Final report PoC ESO

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Microsoft

METRICARTS

OUTLINE

- Team members
- Goals
- Resources
- Methodology
- Main results
- Future work

TEAM MEMBERS

- **MetricArts**
  Roberto Muñoz
  Joaquin Prieto

- **ESO**
  Nicolas Haddad
  Eduardo Peña
  Luca Sbordone
  Willem-Jan de Wit
  Cristian Romero

- First meeting: May 8th, 2019
- Last meeting: August 2nd, 2019

GOALS

- General Goal
  - Develop a method to supplement the visual spot check of calibration images done during daytime by experts. The method should identify anomalous images.
  - Knowledge transfer on ML techniques from MetricArts to ESO team to work
- Technical goal
  - Design a method to detect anomalous and defectuous images based on Deep Learning and clustering techniques

RESOURCES

- Microsoft Azure environment
- Azure storage container
- CPU and GPU VM

- Jupyterlab
- Tensorflow framework
- Keras library
- Scikit-learn library
- Astropy library

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DATA SOURCES

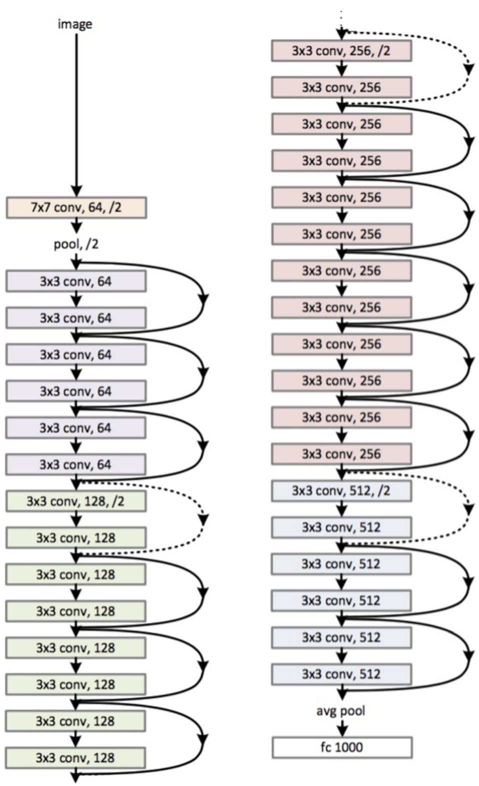
- UVES Calibration images
  - Bias Blue & Red
  - Flat Blue & Red
  - Arclamps Blue & Red
- UVES corrupted file list (Garching)
- Corrupted mock images (Nicolas Haddad)

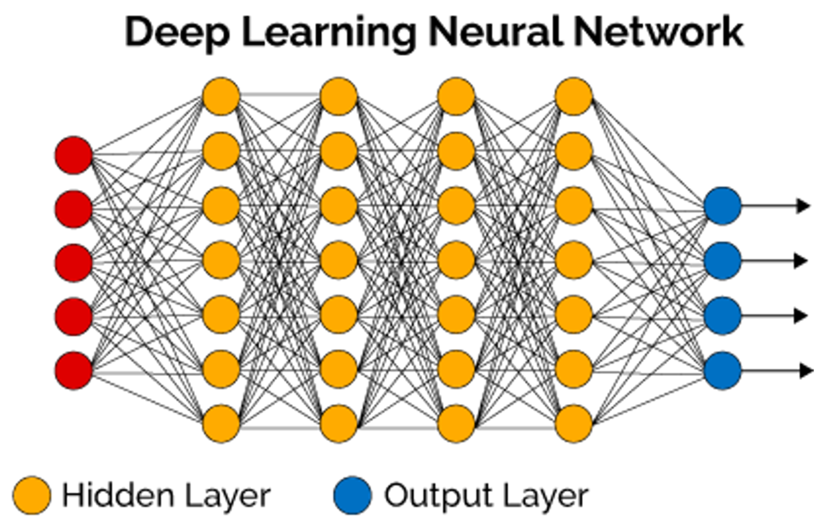
DATASET AND PIPELINE

- Raw data in fits.Z format
- Raw data about 500 MB
- Uncompressed data about 1.2 TB
- Image extensions were splitted and converted into numpy format
- Individual extensions were processed using Convolutional neural network
- Embeddings (descriptors) were obtained for every individual extension

DEEP LEARNING

- Embedding were computed using a ResNet-50 Convolutional neural network (CNN). This architecture has 50 CNN layers.





