Deep Multi-Sensor Domain Adaptation on Active and Passive Satellite Remote Sensing Data

2nd NOAA Workshop on Leveraging AI in Environmental Sciences
AI/ML for Data Fusion/Assimilation

Sanjay Purushotham
University of Maryland, Baltimore County (UMBC)

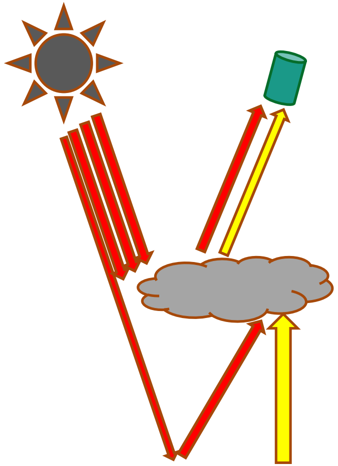
Collaborators: Xin Huang, Sahara Ali, Chenxi Wang, Zeyu Ning, Jianwu Wang, Chenxi Wang, Zhibo Zhang

Satellite-based Remote Sensing

Aqua MODIS Orbit/Swath
(Sun-synchronous orbit)

From NASA Scientific Visualization Studio
Source: https://www.youtube.com/watch?v=d4QLDlAumOc

Passive and Active Sensors



Source:
- Solar reflection
- Thermal emission

Passive

Source:
Reflective Laser signal/Radar echo

Active

Spatial coverage of Active and Passive Sensors

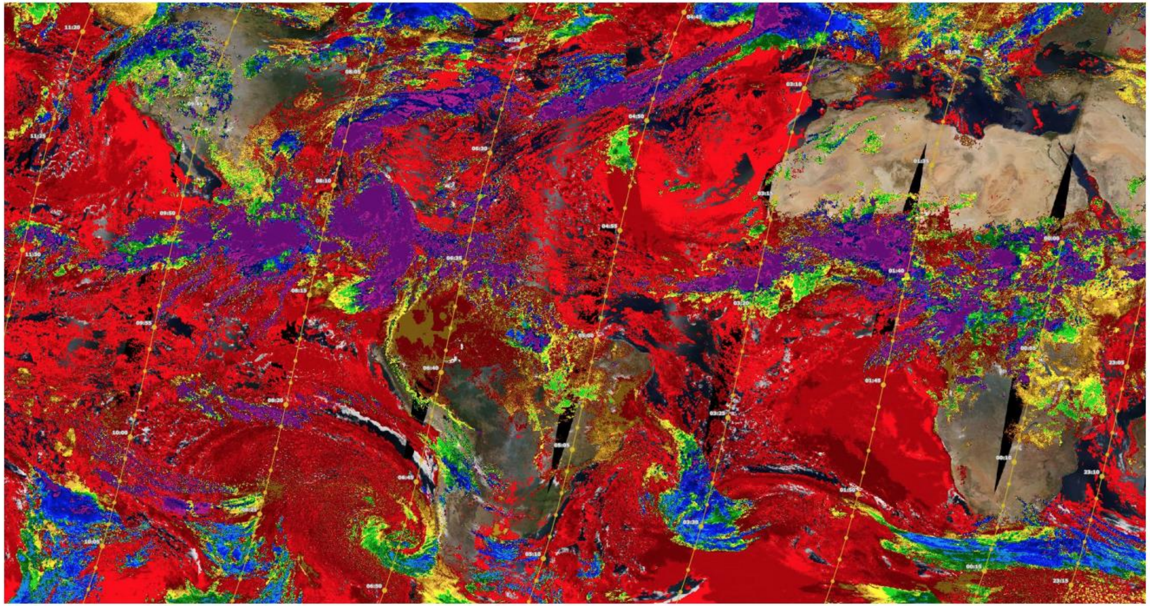


Fig. 1. An example showing the spatial coverage differences between VIIRS (global coverage) and CALIOP (yellow lines) data (Credits: NASA).

Prior Work

Atmos. Meas. Tech., 13, 2257–2277, 2020
https://doi.org/10.5194/amt-13-2257-2020

Atmospheric Measurement Techniques
Open Access

A machine-learning-based cloud detection and thermodynamic-phase classification algorithm using passive spectral observations

Chenxi Wang[1,2], Steven Platnick[2], Kerry Meyer[2], Zhibo Zhang[3], and Yaping Zhou[1,2]

[1]Joint Center for Earth Systems Technology, University of Maryland Baltimore County, Baltimore, MD, USA
[2]Earth Science Division, NASA Goddard Space Flight Center, Greenbelt, MD, USA
[3]Department of Physics, University of Maryland, Baltimore County, Baltimore, MD, USA

Correspondence: Chenxi Wang (chenxi.wang@nasa.gov)

Received: 29 October 2019 – Discussion started: 20 November 2019
Revised: 21 February 2020 – Accepted: 12 April 2020 – Published: 11 May 2020

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?

