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Impact Assessment of Missing Data in Model Predictions for Earth Observation Applications

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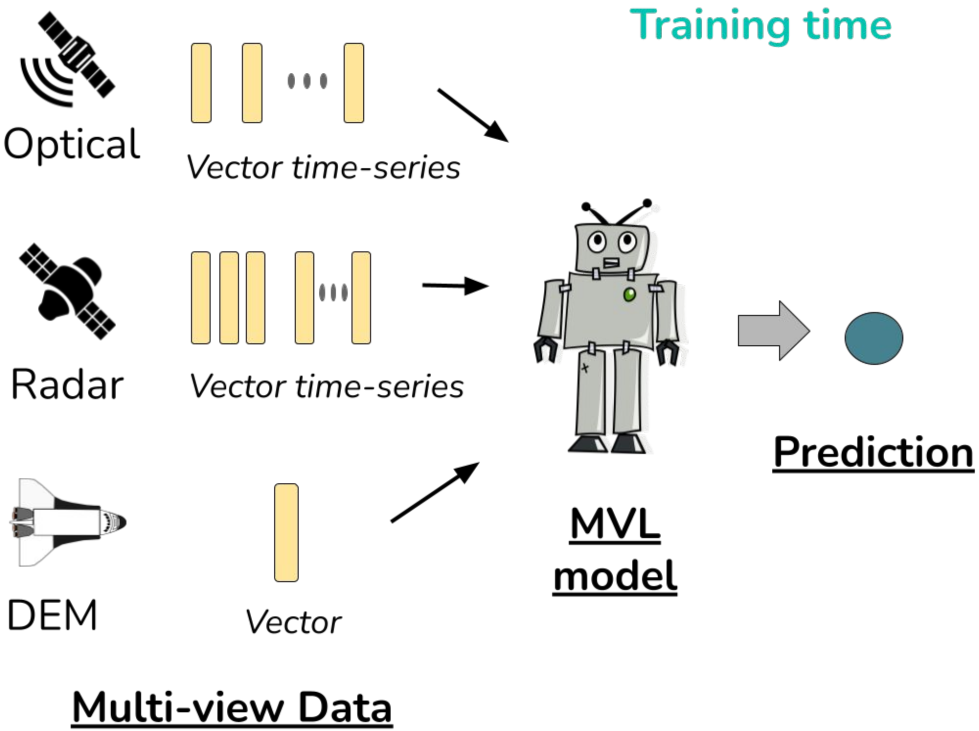
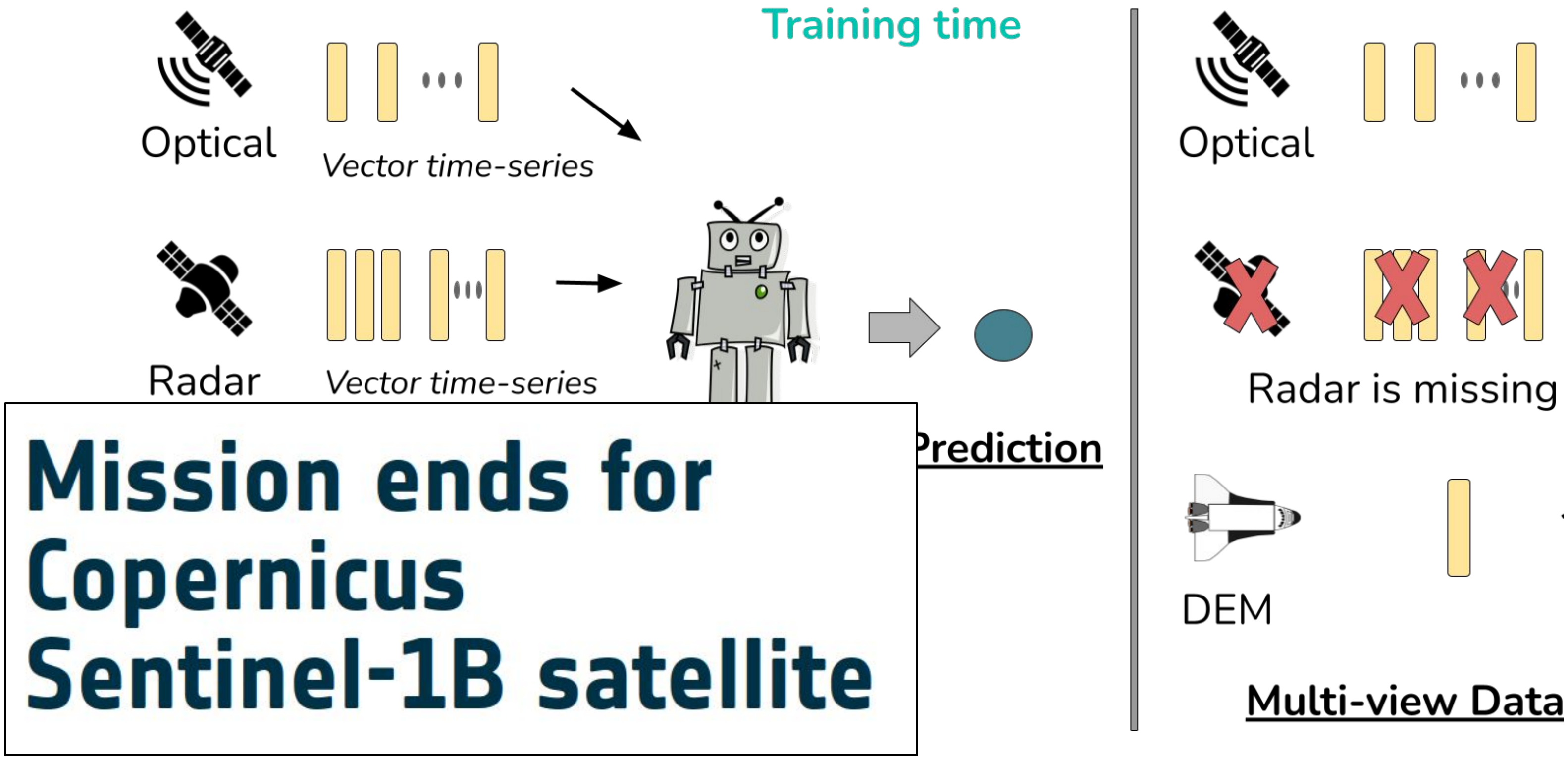
esa

