Filtering Meteors from Automatic Captures

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***Abstract*—The surveillance of meteors in the Earth's atmosphere has attracted interest of astronomers, that employ cameras that automatically capture moving objects in the night sky, and as such deal with a high number of false positives. Our research tackles the problem of automatically filtering the false captures made by those cameras and estimating uncertainties of the predictions. Our main contributions are proposing a methodology that provides a more realistic estimate of performance in the wild and applying an Uncertainty Estimation method for Neural Networks.**

I. Introduction

EXOSS[1] (*Exploring the Southern Sky*) is a non profit organization that studies and monitors the incidence of meteors on the earth's atmosphere [**?**], [**?**]. The project is centered around the citizen science model, counting with around 50 stations equipped with CCTV (*Closed-circuit television*) cameras that monitor the night sky, capturing meteor images. The identification of meteors can be used to aid defense strategies against possible impacts on populated areas, to detect new meteor showers, and to study the origin of meteors.

By using specialized software and integrating data from various stations around different cities and regions, EXOSS is able to gather information surrounding the trajectory and velocity of the meteors, among other data. The cameras will also undesirably capture others events, such as the passage of planes, storms, and upper atmosphere electrical discharges. Therefore, the captures must be filtered, in order to select the ones that correspond to actual meteor images. This task is done manually by astronomers involved in the project, that must classify an average of over 100 images a day in order to maintain the database free of non meteor captures.

We are currently experimenting with a dataset of about 6000 images, with roughly the same number of examples for each class. Difficulties of detecting meteors from automatically captured images include the high variance of the non meteor class, that may contain any non meteor object, the object of interest being small, out of focus or partially occluded, the image containing glitches and noises, and the presence of various objects in the same picture. For example, while clouds are frequently mistakenly captured, various meteor captures will also contain clouds. Other objects that trigger non meteor captures, such as planes, birds and satellites, can also be present in meteor captures. Background objects such as the Moon, stars and trees, may be present in both types of captures. Examples of captures are present in figures 1 and 2.

[1]http://press.exoss.org/

We show that the methodology applied in previous work [**?**], [**?**], [**?**] leads to overestimation of the performance on new captures, and propose that test data should come from different regions or time periods. We also lay some initial work on Uncertainty Estimation by applying Monte Carlo Dropout [**?**].

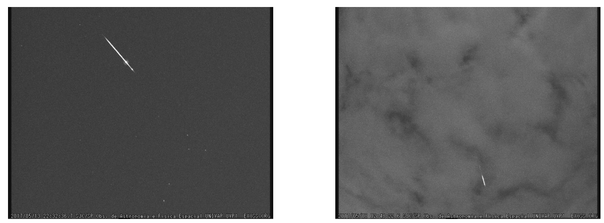

Fig. 1: Examples of meteor images.

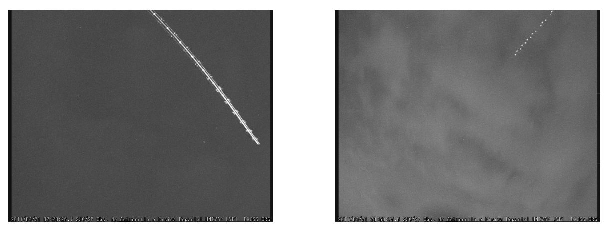

Fig. 2: Examples of non meteors

II. Methods

A. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are Feed Forward Neural Networks inspired in the visual cortex [**?**] that aggregate the weights in kernels. The kernels perform a 2D convolution with the inputs, resulting in a 2D output. The output of each kernel goes through an activation function, resulting in an "activation map". Multiple kernels can exist in a layer, and each activation map resulting from each kernel will serve as channel for the subsequent layers. The kernels from lower layers have been shown to capture low level features such as curves and lines, and the last layers will capture high level features such as the presence of a class object [**?**].

The ability of CNNs of learning features has led to the adoption of activation of high level layers as features for various applications, such as style transfer [**?**], image captioning [**?**], and classification, through the use of transfer learning. Transfer learning for CNNs works on the assumption that the features learned for classification on one domain are useful for classification on a new domain, and the approach has been largely successful for problems with small amounts of data [?]. A network trained on a large amount of data can be used as a feature extractor for a classification algorithm, or as an initialization for the weights that will be further trained in the new data to extract more specific features, in a process called fine tuning.

Our current model is an AlexNet pre trained in ImageNet. We replaced the fully connected layers by a convolutional layer with 2 kernels followed by global average pooling, corresponding to activations for each class. This reduces the number of parameters and makes the application to images of variable resolutions possible. Following the theory developed in [?], we apply dropout at each layer and make multiple predictions at test time in order to estimate the uncertainty of the predictions.

B. Uncertainty Estimation

Generally, Deep Learning models for classification problems will give a point estimate of the class given the inputs, rather than a distribution. Although the use of the softmax function and cross entropy loss make the model approximate the likelihood of each class given the data, Neural Networks have been shown to vastly overestimate the confidence on unseen data [?]. In Yarin Gal's doctorate thesis [?], it is shown that a model can have a high softmax value even when it is uncertain, and it is proposed a framework for using Deep Learning models for Bayesian modelling.

Gal shows that Neural Networks that make use of Stochastic Regularization Techniques, techniques that regularise deep learning models through the injection of stochastic noise such as dropout or Gaussian multiplicative noise, can incorporate uncertainty on the weight space. The weights of a network that employs dropout can be seen as a realisation a random variable. Therefore, we can interpret these Stochastic Neural Networks as a set of predictive functions, from which we can sample one function to make predictions. As the training converges, the distribution of predictive functions will approximate the posterior distribution of likely functions given the data seen in training. Predictions from samples from this distribution will yield higher variance in points that are further from the ones seen in training.

