CMPT 318 Report

--Topic: Webcams, Predictions, and Weather

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Introduction

In this project, our group choose one interesting topic: Webcams, Predictions, and Weather. The reason that we pick this topic is nowadays, computer can easily scan the weather picture and then make a judgement about which weather it is. With each pixel's RGB value, computer can predict weather quality, which is clear or not clear. By some of the statistic analysis model, we can know what the weather is going to be in the future. It really helps people in the daily life and for the weather forecast, it is even more useful.

In this topic, we basically convert each weather picture into pixel table, then we do analysis by statistical model. At last, we use these data to get the best result for audiences.

Refine data procedure

Combine datasets

Data comes with multiple csv files of readings from weather station and about seven thousand photos. We first combined all csv files to have a general look. We observed that many readings like wind chill and humidity are empty, we dropped them.

Also, not all rows are with a weather assigned so we copied what's next to fill them in. Which means if a row of readings is without a weather assigned, we copy the previous weather to this row. We thought about dropping all rows without a weather, but turns out more than half of the dataset was deleted and leaves not enough data to train the model.

Lastly, we removed rows with any entry empty to finalize our dataset.

Process images

Images are in size of 192x256 and are RGB, when we read in images, every image becomes a 3d-array of size 192x256x3. For later use in the model we defined to predict weather, we resized every image to size 224x224 to fit the model.

Combine these images with their is not hard, pandas has well defined methods to do that. However, saving them to a file took us a while to figure out how. Because the images are converted to arrays when they are read in, the arrays are too large for encodings to convert them to a file. We first thought csv file can do the job, turns out the saved file can be read by the program but unable to be viewed by a human. To solve that, we changed our data file format from csv to pickle so that the data is stored in binary form without any encoding. However, file is much larger in this format.

Combine readings and images

We use the dates from both files generated above to create a merged dataset with images and readings corresponding to each other. This, however, left may rows without an image because photos taken are not as many as readings.

We then remove the rows without a image, this leaves the dataset with about 7000 rows from training and testing. At this moment, all data preparation are done and we are ready to train some models.

Algorithms

For the project, we choose to use MLPClassifier(the Multi-Layer Perceptron Classifier model) which can build a neural network. The reason we choose this model is it can learn a non-linear model. We found out that Sklearn doesn't support taking n-dimensional arrays as a training input, which means we cannot create a model that take both the original weather csv and those images taken from the weather station.

So, for MLPClassifier, we didn't use images to train the model.

The refined csv we get from the original csv has size of 13156*11 which we think is a big data. So, the first thing comes to our mind is to use a scaler to reduce the dimension of the input data. Then, the hardest part is to test the parameters and get the highest score.

The scaler we use is StandardScaler. The reason is those training inputs (such as temperature and wind speed) should be considered by taking mean/average value. Taking minimum and maximum values as training inputs does not match reality.

We choose to use the following parameters: solver, alpha, hidden_layer_sizes, random_state, activation, batch_size, max_iter, learning_rate, and tol.

First, we will introduce the non-numeric parameters. For solver, we choose to use 'lbfgs' because it can converge faster and perform better. For activation, we choose to use 'logistic' which applies logistic sigmoid function and returns f(x) = 1 / (1+exp (-x)). For learning_rate, we choose to use 'adaptive' because it can keep the learning rate constant to 'learning_rat_init' as long as training loss keeps decreasing. [1]

Second, we will introduce numeric parameters. Our first idea is to use a nested loop to test each parameter and get the best score. However, it is not possible to testing in this way because we tried to use one loop to test for only one parameters. The iteration time is about 1000 times. It takes a computer more than 20 hour to finish that loop which surprising us. We couldn't image how long it will take to finish 6 for loops.

The solution is the following:

Step 1: choose a parameter and check the score with default value.

Eg. alpha=0.0001

Step 2: test that parameter with two values, one is larger than default (right side), one is smaller than default (left side).

Eg. alpha=0.001 & alpha=0.00001

Step 3: test more values on the side that has better score.

Eg. Larger alpha is better, so test more values on right side.

Step 4: For further testing, I will use a number that is much larger/smaller than the default depending on step 3.

Eg. alpha = 1

Step 5: If the score we get from setp.4 is better, repeat step 4 with a larger/smaller value.

