depicted in the image. While similar studies have attempted to use satellite imagery for this, few have directly used ground-level photos.

To accomplish this task we built a dataset of images of varying climates and then trained a logistic regression model, an SVM, and a transfer learning convolutional neural network.

Data + Features

Our dataset consists of 320,000 geotagged color photos of natural landscapes from Flickr, which were filtered based on user tags. The images were uniformly resized to 224 x 224 px. Based on their latitude and longitude, the images were labeled with one of 32 climate types. Due to the underrepresentation of some climates in our dataset, these climates were then sorted into 13 superclasses.

For our baseline models, we experimented with using raw pixel values and features shown to perform well in image classification, like PCA components and histogram of gradients. These also reduce dimensionality. For the CNN, we used raw pixel values.

Trop. Sava.

Warm Arid

Models

Logistic Regression (LR):
To establish a baseline we used a logistic regression model which uses a sigmoid activation function:

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

With a cost function given by:

$$\min_{w,c} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \log(\exp(-y_i(X_i^T w + c)) + 1).$$

SVM:
We also ran an SVM model on the data using a one vs. one approach.
SVM maximizes the cost function

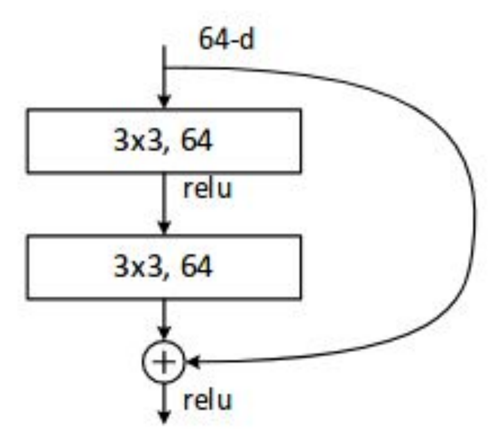
$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y^{(i)} y^{(j)} \alpha_i \alpha_j \langle x^{(i)}, x^{(j)} \rangle.$$

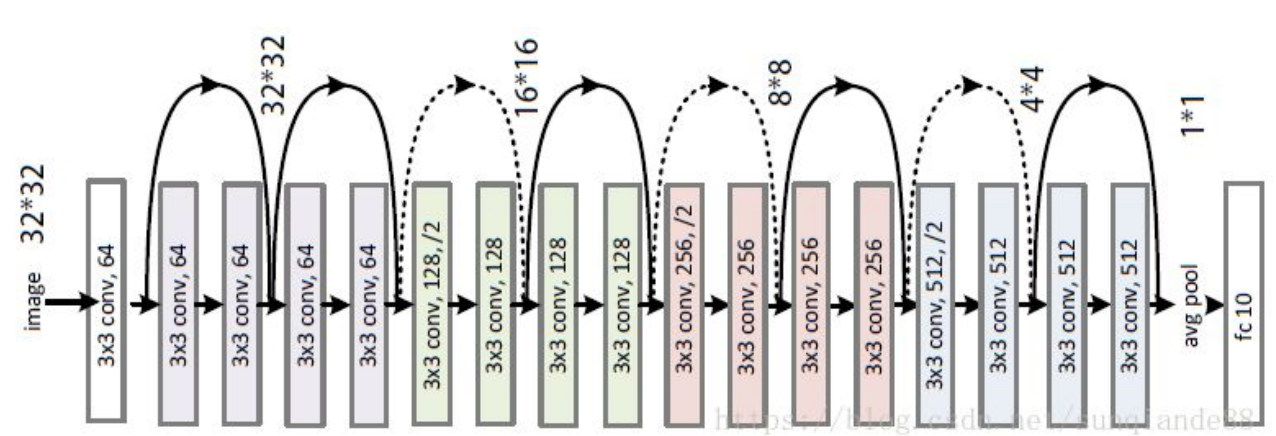
Subject to the constraint that

$$\sum_{i=1}^{n} \alpha_i y^{(i)} = 0.$$

With $\alpha_i \geq 0, \quad i = 1, \ldots, n$

CNN - ResNet:
We used a CNN with a ResNet-18 architecture, which consists of a convolutional layer, 8 two-layer ResNet blocks, and a final fully-connected layer.