Motivation


Training time
Optical
Vector time-series
Radar
Vector time-series
DEM
Vector
Multi-view Data
MVL
model
Prediction

Motivation

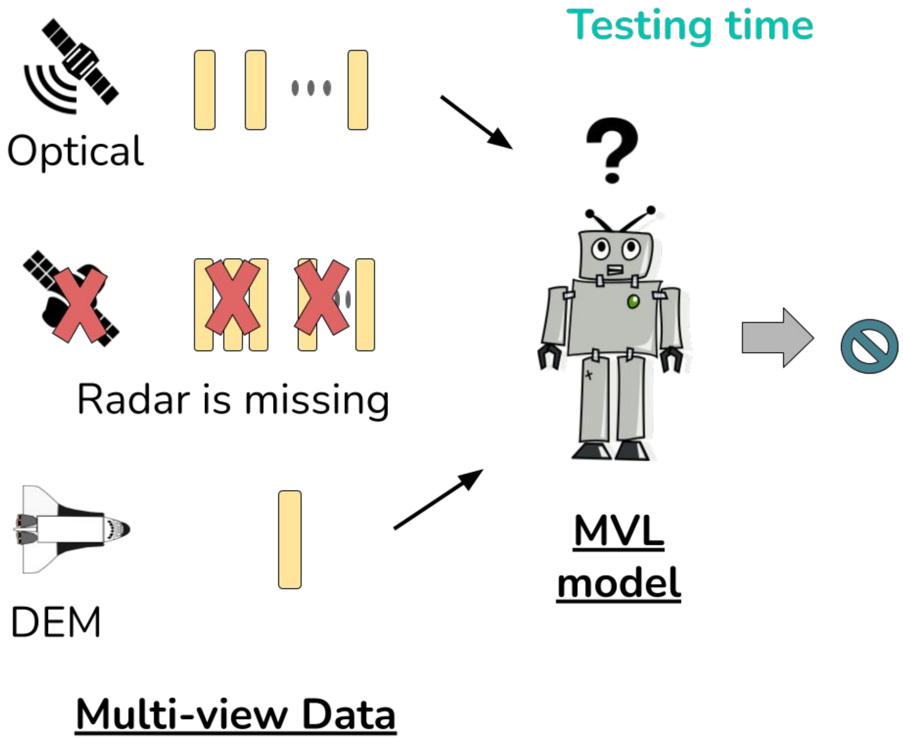


https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Mission_ends_for_Copernicus_Sentinel-1B_satellite