Our Solution

End-to-end **deep domain adaptation** to learn domain invariant feature representation from multiple heterogeneous satellite remote sensing sensors

X. Huang, S. Ali, C. Wang, Z. Ning, S. Purushotham, J. Wang, Z. Zhang. *Deep Domain Adaptation based Cloud Type Detection using Active and Passive Satellite Data,* In Proceedings of the 2020 IEEE International Conference on Big Data (BigData 2020), pages 1330-1337, IEEE, 2020

Heterogeneous Data - Passive and Active Sensors

CALIOP Attributes

	Name
1	CALIOP_N_Clay_1km
2	CALIOP_N_Clay_5km
3	CALIOP_Liq_Fraction_1km
4	CALIOP_Liq_Fraction_5km
5	CALIOP_Ice_Fraction_1km
6	CALIOP_Ice_Fraction_5km
7	CALIOP_Clay_Top_Altitude
8	CALIOP_Clay_Base_Altitude
9	CALIOP_Clay_Top_Temperature
10	CALIOP_Clay_Base_Temperature
11	CALIOP_Clay_Optical_Depth_532
12	CALIOP_Clay_Opacity_Flag
13	CALIOP_Clay_Integrated_Attenuated_Backscatter_532
14	CALIOP_Clay_Integrated_Attenuated_Backscatter_1064
15	CALIOP_Clay_Final_Lidar_Ratio_532
16	CALIOP_Clay_Color_Ratio
17	CALIOP_Alay_Top_Altitude
18	CALIOP_Alay_Base_Altitude
19	CALIOP_Alay_Top_Temperature
20	CALIOP_Alay_Base_Temperature
21	CALIOP_Alay_Integrated_Attenuated_Backscatter_532
22	CALIOP_Alay_Integrated_Attenuated_Backscatter_1064
23	CALIOP_Alay_Color_Ratio
24	CALIOP_Alay_Optical_Depth_532
25	CALIOP_Alay_Aerosol_Type_Mode

VIIRS Attributes

	Name	Description
1	VIIRS_SZA	viirs solar zenith angle in degree
2	VIIRS_SAA	viirs solar azimuthal angle in degree
3	VIIRS_VZA	viirs viewing zenith angle in degree
4	VIIRS_VAA	viirs viewing azimuthal angle in degree
5	VIIRS_M1	Band wavelength range 0.402-0.422μm
6	VIIRS_M2	Band wavelength range 0.436-0.454μm
7	VIIRS_M3	Band wavelength range 0.478-0.488μm
8	VIIRS_M4	Band wavelength range 0.545-0.565μm
9	VIIRS_M5_B	Band wavelength range 0.662-0.682μm
10	VIIRS_M6	Band wavelength range 0.739-0.754μm
11	VIIRS_M7_G	Band wavelength range 0.846-0.885μm
12	VIIRS_M8	Band wavelength range 1.23-1.25μm
13	VIIRS_M9	Band wavelength range 1.371-1.386μm
14	VIIRS_M10_R	Band wavelength range 1.58-1.64μm
15	VIIRS_M11	Band wavelength range 2.23-2.28μm
16	VIIRS_M12	Band wavelength range 3.61-3.79μm
17	VIIRS_M13	Band wavelength range 3.97-4.13μm
18	VIIRS_M14	Band wavelength range 8.4-8.7μm
19	VIIRS_M15	Band wavelength range 10.26-11.26μm
20	VIIRS_M16	Band wavelength range 11.54-12.49μm

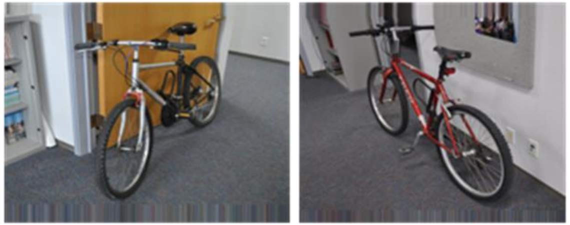
Domain Adaptation

Visual domain shift

Accuracy: 80%

Accuracy : 50%

Domain 2: Real-world images



$X \subseteq \mathbb{R}^d$ input space, $Y = \{-1, +1\}$ output space

P_S **source** domain: distribution over $X \times Y$

D_S marginal distribution over X

P_T **target** domain: different distribution over $X \times Y$

D_T marginal distribution over X

$\mathcal{H} \subseteq Y^X$: hypothesis class

$\boxed{P_S(X) \neq P_T(X'); P_S(Y|X) \approx P_T(Y'|X')}$

Expected error of a hypothesis $h : X \to Y$

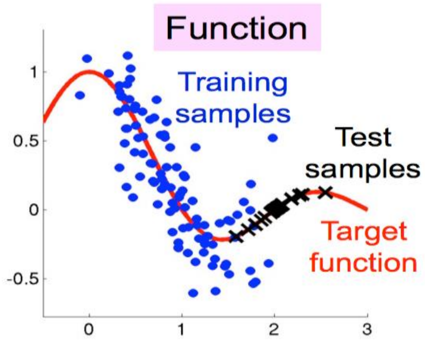
- $R_{P_S}(h) = \underset{(\mathbf{x}^s, y^s) \sim P_S}{\mathbf{E}} \mathbf{I}\left[h(\mathbf{x}^s) \neq y^s\right]$ **source** domain error
- $R_{P_T}(h) = \underset{(\mathbf{x}^t, y^t) \sim P_T}{\mathbf{E}} \mathbf{I}\left[h(\mathbf{x}^t) \neq y^t\right]$ **target** domain error

Domain Adaptation: find $h \in \mathcal{H}$ with R_{P_T} **small** from data $\sim D_T$ and P_S