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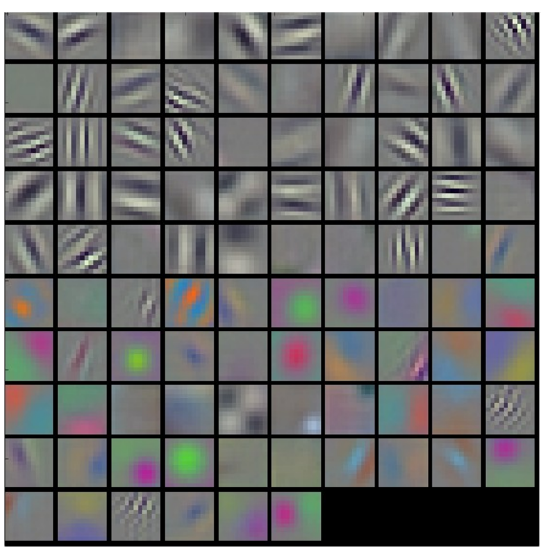
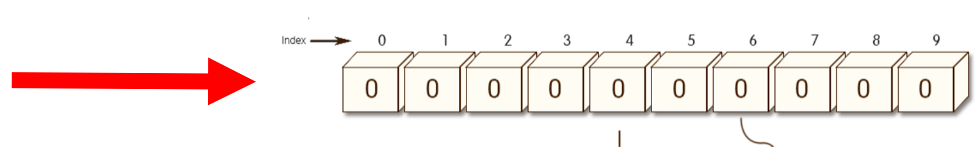
DESCRIPTORS

- Raw image resolutions
  - 4096x2048
  - 3000x2148
  - 3000x1074
- Images were passed through RestNet-50 network and a descriptor length of 2048 was computed





METHODOLOGY

1. Unsupervised method
   - Affinity matrix computed using cosine distance metric
   - Classification based on hierarchical clustering

2. Supervised method
   - Classification method using fully connected network

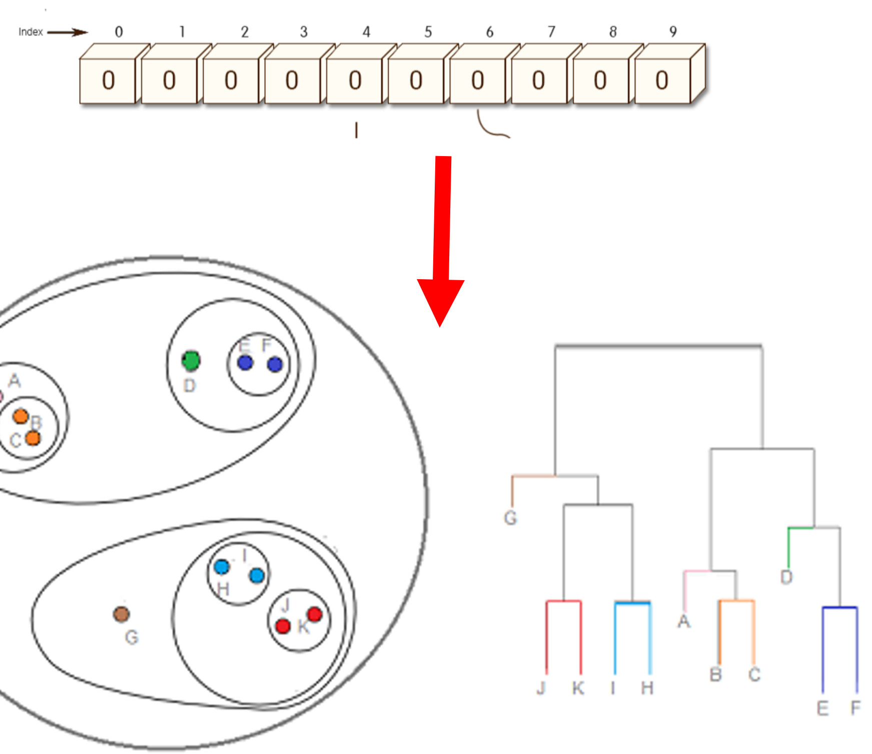
UNSUPERVISED LEARNING

- Compute similarity between images using the cosine metric distance
- Apply several clustering techniques
  - K-means
  - Spectral clustering
  - Hierarchical clustering