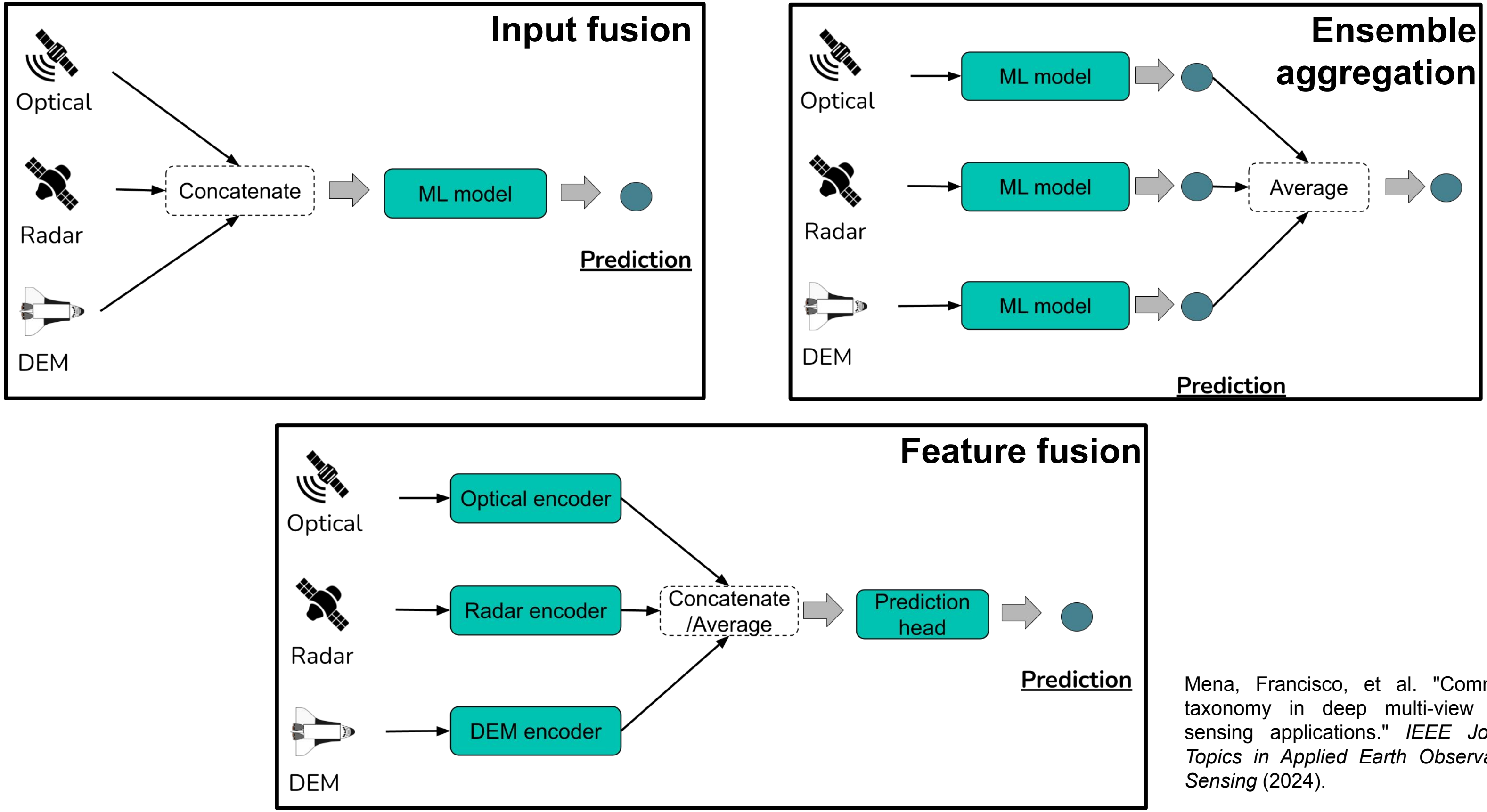
Research question

- What is the impact of missing views in MVL models with time series and static EO sources?