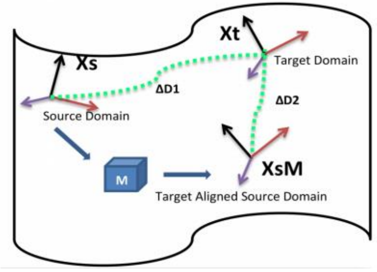
Domain Adaptation – Related Works

- Domain discrepancy reduction [Ben-David et. al, 2007]
- Instance re-weighting [Jiang and Zhai, 2007]
- Subspace alignment [Fernando et. al, 2013]
- Deep learning approaches [Ganin et. al, 2016, Tzeng et. al, 2015]

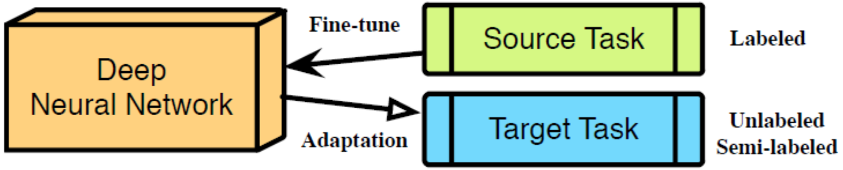
Distribution re-weighting



Subspace alignment



Deep domain adaptation



Problem Definition

Given CALIOP (source domain) training examples $D_s = \{x_i\}, x_i \in R_s^{d_s}$ with labels $L_s = \{y_i\}, y_i \in \{1, ..., L\}, i \in \{1, .., N\}$ and unlabeled VIIRS (target domain) dataset $D_t = \{u_i\}, u_i \in R_t^{d_t}$, our model is to learn a domain invariant labeling function (classifier) $f : R_s^{d_s} \longrightarrow L_s$ with $f(D_s) = f(D_t)$.

Our Proposed Deep Domain Adaptation Models

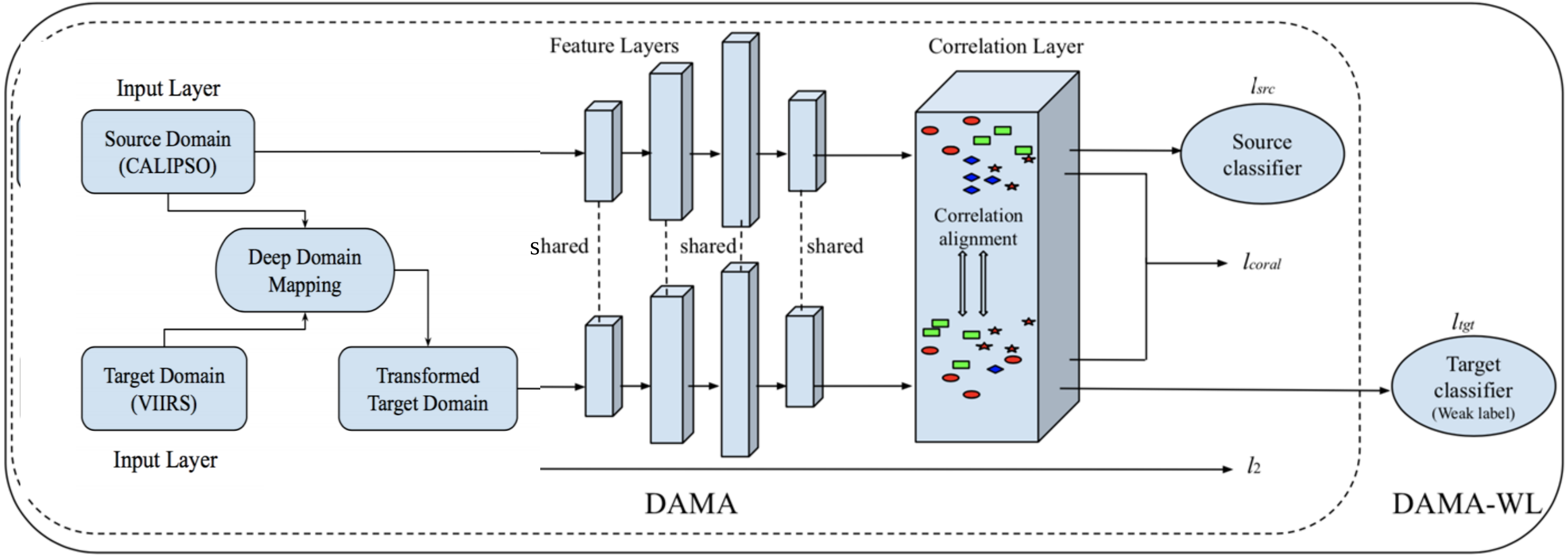
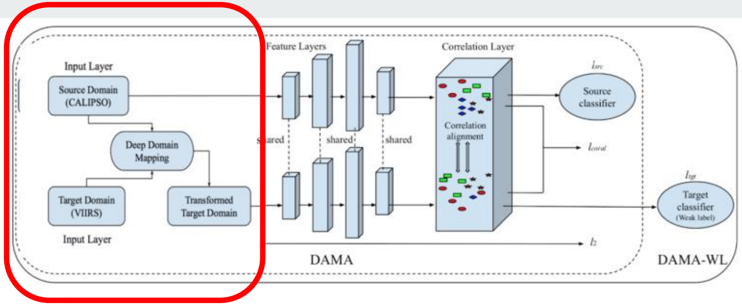


Fig. 2. DAMA: Network architecture of deep domain adaptation with domain mapping and correlation alignment. Deep domain mapping is used to map the target domain into the feature space of source domain. The model uses several multilayer perceptron (MLP) layers to learn the shared representative features 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 classifier 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.