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$

HIERARCHICAL CLUSTERING

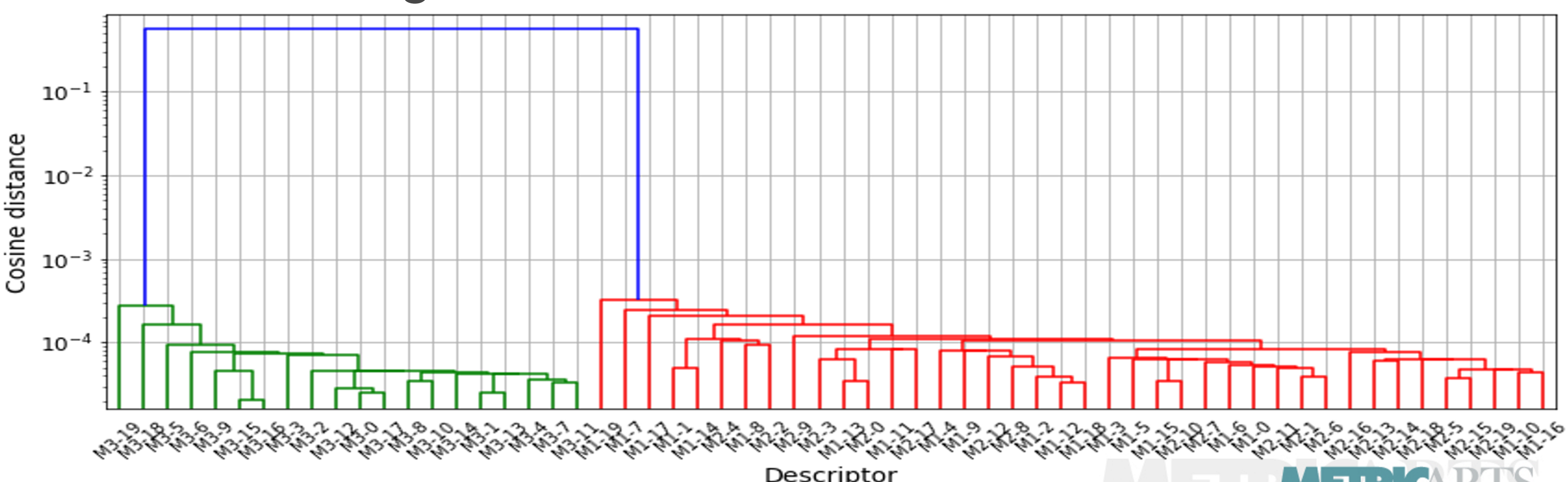
- Best results obtained using a hierarchical clustering technique
- We obtained a dendrogram or agglomeration tree



COMPARISON BETWEEN METHODS 1 & 2

- Dendrogram visualization reveals method 1 and 2 produce verysimilar embeddings.
- Method 1 and 2 descriptors are very close.
- Method 3 descriptors are far from method 1 and 2 embeddings.

UVES_BLUE_BIAS - 20 images/method



COMPARISON BETWEEN METHODS 3 & 4

- Dendrogram visualization reveals method 3 and 4 produces a cluster far from method 2 descriptors.