Results + Discussion

Model Performance

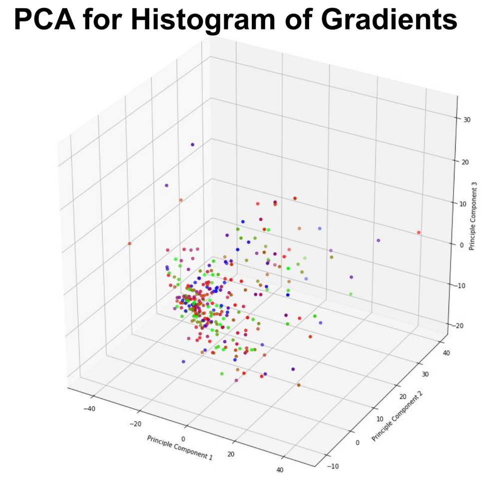
	Train acc. (11517 samples)	Val. acc. (3839 samples)	Test acc. (3839 samples)
LR	0.27	0.13	0.10
SVM	0.77	0.12	0.15
CNN	0.82	0.32	0.31

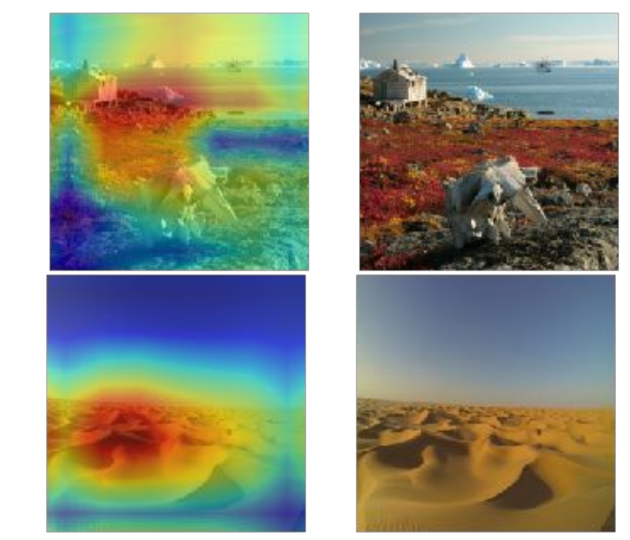
Test Results for CNN

	0	1	2	3	4	5	6	7	8	9	10	11	12
Arctic 0	151	12	10	4	5	9	12	5	64	6	1	1	15
Cold_Arid 1	6	121	33	17	13	24	17	11	11	13	4	13	14
Hot_Arid 2	7	76	89	19	8	20	12	8	6	17	9	15	9
Hot_Continental 3	2	15	15	97	19	18	19	23	8	17	8	13	44
Humid_Subtropical 4	1	18	25	41	43	17	22	25	8	20	15	33	32
Mediterranean 5	8	27	17	20	23	50	28	29	24	23	7	14	30
Ocean 6	6	13	8	12	12	15	118	13	8	44	9	18	17
Oceanic 7	12	22	14	20	18	28	19	47	23	25	10	17	45
Subarctic 8	62	8	9	13	12	19	9	12	104	11	4	2	33
Tropical_Monsoon 9	3	8	14	12	19	14	22	7	3	126	22	23	14
Tropical_Rainforest 10	6	6	11	15	9	9	30	12	7	54	91	20	17
Tropical_Savanna 11	2	9	7	16	27	19	22	10	4	55	23	84	12
Warm_Continental 12	15	17	10	26	27	18	24	38	27	17	7	10	63

The baselines did not perform accurately. This is because climates are very nuanced making it hard to distinguish classes with the features given as can be seen from the PCA analysis.

PCA for Histogram of Gradients





The CNN performed better than we expected. As can be seen from the confusion matrix, even when predicting incorrectly, often these errors were for very similar climates such as arctic and subarctic or amongst the tropical categories of climate. A major source of errors stemmed from images in the dataset not directly related to climate such as interiors of houses, etc. While we tried to filter them out, inevitably some made it into our final dataset.

Future Work

Given more time we would ideally like to better curate the dataset. This would involve removing noise such as non-landscape photos or incorrectly tagged photos from the original Flickr dataset. We could also find a better proxy for climate than GPS coordinates. Ideally we would like our model to also take into account the season when the photo was taken as photos of the same place will naturally look different during different seasons, so this would likely improve accuracy.

References

M. Kottek et al., "World Map of the Köppen-Geiger climate classification updated," *Meterol. Z.*, vol. 15, pp. 259-263, 2006. DOI: 10.1127/0941-2948/2006/0130.

H. Mousselly-Sergieh et al., "World-wide scale geotagged image dataset for automatic image annotation and reverse geotagging," *Proceedings of the 5th ACM Multimedia Systems Conference*, pp. 47-52, Mar. 2014. DOI: 10.1145/2557642.2563673.