Eg. alpha = 2

Else, decrease the changes by 50%,

Eg. alpha = 0.5

Step 6: repeat step 5 until we get the best score.

Eg. the sequence for testing alpha is {0.0001, 0.001, 1, 2, 4, 3, 2.5} and the best score we can get is when alpha = 2.

Then the main idea is binary search. And it is much efficient than using loops because the score may stay at same for many different input parameters. We do the above steps for every parameter. By using loop, it is not possible to get the best score in three days. However, we get the best score manually in three days.

After the scikit-learn model, we decide to produce something more flexible. We decide to use tensorflow to create two model, one for dataset without images and one for images. We learned tensorflow from scratch on Youtube[2].

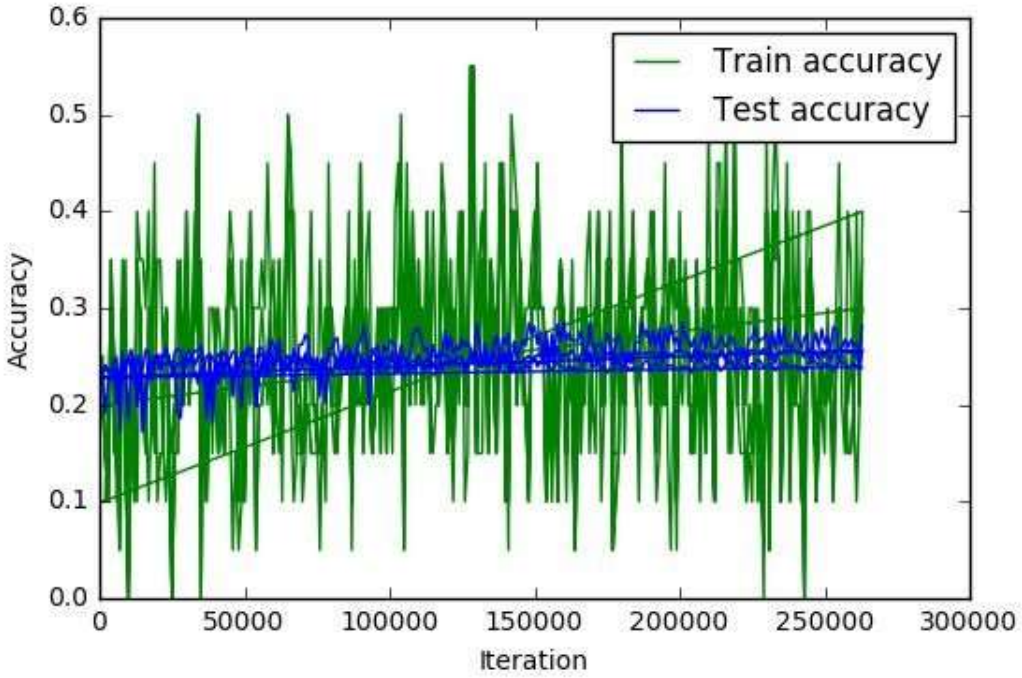
The model we used without images is a full connections neural network with 4 layers, one input layer, one output layer and 2 hidden layer. two hidden layer have 28 and 128 neurals respectfully. Comparing to scikit-learn, this model have more flexibility, it can set learning rate to change while the model is training and have activation function differently on each layer.

Lastly, the model with image included. This model is created by Alex Krizhevsky (google)[3], the picture resize in the data preparation step is for this because alexnet uses images with size 224x224. We think this model is created for some other purpose hence this does not give a

promising result as expected, we might change model or implement one ourselves as a side project afterward and for now, we'll stick to alexnet model.