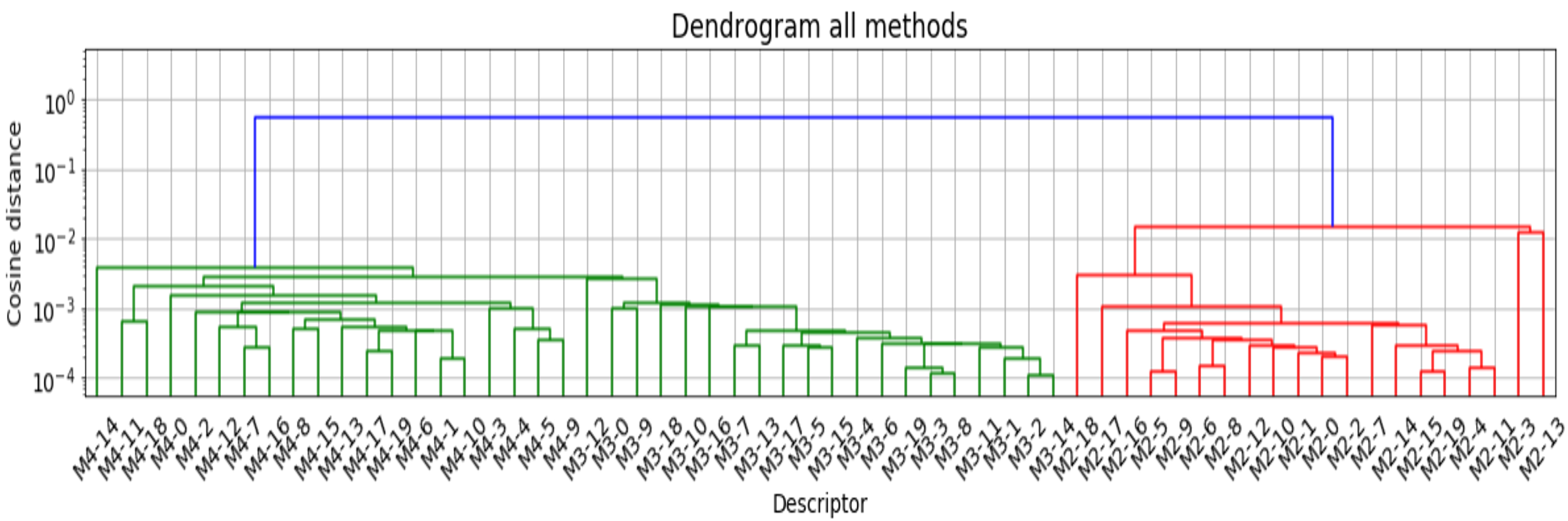


IMAGE TYPE CLUSTERING

- Dendrogram visualization reveals that it is possible to use it for image type identification (clustering).
- It uses a number of clusters based approach for years 2010 to 2019.

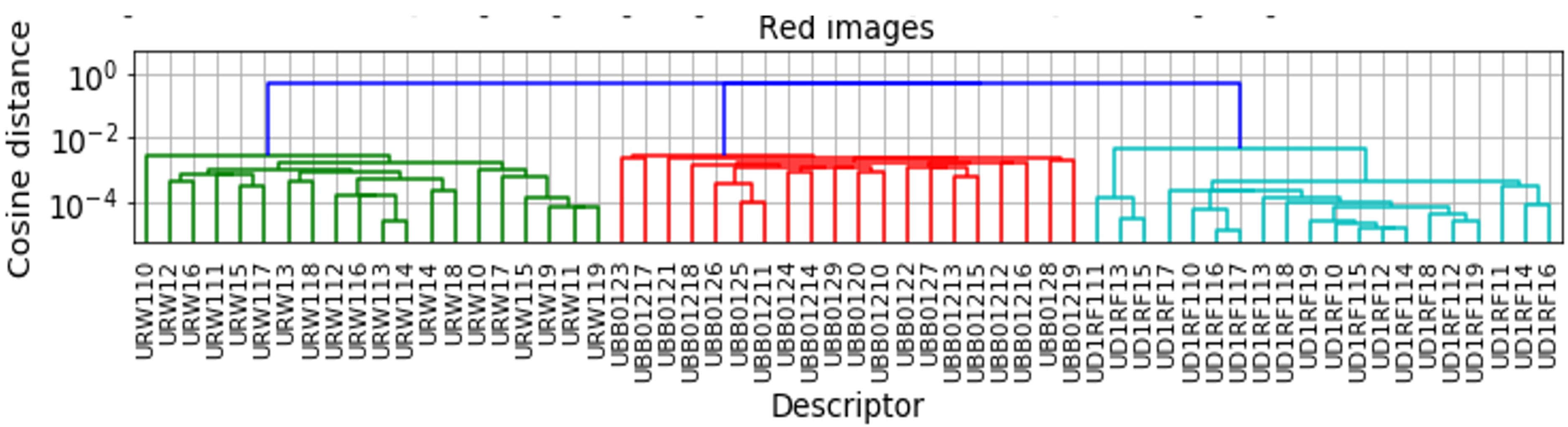


IMAGE TYPE CLUSTERING

Image type	Method	Recall	Precision	F1
BLUE-ext012	2	0.8	0.92	0.8
	3	0.95	0.98	0.96
	4	0.95	0.98	0.96
RED-ext1	2	0.99	1	0.99
	3	0.99	1	0.99
	4	0.99	1	0.99
RED-ext2	2	1	1	1
	3	0.99	1	0.99
	4	0.99	1	0.99