III. Results

In possession of metadata regarding the region and time of the captures, by classifying images by hand we observed a high correlation between some captures. Captures from similar periods of time may capture the same object multiple times, for example. A common occurrence of this phenomena is related to storms, when the same group of clouds may be the focus of hundreds of pictures, as can be seen in fig **??**. We also noticed that some type of objects are restricted to certain regions, and some regions may have frequent captures of the same type of objects. Cameras from some regions may have frequent captures of close planes, rarely seen in other regions, while some regions have insects that do not appear on other cameras. An example is the object captured in fig 4, only seen in that region and that is frequently classified as a meteor when not present in training examples.

In order to take account of the correlation present in the data, we propose splitting the training and test data by different time periods and/or different regions. The time split will prevent the presence of images from the same set of captures in the training and test sets, while the performance region split can measure the generalization for unseen events. We measured the performance of the model with 5-fold cross validation splitting the folds randomly, by time, and by region. As seen in fig 5, splitting randomly leads to an overestimation of the performance. The region split gives the worse performance, showing that the model is weak at classifying never seen before objects.

By applying the proposed method for estimating uncertainty, we could predict only for the images that had over 90% agreement on predictions. This lead to an average gain of 2% accuracy and loss of 5% in coverage, over all splits. The estimations of uncertainty were uncalibrated for out of distribution predictions, and as such the model still performed poorly in the region split, with high confidence on wrong predictions. The use of higher dropout rates, deeper networks, and Stochastic Regularization Techniques more appropriate for convolutions are possibilities for improvement of uncertainty estimations. Splitting by time, the model obtained 93% accuracy and 0.93 F1 score with 95% coverage.

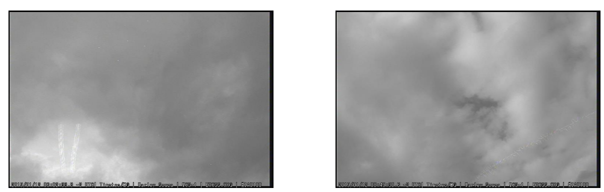

Fig. 3: Captures from the start and end of a storm, a series spanning 93 pictures.

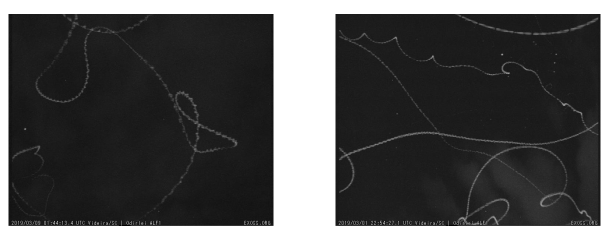

Fig. 4: Captures from the same region, a week apart

IV. Related Work

[?] and [?] have worked with similar datasets, both training models to classify images from night sky surveillance cameras in order to filter non meteor captures. [?] used a bigger and unbalanced dataset, comprised of 200 000 CAMS (Cameras for Allsky Meteor Surveillance) captures of which approximately 3% contained meteors. All of these separated training

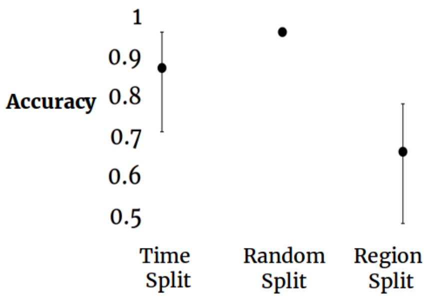

Fig. 5: Performance on different methodologies for splitting training and test datasets. The circle correspond to the averages, and the bars the maximum and minimum values.

and test data randomly, which we showed that leads to over estimation of performance.

The data used to train the model in [?] is a subset of the data we use, with the exception of some images taken from non EXOSS sources that are not currently being used. It cointained 1000 meteor images and 660 non meteor images. They employed Deep Convolutional Networks, ranging from 18 to 101 layers and using the Resnet architecture [?]. The effectiveness of transfer learning was evaluated, with the comparison between models trained from scratch and pre-trained in ImageNet [?] and Fashion-MNIST [?]. The work reported that the use of very deep Resnets did not impair performance, and that data augmentation based on image flipping and rotation worsened the results. The use of Transfer Learning was successful, and an 18 layer CNN pre trained in Fashion-MNIST achieved 96% accuracy and 0.94 F1 score.

[?] employed a random forest classifier based on engineered and selected features related to the trajectories and light curves of each object, achieving 90% precision and 81% recall. A CNN with 5 convolutional and 2 fully connected layers was trained from scratch and used to classify images that contain meteors, in a similar fashion to our approach. The reported precision and recall for the test set is 88% and 90%, respectively. A Long Short Term Memory Network (LSTM) was also trained to classify light curve tracklets, achieving 90% precision and 89% recall.

V. Future Work

Alternatives to the architecture must be better studied, experimenting with deeper networks and higher dropout rates. An alternative to using a pre trained small network such as AlexNet is to employ a bigger network and make use of pruning [?]. Other alternatives to dropout must also be tested, such as dropblock [?]. There are other methods for Uncertainty Estimation that can be studied, such as [?]. A field that may be of interest is One Class Classification [?], [?], since it provides methods for modelling the positive class differently and may be more robust to outliers and out of distribution examples.

VI. Acknowledgments

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References