Argonne Summer 2020

Rick Nueve: Update Week 6 (DataSet and LSTM V2)

Overview

- For ten weeks, I (Rick Nueve) am an intern at Argonne National Lab under the SAGE project.
- **MISSION STATEMENT**: My primary tasks are to design a Deep Learning model that uses images and FLIR images from a node, have the model be able to run on a node, and also to write a tutorial explaining to students how to make their programs be able to run on the nodes.

TimeLine

Done	Doing	TODO			
Week: 1-5	Week: 6	Week: 7	Week: 8	Week: 9	Week: 10
• Learn about SAGE • Make dataset • WeatherNetV1 • LSTM Test • Draft 1 of paper	Make v2 of dataset (images and 15min weather). Run LSTM Test v2 Start working on data loader v2	Finish data loader v2. Run WeatherNetv2 Test Run joint test Update paper	Make docker image for plugin friendly Start writing tutorial Update paper	Finish plugin tutorial. Finish paper draft	Finish poster and present.

Updated Paper

WeatherNet: Pocketcasting Solar Radiation on the Edge

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Abstract—**Due to the complexity of atmospheric systems, the task of nowcasting (short term weather forecasting) is a challenging problem. However, with the rise of Deep Learning, scientists are exploring ways to use Neural Networks to perform nowcasting. In this paper, we explore the use of Deep Learning to predict future solar radiation values uniquely using remote camera systems on the ground in a single location. To the best of our knowledge through our literature review, this task has not been performed or documented where nowcasting is attempted with only using cameras placed at a single location. Due to the uniqueness of this task, we are proposing to call this problem pocket-casting. The remote camera system consists of three cameras: a top facing camera, a leveled facing camera, and a FLIR (forward-looking infrared) camera. These three camera's photos from the current hour are fed into a ConvLSTM variation, which then predicts categorically (low, medium, or high) the amount of solar radiation for the following hour. To perform the nowcasting on the remote camera system, Edge Computing is employed. The inference is performed on the the Edge, and the predicted values of the future solar radiation are sent back to a server. To perform the Edge Computing, SAGE, a Cyber-infrastructure for Edge computing, is used. Leveraging Sage Cyber-infrastructure allows the code to be run at the edge enabling a dramatic reduction in needed bandwidth. By employing SAGE, only the predicted solar radiation values, which are only $1.92e^{-7}$ GB, are sent back to the server. Otherwise, each day's worth of photos, which is 0.6912 GB, would have to be sent back to the server for inference. Overall, the model was able to predict solar radiation values of the following hour with " TBD " percent accuracy.**

I. Introduction

Short term weather forecasting (referred to as Nowcasting) is a challenging task. To meet the opposition, Researchers have been trying to use Deep Learning on sequenced radar Images, forming a spatiotemporal forecasting problem. The first paper to show Nowcasting using radar images in the form of a sequence was [Shi+15], which also was the defining paper that proposed the Convolution LSTM, a model that has dramatically influenced video analysis in Deep Learning. In this paper, the authors seek to build off this idea of Nowcasting using imagery; however, in the context of forecasting solar radiation over Edge Computing.

The concept being explored in this paper is the following: through remotely placed sensors and ground-based cameras alone, is it possible to forecast future solar radiation using Deep Learning methods over Edge Computing. This task is unique for several reasons. Since the Deep Learning model will be deployed locally on a machine in an outdoor setting, internet communication may be limited or not accessible at all. This is why transferring external data to the machine, such as radar imagery, would not be feasible. This leaves the model to use only data that can be collected at the sight at which it is placed through connected sensors and cameras. This also brings the unique challenge of trying to deploy a Convolution LSTM (a model that is rather computationally expensive) on a remote machine outdoors with limited computational resources. To our best knowledge from our literature review, we have not found any publications attempting to perform Nowcasting over the edge using ground based cameras and local sensors. Due this assumed novelty, we shall be naming the task of Nowcasting over Edge Computing using only locally connected sensors as Pocketcasting Through this paper, which documents our conducted research, we intend to share insight into our findings on how to create a system to perform Pocketcasting for solar radiation.

II. Literature Review

With the growing field of Deep Learning, applications of Deep Learning for IOT systems are being explored. However, with the limited computational resources of most IOT systems, scientists and industry look towards Edge Computing to provide a feasible way of deploying Deep Learning models on IOT systems. Edge computing provides the benefits of backbone network alleviation, agile service response, and powerful cloud backup. All of the previously mentioned properties which can assist in deploying a Deep Learning model on an IOT system.[Wan+20]

In previous works, such as [Ric+17], scientist explore the option of forecasting intra-hour irradiance on the Edge using camera imagery. However, to build upon past work, in this research, we look at solar forecasting using cameras facing upward, like previous literature, but also originally decide to use flir imagery and ground facing cameras.

A key challenge with deploying Deep Learning models on the Edge is the limited computational resources. Approach's to face the issue of limited computational resource have been in developing efficient models such as MobileNet[How+17] which uses an efficient convolutions method called separable convolutions.

III. SAGE Cyber-Infrastructure

I still need to write this.

IV. Data Set

The data that was used for this research was gathered using the SAGE Cyber-infrastructure. In particular, the data was collected from a node connected to the SAGE Cyber-infrastructure located on the premises of Argonne National Laboratory in Lemont, Illinois,(Lat: 41.701538, Lon: -87.994742). The data sampling took place from January to April of 2020 during all hours of the day. The methods for collecting and preparing the data are described in the following sections.

