Multi-Sensor Deep Domain Adaptation for Cloud Bulk Property Retrieval

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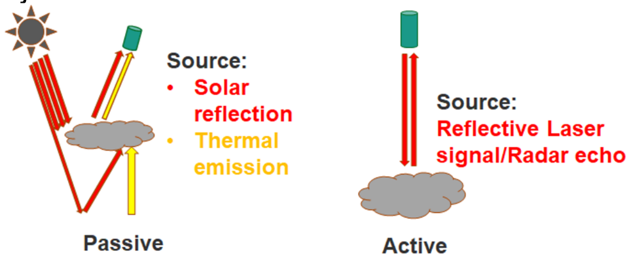
Introduction

- **Active and Passive sensors** have been developed to observe and retrieve aerosol and cloud properties. Active sensors provide **their own source of energy** to illuminate the objects they observe. Passive sensors detect **natural energy** (radiation) that is emitted or reflected by the object.



- **Objective**: How to leverage the high data quality of active sensors and the global spatial coverage of passive sensors so that we can retrieve high quality cloud properties globally?

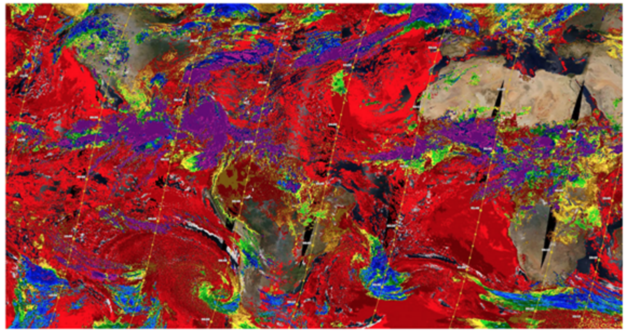


Fig. 1. An example showing the spatial coverage differences between VIIRS (global coverage) and CALIOP (yellow lines) data (Credits: NASA).

Contribution

- Develop a novel end-to-end deep domain adaptation with domain mapping and correlation alignment (**DAMA**) to classify the heterogeneous remote satellite cloud types.
- Enhance DAMA model with weak supervision by incorporating the weak labels (DAMA-WL) from the target domain and achieve higher accuracy in cloud type detection.

Proposed Methods

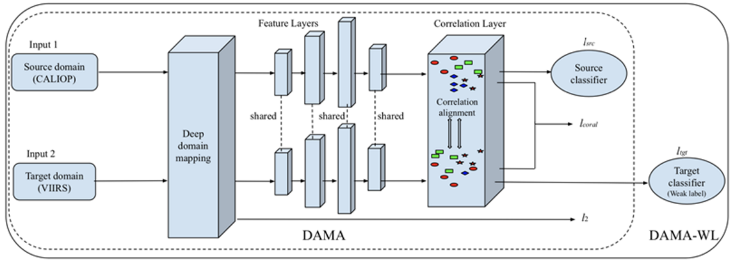


Fig. 2. DAMA: Network architecture of deep domain adaptation with domain mapping and correlation alignment. Deep domain mapping is used to map tl target domain into the feature space of source domain. The model uses several multilayer perceptron (MLP) layers to learn the shared representative featur between the source and target domain. A correlation layer is added to output of the feature extractor layer. At the end of the network is the source classifi that classifies the source domain in training phase. DAMA-WL adds a target classifier trained with weak label of the target domain in addition to DAMA.

- **Deep Domain Mapping (DDM) loss**

$$l_2 = \frac{1}{n_t} \sum_{(i=1)}^{n_t} (DDM(u_i) - x_i)^2$$

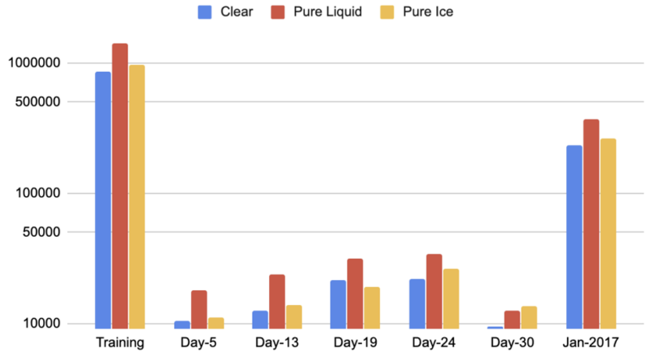
- **Correlation alignment loss**

$$l_{coral} = \frac{1}{4d^2} ||C_s - C_t||_F^2$$

- **DAMA-WL joint loss**

$$l^* = l_{src} + \sum_{(i=1)}^{t} \lambda_i l_{coral} + l_{tgt}$$

Dataset



Data distribution (data point count for each of 3 cloud types) for training and test VIIRS datasets.

Result

TABLE II
ACCURACY ON PREDICTING THE CLOUD TYPES ON VIIRS (TARGET) DATASET WITH WEAK LABEL.

Models - Single Domain	**Label**	**Source**	**Target**	**Day-005**	**Day-013**	**Day-019**	**Day-024**	**Day-030**	**Jan. 2017**
Random Forest	CALIOP	VIIRS	VIIRS	0.957	0.947	0.934	0.933	0.917	0.939
Random Forest-WL	VIIRS	VIIRS	VIIRS	0.905	0.911	0.883	0.878	0.854	0.889
MLP-VIIRS	CALIOP	VIIRS	VIIRS	0.896	0.907	0.878	0.877	0.865	0.885
MLP-CALIOP	CALIOP	CALIOP	CALIOP	1.000	1.000	1.000	1.000	1.000	1.000
Models - Multiple Domains									
Domain Mapping Only	CALIOP	CALIOP	VIIRS	0.910	0.913	0.890	0.896	0.885	0.899
Correlation Align. Only	CALIOP	CALIOP	VIIRS	0.428	0.473	0.394	0.378	0.321	0.408
DAMA	CALIOP	CALIOP	VIIRS	0.956	0.948	0.934	0.936	0.926	0.941
DAMA-WL	CALIOP + VIIRS	CALIOP	VIIRS	**0.963**	**0.964**	**0.958**	**0.958**	**0.949**	**0.960**

Future Work

- Interpret the model classification result and evaluate it with domain expert
- Investigate neighboring pixels and use of deep learning models that can capture spatial information (e.g., CNN)
- Develop interpretable deep domain alignment approach to improve the classification of cloud types

Additional Information

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