- Models are trained on full-view scenario.
- **Prediction impact** on testing samples.



Basis of MVL
Fusion strategies



Mena, Francisco, et al. "Common practices and taxonomy in deep multi-view fusion for remote sensing applications." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (2024).

MVL with missing views
Techniques

1. **Impute**: replace the input features that are missing with a numerical value [1].
   a. Imputation value: average of the features of each view in the training data.

2. **Exemplar**: replace the features of the missing view with a similar sample in the training set, based on available views and a shared space [2].
   a. Shared space: multi-view linear projection based on CCA [2].

3. **Ignore**: omit the features of the missing views by using a dynamic merge function.

[1] Hong, Danfeng, et al. "More diverse means better: Multimodal deep learning meets remote-sensing imagery classification." *IEEE Transactions on Geoscience and Remote Sensing* (2020)
[2] Srivastava, Shivangi, et al. "Understanding urban landuse from the above and ground perspectives: A deep learning, multimodal solution." *Remote Sensing of Environment* (2019)
[3] Mena, Francisco, et al. "Adaptive Fusion of Multi-view Remote Sensing data for Optimal Sub-field Crop Yield Prediction." *arXiv preprint arXiv:2401.11844* (2024)

MVL with missing views
Techniques

1. **Impute**: replace the input features that are missing with a numerical value [1].
   a. Imputation value: average of the features of each view in the training data.
   b. in combination with *Input-concat* and *Feature-concat.*

2. **Exemplar**: replace the features of the missing view with a similar sample in the training set, based on available views and a shared space [2].
   a. Shared space: multi-view linear projection based on CCA [2].
   b. in combination with *Feature-concat.*

3. **Ignore**: omit the features of the missing views by using a dynamic merge function.
   a. in combination with *Feature-avg*, *Feature-gated* [3], and *Ensemble-avg.*

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Pixel-wise datasets

- Classification datasets:

Predictive Task	Samples	Where	Pixel resolution	Temporal length	Temporal views	Static views
Cropland classification [1]	69,000	Global	10 m	12 months	optical, radar, weather	topographic
Crop-type classification [1]	29,642	Global	10 m	12 months	optical, radar, weather	topographic

- Regression datasets:

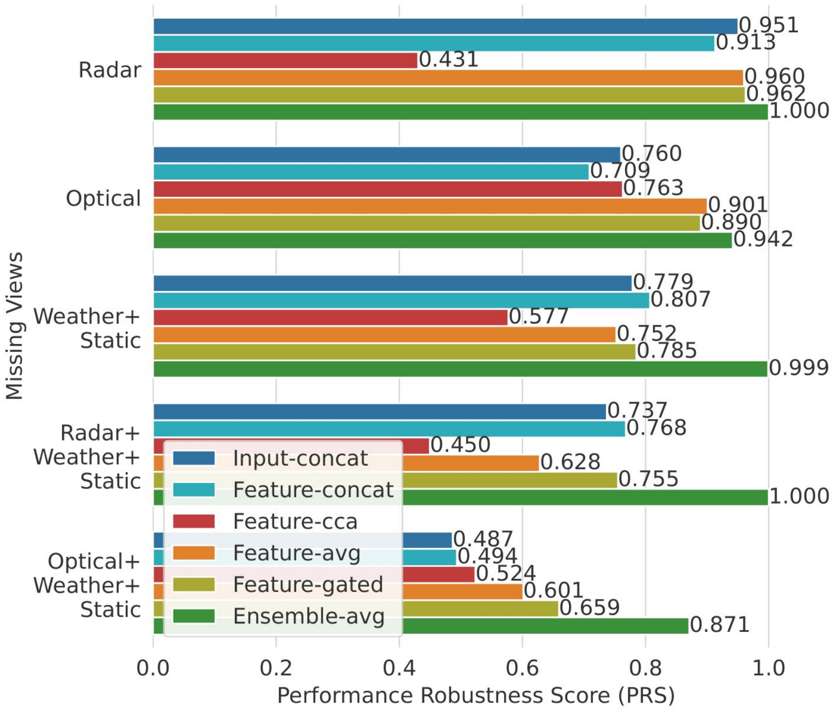
Live fuel moisture content [2]	2,578	USA	250 m	4 months	optical, radar	topographic, soil, land cover, canopy height
Crop yield prediction [3]	54,098	Swiss	10 m	seeding - harvesting	optical, weather	-