A. Weather Data

The data collected and used to perform Pocketcasting consisted of two parts: weather data and camera data. The weather data consisted of hourly samples from January to April of 2020. The data was sampled at 1 Hz and then averaged out to form five minute samples. Then the five minute averaged samples are averaged out into fifteen minute samples which then are averaged out to form one hour samples. The one hour samples are the data which was used in our research.

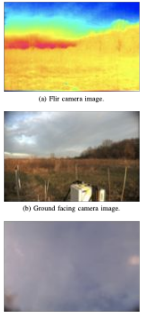
Weather Data	
Average 60 m wind direction	deg
Average 60 m wind speed	m/s
Standard deviation of 60 m wind direction	deg
Average 60 m temperature	deg C
Average 10 m wind direction	deg
Average 10 m wind speed	m/s
Standard deviation of 10 m wind direction	deg
Average 10 m temperature	deg C
Average dew point temperature	deg C
Average relative humidity	%
Average temperature difference/100m	deg C/100m
Total precipitation	mm
Average solar radiation	Watts/m^2
Average net radiation	Watts/m^2
Average barometric pressure	kPa
Average water vapor pressure	kPa
Average 10 cm soil temperature	deg C
Average 100 cm soil temperature	deg C
Average 10 ft soil temperature	deg C
Hour of the day	[0-24]

TABLE I: Weather Data names and units

The instruments used to collect the data were all located on the Argonne National Laboratory property in Lemont, Illinois. The data collected consisted of the following variables listed in "TABLE: I: Weather data Names and units." Besides the weather data, images of the environment on the premises of Argonne National Laboratory were also collected to be used as information for Pocketcasting.

B. Camera Data

The camera data used to perform Pocketcasting came from three different cameras located on the Argonne National Laboratory premises connected to a node on the SAGE Cyber-infrastructure. The three cameras consisted of a vertical facing camera, a ground facing camera, and a flir camera that was ground facing. The cameras take images every minute at all times of the day. The photos of all three cameras were of the size of 640 480 pixels. An example of a set of images from the three cameras can be seen in "Fig 1."



(a) Flir camera image.

(b) Ground facing camera image.

(c) Top facing camera image.

Fig. 1: Sample of images from SAGE node.

C. Data Preparation

Upon collecting the weather and images from the sensors connected to the node on SAGE, the data was prepared to perform forecasting of average solar radiation. The data was formatted to perform forecasting for the average solar radiation one hour ahead. Although the measurements for solar radiation were continuous value from the real numbers, for the sake of forecasting with a Deep Learning model, the solar radiation values were converted to three categories expressed by one-hot encoded vectors. The three categories were low, medium, and high based on historical data that was not used for forecasting. The categories were based on three equal sized quantiles that encode the continuous values as follows: low $\in (0.0, 0.3]$, mid $\in (0.3, 111.6]$, and high $\in (111.6, 894.1]$. As a target value, the period's one-hot encoded average solar radiation value was used. In the following section, the use of the weather data and images from the SAGE node for Pocketcasting are explored through an array of Deep Learning models designed for Edge Computing.

V. Experiments

Through experimentation, the authors sought to gain insight into how informative photos from a ground based camera system consisting of a flir camera, a top facing camera, and a bottom facing camera could be for forecasting future solar radiation at the position in which the camera was placed.

A. Pocketcasting with Ground Based Cameras

The model consisted of a cnn-lstm variant

B. Pocketcasting with Local Weather Sensors

The model consisted of a cnn-lstm variant

C. Pocketcasting with Ground based Cameras and Local Weather Sensors

The model consisted of a cnn-lstm variant

VI. Results

uhhhhhhhhhh idk

	Precission	Recall	F1	Support
Low	0.00	0.00	0.00	0
Medium	0.00	0.00	0.00	0
High	0.00	0.00	0.00	0
Accuracy			0.00	0

TABLE II: Pocketcasting with Ground based Cameras Results

	Precission	Recall	F1	Support
Low	0.73	1.00	0.84	97
Medium	0.67	0.35	0.46	68
High	0.81	0.77	0.79	84
Accuracy			0.75	249

TABLE III: Pocketcasting with Local Weather Sensors Results

	Precission	Recall	F1	Support
Low	0.00	0.00	0.00	0
Medium	0.00	0.00	0.00	0
High	0.00	0.00	0.00	0
Accuracy			0.00	0

TABLE IV: Pocketcasting with Ground based Cameras and Local Weather Sensors Results

VII. Conclusions and Future Research

lalalalallallalalla

VIII. Quotes from papers

benefits of edge computing [Wan+20]

Cloud of Things in Smart Agriculture: Intelligent Irrigation Monitoring by Thermal Imaging[RRC17]

A fast contrast enhancement method for forward looking infrared imaging system[PY09]
It is important to remember that the objective of the cp problem is to obtain a closed system for predicting weather and climate. [Ara04]

The goal of precipitation nowcasting is to predict the future rainfall intensity in a local region over a relatively short period of time. [Shi+15]

The problem I am working on is called a spatiotemporal sequence forecasting problem.[Shi+15]

The major drawback of FC-LSTM in handling spatiotemporal data is its usage of full connections in input-to-state and state-to-state transitions in which no spatial information is encoded.[Shi+15]

Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. [TL19]

Data Set V2

- Uses weather data sampled at every 15 minutes
- Images are sampled every hour at 00, 15, 30, and 45 minute.
- Data is from January to May 2020
- 8000 samples

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