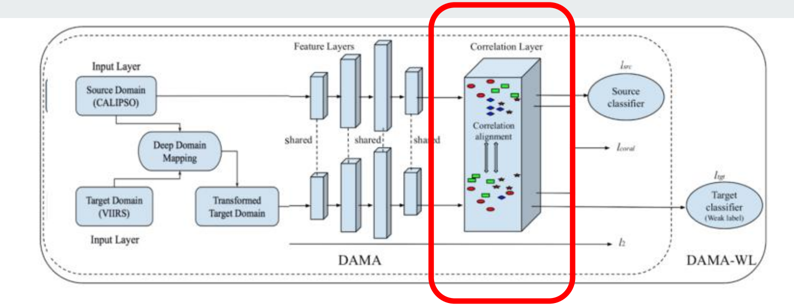
Deep Domain Mapping



- Source domain data and target domain data are collocated
- Transform the target domain into source domain feature space with L2 loss

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

Correlation Alignment



- **Correlation loss**
  - Measure the distance between the second order statistics (covariances) of the source and target data

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

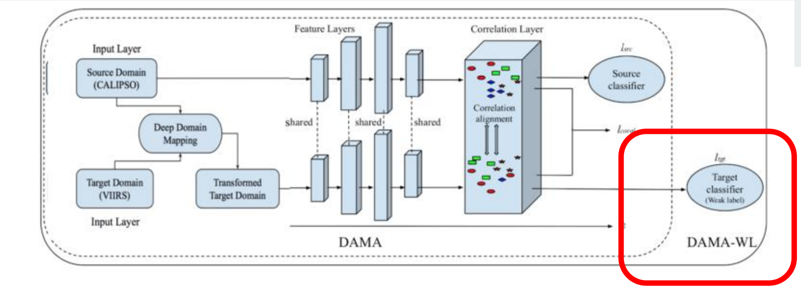
$$C_s = \frac{1}{n_s - 1}(D_s^T D_s - \frac{1}{n_s}(\mathbf{1}^T D_s)^T(\mathbf{1}^T D_s))$$

$$C_t = \frac{1}{n_t - 1}(D_t^T D_t - \frac{1}{n_t}(\mathbf{1}^T D_t)^T(\mathbf{1}^T D_t))$$

- **Combine correlation loss with source classification loss**

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

Domain Adaptation with Weak Supervision



- Incorporate the weak label information from the **target** domain
- **DAMA-WL**: weakly supervised learning

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

Experiments

Dataset

- CALIOP: **source** domain, 31 features, **Active** sensor, **full label**
- VIIRS: **target** domain, 26 features, **passive** sensor, **no label or inaccurate label**

Prediction tasks: Predict Cloud Types (Pixel_Label)

Training data collocated for 4 Jan. months in 2013-16.

- **Label Setting 1 (6 labels) : 5,633,322 train data points**
  - **Caliop label:** Clear and Clean (no cloud, no aerosol) 2: Pure Liquid Cloud (no ice cloud, no aerosol) 3: Pure Ice cloud (no liquid cloud, no aerosol) 4: Pure cloud (have both ice and liquid clouds, no aerosol) 5: Pure aerosol (no cloud, aerosol only) 6: Cloud and aerosol
- **Label Setting 2 (3 labels) : 4,711,554 train data points**
  - **Caliop label:** Label 1, 2, 3 in Label setting 1 above
  - **VIRRS label: weak/noisy** label, 1 Clear Sky (no cloud), 2 Pure Liquid Cloud, and 3 Pure Ice Cloud

Experiments

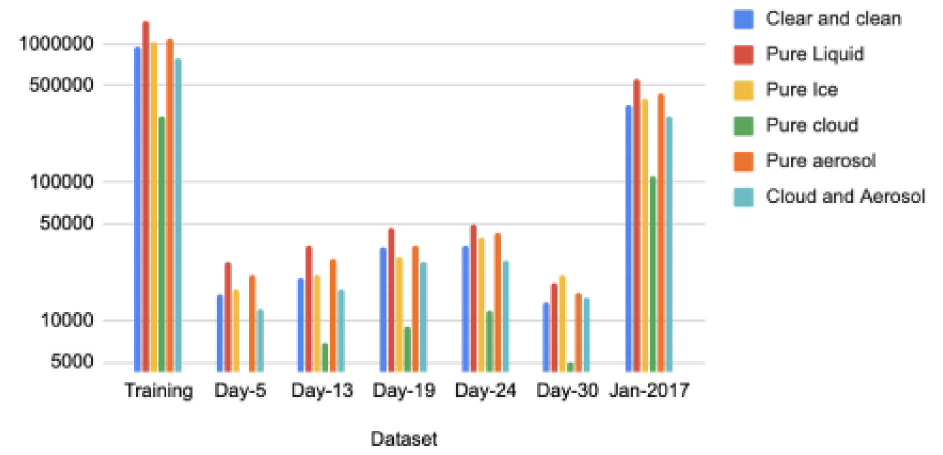


Fig. 3. Data distribution (data point count for each of 6 cloud/aerosol types) for training and test VIIRS datasets.