[1] Tseng, Gabriel, et al. "Cropharvest: A global dataset for crop-type classification." *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track* (2021)
[2] Rao, Krishna, et al. "SAR-enhanced mapping of live fuel moisture content." *Remote Sensing of Environment* (2020)
[3] Perich, Gregor, et al. "Pixel-based yield mapping and prediction from Sentinel-2 using spectral indices and neural networks." *Field Crops Research* (2023)

Classification Results
Robustness (Cropland classification)

- PRS [1]: Performance Robustness Score.

$$\mathrm{PRS}(y, \hat{y}_{miss}, \hat{y}_{full}) = \min\left(1,\ \exp\left(1 - \frac{\mathrm{RMSE}(y, \hat{y}_{miss})}{\mathrm{RMSE}(y, \hat{y}_{full})}\right)\right)$$



[1] Heinrich, René, et al. "Targeted adversarial attacks on wind power forecasts." Machine Learning (2024)

Classification Results
Predictive performance

- Average Accuracy in **Cropland classification**:

Method	Technique	No Miss	Radar	Optical	Weather+Static	Radar+Weather+Static	Optical+Weather+Static
Input-concat	Impute	0.847	**0.831**	0.717	0.674	0.642	0.554
Feature-concat	Impute	**0.849**	0.829	0.730	0.712	0.691	0.594
Feature-cca	Exemplar	0.829	0.491	0.724	0.608	0.543	0.570
Feature-avg	Ignore	**0.848**	**0.836**	**0.797**	0.768	0.729	0.668
Feature-gated	Ignore	**0.849**	**0.836**	**0.797**	**0.773**	**0.748**	**0.700**
Ensemble-avg	Ignore	0.828	0.822	**0.792**	**0.822**	**0.824**	**0.740**

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- Same behavior observed in **Crop-type classification**:

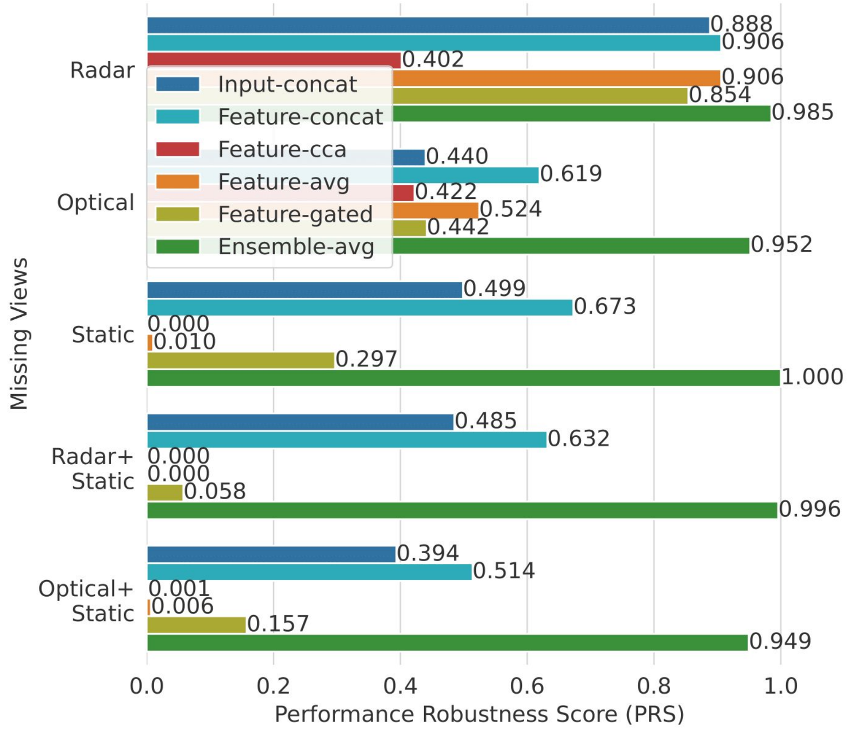
Method	Technique	No Miss	Radar	Optical	Weather+Static	Radar+Weather+Static	Optical+Weather+Static
Input-concat	Impute	**0.738**	0.641	0.296	0.534	**0.534**	0.142
Feature-concat	Impute	0.727	0.624	0.290	0.558	0.390	0.159
Feature-cca	Exemplar	0.727	0.285	0.384	0.094	0.107	0.100
Feature-avg	Ignore	0.726	**0.674**	0.542	**0.582**	0.529	**0.306**
Feature-gated	Ignore	**0.734**	0.652	**0.561**	0.511	0.440	**0.306**
Ensemble-avg	Ignore	0.715	**0.708**	**0.613**	**0.711**	**0.715**	**0.523**