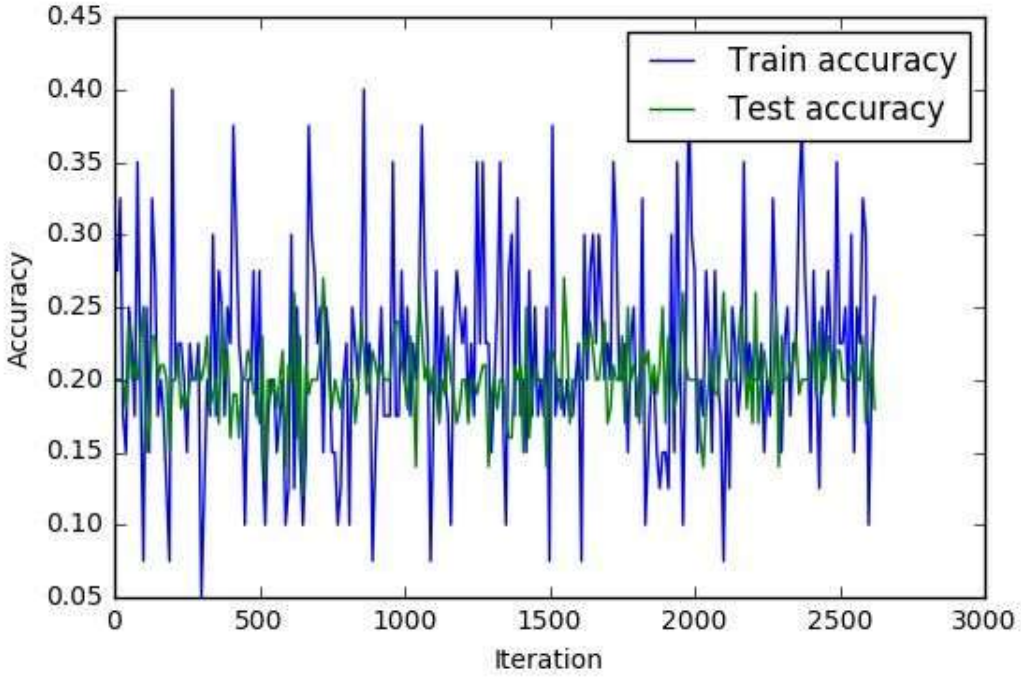
Visualization

Using tensorflow without image, we got the following accuracy plot. It doesn't gives a very promising output



figer 4.1.1 tensorflow without image

and the following plot is from alexnet model



figer 4.1.2 tensorflow with image

Limitations

Dynamic pictures

One of the limitations of our design is it only supports static pictures. But in reality, the weather is changing all the time. If we can identify the weather by a piece of video, it would be much better.

Weather predictions

In our project, we can only identify which weather it is and show people the weather conditions. But what if we can make weather predictions by some statistic model and other extra stations information?

I believe with more information, we can make a simple and short weather predictions with more than 80% accuracy rate.

Accuracy improvement

At present, the best score that we can get is 86.9%. However, it is not perfect enough. We can either write a simple loop to improve it or change another model to make it better. The problem is if we write a loop, but it takes too much time to execute. And we tried to use multiple models, unfortunately, so many of them are failed.

Time complexity

Until now, the total execution time is still a huge problem. Generally, it takes us hours to test a piece to code, especially in statistic model. The main reason is if we train the data, the algorithm is too much complex.

Project Experience Summaries

Haosen Cheng:

Webcams, Predictions, and Weather – CMPT318(Big Data analysis)

Sept – Dec 2017

- Collaborate with two other students on refine weather-related data set from GHCN, develop machine learning models and analyze results.
- Create a neural network machine learning model(MLPClassifier) and improve the model score (accuracy) from 40% to 86.9%.
- Using Pipeline to create a model that first use StandardScaler to decrease the dimension of the training data set and then trained by MLPClassifier. This method improves the efficiency, it reduces run time from 30 minutes/time to 15 minutes/time.
- Manually testing for parameters instead of using nine nested for loops. Reduces calculations from millions of times to less than a hundred times.
- Find parameters with highest score manually by using binary search algorithm.

Qifan Wu:

Webcams, Predictions, and Weather – CMPT318(Big Data analysis)

Sept – Dec 2017

1. Data cleaning and preparation, combine datasets to one for training a machine learning model.
2. Data refining, identifying and dropping useless columns and null columns.
3. Report writing, changing layout.
4. Problem analysis, find limitations and program testing.

Yifan Liu:

Webcams, Predictions, and Weather – CMPT318(Big Data analysis)

Sept – Dec 2017

- Algorithm designer for the project, implement deep learning neural network with tensorflow.
- Developed a model and program to predict weather using given readings from weather station and images of English bay.
- Specialize in how to make precision predict by modifying parameters of tensorflow model.

Reference

[1] http://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

[2] https://www.youtube.com/playlist?list=PLjSwXXbVlK6IHzhLOMpwHHLjYmINRstrk

[3]https://github.com/tensorflow/tensorflow/tree/master/tensorflow/contrib/slim/python/slim/nets