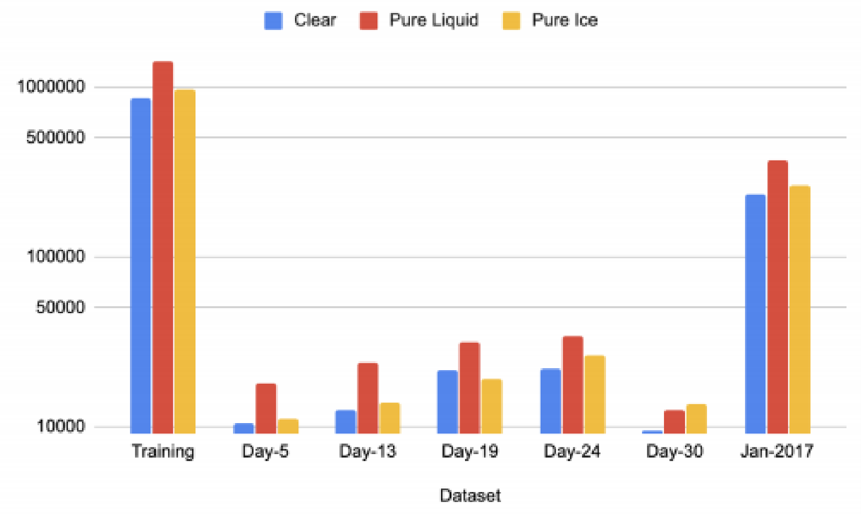


Fig. 4. Data distribution (data point count for each of 3 cloud types) for training and test VIIRS datasets.

Class distribution against each cloud type (class) for the training and test VIIRS datasets

Experiments

Comparison

- Non-domain adaptation (Single domain): Random Forests, Deep learning model (MLP) for VIIRS, Deep learning model (MLP) for CALIOP
- Domain adaptation (Multiple domains): Domain mapping only, Correlation Alignment Only, DAMA, DAMA-WL

Evaluation Metrics: Accuracy

Results (Label 1 Setting)

TABLE I
ACCURACY ON PREDICTING THE CLOUD TYPES ON VIIRS (TARGET) DATASET.

Models - Single Domain	**Source**	**Target**	**Day-005**	**Day-013**	**Day-019**	**Day-024**	**Day-030**	**Jan. 2017**
`Random Forest`	VIIRS	VIIRS	0.778	0.738	0.731	0.726	0.710	0.739
`MLP-VIIRS`	VIIRS	VIIRS	0.770	0.750	0.724	0.729	0.718	0.743
`MLP-CALIOP`	CALIOP	CALIOP	1.000	1.000	1.000	1.000	1.000	1.000
Models - Multiple Domains								
`Domain Mapping Only`	CALIOP	VIIRS	0.728	0.705	0.696	0.695	0.674	0.695
`Correlation Align. Only`	CALIOP	VIIRS	0.355	0.333	0.283	0.282	0.251	0.302
DAMA	CALIOP	VIIRS	**0.780**	**0.759**	**0.745**	**0.745**	**0.721**	**0.752**

DAMA outperforms the domain adaptation baselines by ~6% to ~40%

Results (Label 2 Setting)

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**

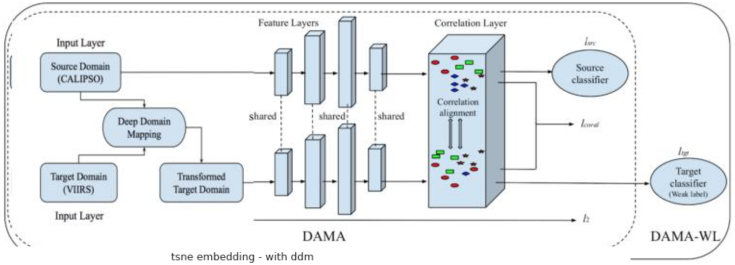
DAMA-WL brings additional ~2% accuracy improvement compared to the DAMA

Visualizations of learned representations

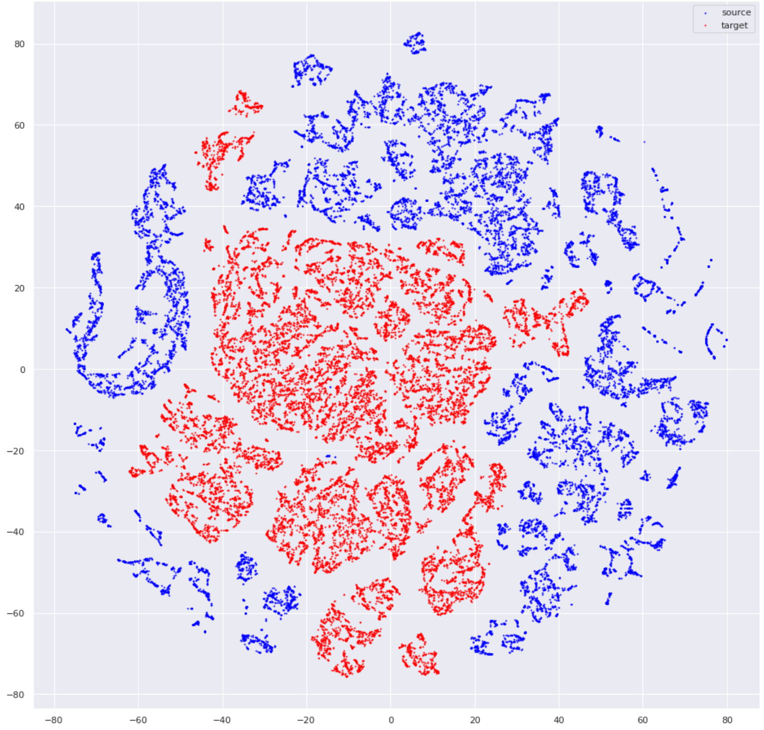
We use t-SNE (t-Distributed Stochastic Neighbor Embedding) a non-linear dimensionality reduction technique to visualize the learned representations