Regression Results

Robustness (Live fuel moisture content)

- PRS: Performance Robustness Score.

$$\mathrm{PRS}(y, \hat{y}_{miss}, \hat{y}_{full}) = \min\left(1,\ \exp\left(1 - \frac{\mathrm{RMSE}(y, \hat{y}_{miss})}{\mathrm{RMSE}(y, \hat{y}_{full})}\right)\right)$$



Regression Results
Predictive performance

- Coefficient of Determination (R^2) in **Live fuel moisture content**:

Method	Technique	No Miss	Radar	Optical	Statics	Radar+Statics	Optical+Statics
Input-concat	Impute	**0.717**	**0.650**	0.060	0.185	0.165	−0.047
Feature-concat	Impute	0.667	0.599	**0.274**	**0.352**	**0.290**	**0.081**
Feature-cca	Exemplar	0.667	†	−0.260	†	†	†
Feature-avg	Ignore	0.683	0.618	0.142	†	†	†
Feature-gated	Ignore	**0.737**	**0.651**	0.138	−0.422	−5.326	−1.693
Ensemble-avg	Ignore	0.312	0.292	**0.243**	**0.407**	**0.392**	**0.239**

Regression Results
Predictive performance

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Ensemble-avg	Ignore	0.312	0.292	**0.243**	**0.407**	**0.392**	**0.239**

- Coefficient of Determination (R2) in **Crop yield prediction**:

Method	Technique	No Miss	Optical	Weather
Input-concat	Impute	0.823	−1.435	0.710
Feature-concat	Impute	**0.827**	−1.058	**0.760**
Feature-cca	Exemplar	**0.827**	−0.343	†
Feature-avg	Ignore	**0.828**	−0.993	−8.664
Feature-gated	Ignore	0.823	**0.193**	−7.534
Ensemble-avg	Ignore	0.768	**0.593**	**0.823**

† Values < -100

Conclusion

- Missing views have a **negative impact** on model predictions.
  - Is more critical when more views are missing.
  - Is more severe in **regression** than in classification task.

- The method design can mitigate the negative effect.
  1. Fusion strategy
  2. Technique

Conclusion

- Missing views have a **negative impact** on model predictions.
  - Is more critical when more views are missing.
  - Is more severe in **regression** than in classification task.

- The method design can mitigate the negative effect.
  1. Fusion strategy
  2. Technique

- **Recommendation**:
  - If views are sufficiently discriminative to allow individual predictions: Ensemble with Ignore.
  - Otherwise: Feature with Ignore in classification, or with Impute in regression.

https://github.com/fmenat/missingviews-study-EO

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Dataset Views Description

Predictive Task	Optical (Sentinel-2)	Radar (Sentinel-1)	Weather (ERA5)	Topographic (NASA's SRTM)
Cropland & Crop-type classification	B2, B3, B4, B5, B6, B7, B8, B8A, B9, B11, B12, NDVI	VV, VH	temperature, precipitation	elevation, slope

Predictive Task	Optical (Landsat 8)	Radar (Sentinel-1)	Topographic (National Elevation Database)	Soil (Unified North American Soil Map)	LIDAR (GLAS)	Land-cover (GLOBCOVER)
Live fuel moisture content	red, green, blue, NIR, SWIR, NDVI, NDWI, NIRV	VV, VH, VH/VV	elevation, slope	silt, sand, clay	canopy height	12 categories

Predictive Task	Optical (Sentinel-2)	Weather (ERA5)
Crop yield prediction	B2, B3, B4, B5, B6, B7, B8, B8A, B11, B12, SCL	precipitation, temperature

Model implementation

- **Encoders**: Two layers with 128 units
  - Static views: MLP
  - Temporal views: 1D CNN
- **Prediction Head**: a MLP with one layer of 128 units.

- Optimization:
  - ADAM
  - 128 batch size
  - early stopping

- Loss function
  - Cross entropy in classification
  - Mean squared error in regression