Mixing of learned representations indicate success of domain adaptation

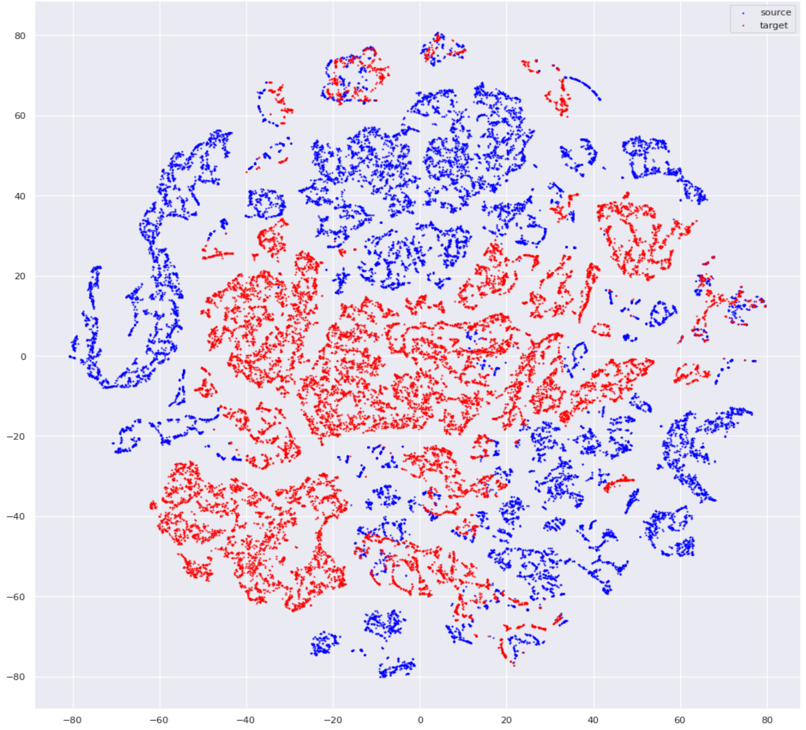
Original -> DDM



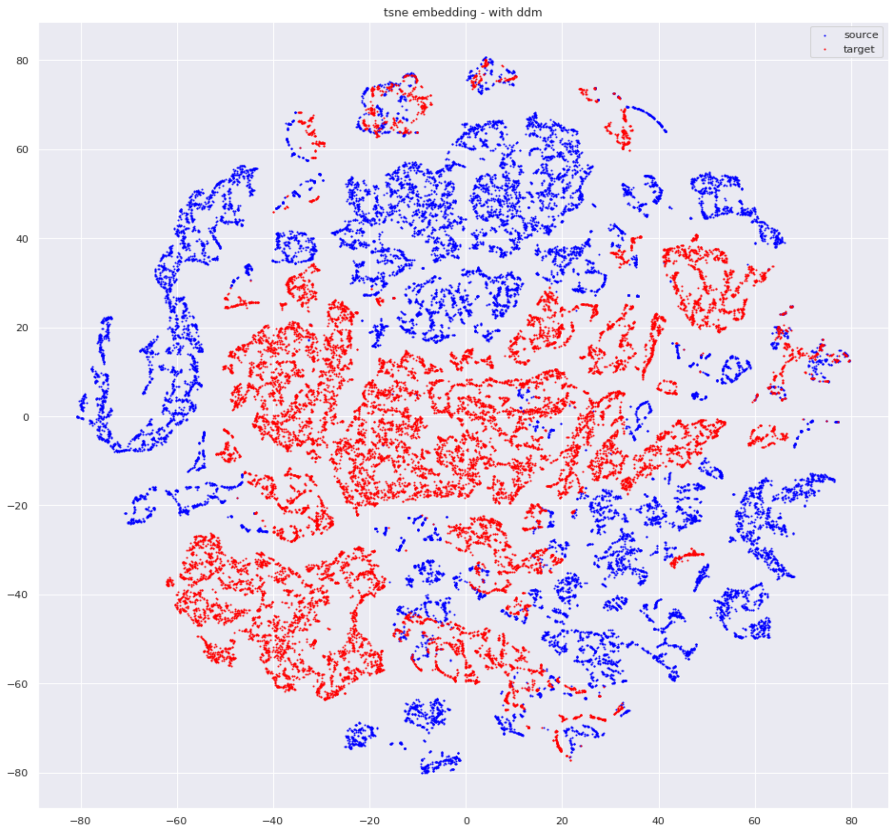
tsne embedding - original

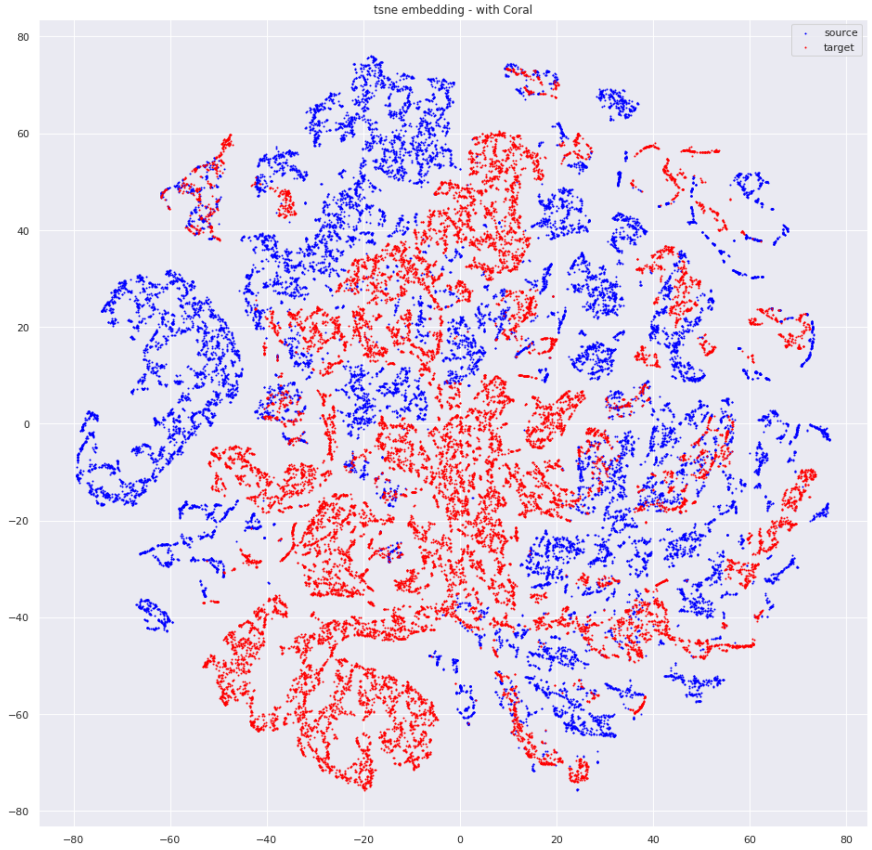


tsne embedding - with ddm

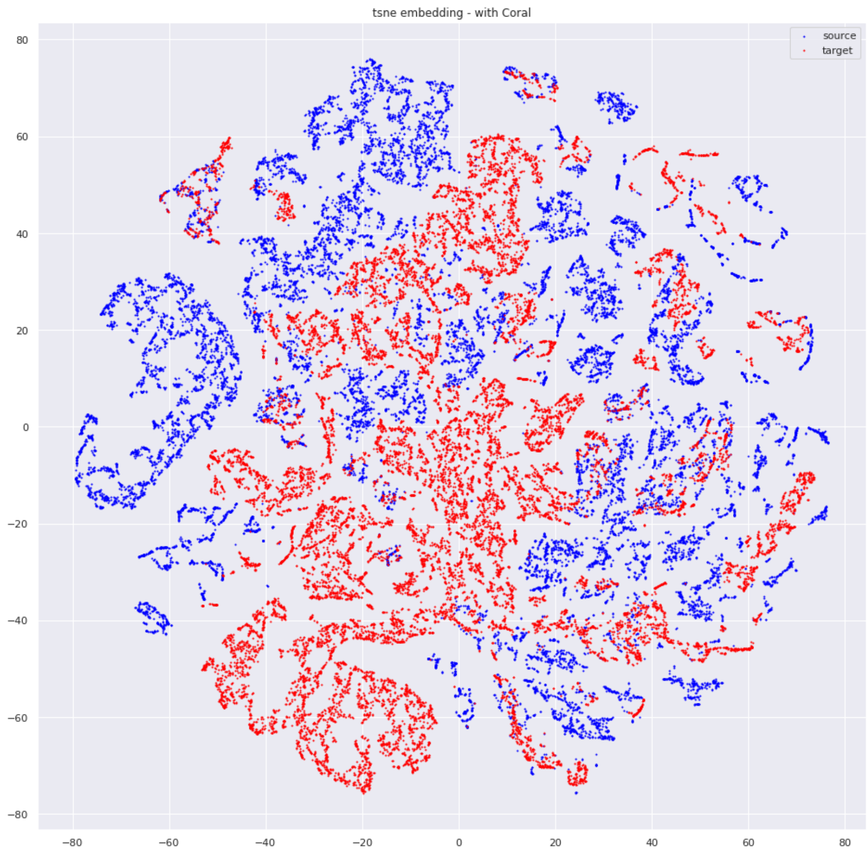


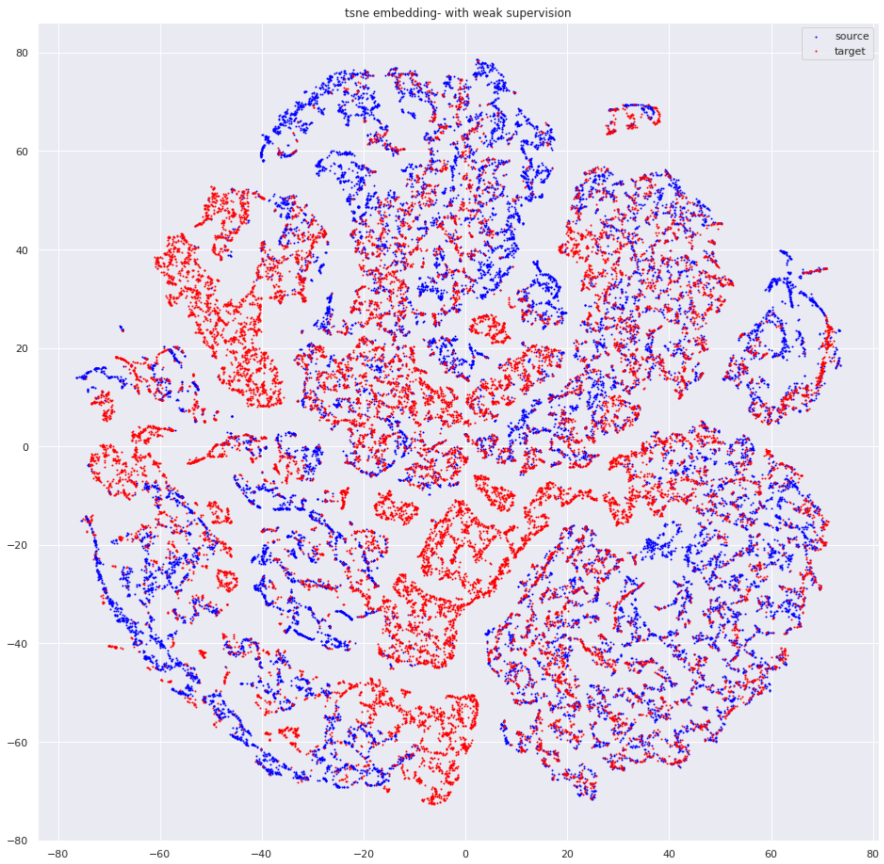
DDM -> Coral


tsne embedding - with ddm
source
target
80
60
40
20
0
−20
−40
−60
−80
−80
−60
−40
−20
0
20
40
60
80

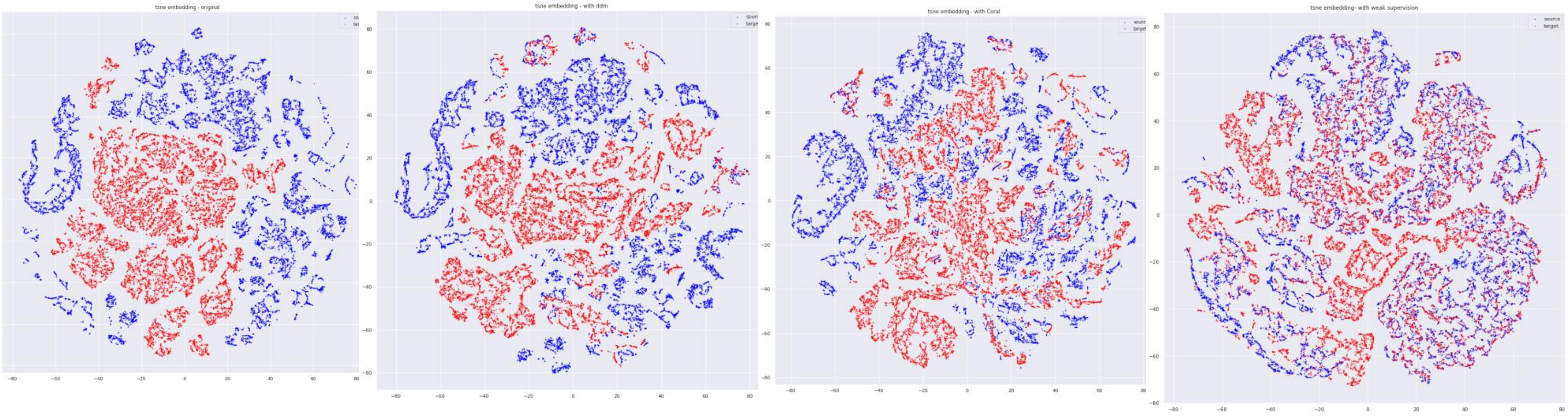

tsne embedding - with Coral
source
target
80
60
40
20
0
−20
−40
−60
−80
−80
−60
−40
−20
0
20
40
60
80

Coral -> WL


tsne embedding - with Coral
source
target
80
60
40
20
0
−20
−40
−60
−80
−80
−60
−40
−20
0
20
40
60
80


tsne embedding- with weak supervision
source
target
80
60
40
20
0
−20
−40
−60
−80
−80
−60
−40
−20
0
20
40
60
80

Put it together: Original->DDM->Coral -> WL



Conclusions

- Utilizing data from multiple satellites jointly, we can achieve better information retrievals for targeted geophysics variables

- We proposed deep domain adaptation methods with heterogeneous domain mapping and correlation alignment to employ both active and passive sensing data in cloud type detection

- Future work will focus on predicting labels for off-track pixels by capturing spatial and temporal information from neighboring pixels

Acknowledgements

This work is supported by grants OAC–1730250, OAC–1942714, IIS–1948399 from the National Science Foundation (NSF) and grant 80NSSC21M0027 from the National Aeronautics and Space Administration (NASA)

Thank You!
Q &A

Contact: Sanjay Purushotham (psanjay@umbc.edu)

More info of our project at https://earthdata.nasa.gov/esds/competitive-programs/access/ml-cloud-properties