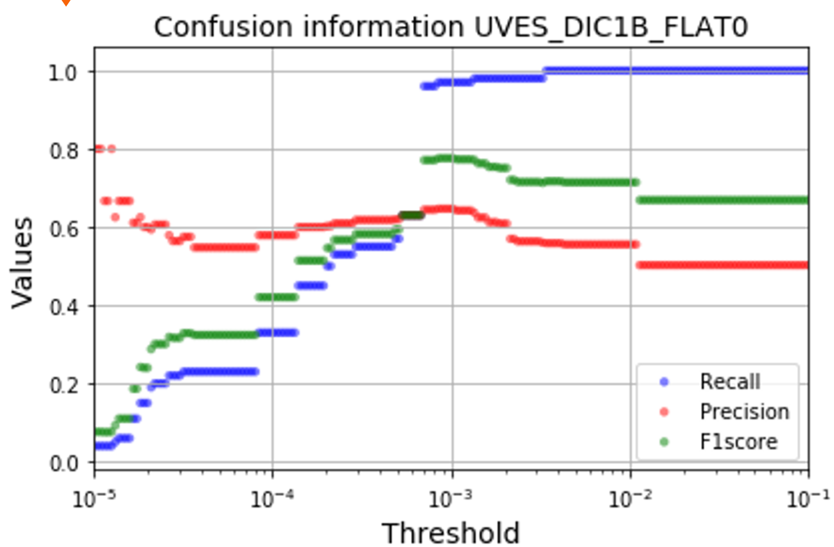
- 200 images for period 2010-2019.
- The number of clusters approach allows to separate different type of images in different clusters with good statistics.

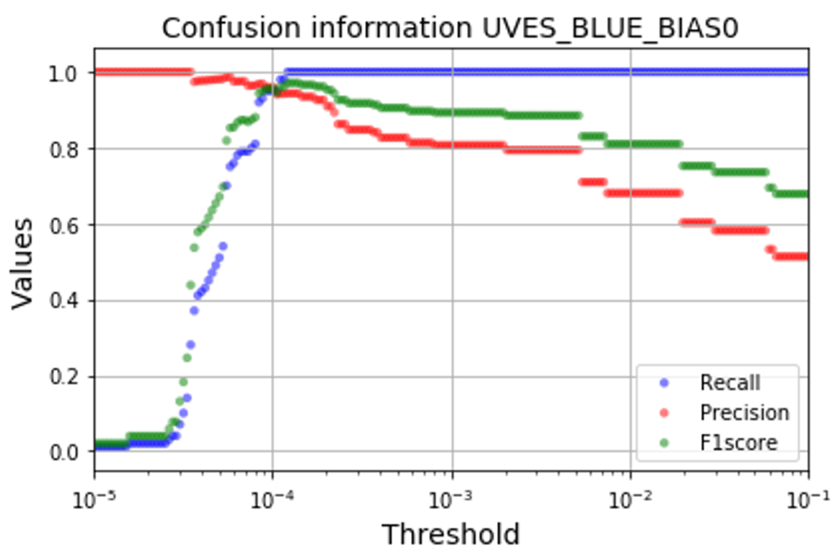
IMAGE TYPE CLUSTERING

- 200 images for every year
- The number of clusters approach allows to separate different type of images in different clusters with good statistics in the most recent years.

Method 2	Year	Recall	Precision	F1
BLUE-ext012	2018	0.98	0.99	0.98
	2017	0.94	1	0.97
	2015	0.86	0.99	0.91
	2010	0.63	1	0.7
	Average	0.85	1.00	0.89

BAD IMAGE IDENTIFICATION





- The threshold based clustering approach is useful to look for bad images.
- It looks for a threshold to maximize the F1-score indicator.

BAD IMAGE IDENTIFICATION

- The threshold based clustering approach is useful to look for bad images.
- It looks for threshold to maximize the f1-score estimator.

Method 3			
Image type	Recall	Precision	F1
UBB0	1	0.94	0.97
URB1	0.92	0.86	0.89
URB2	0.97	0.91	0.94
UBW1	0.94	0.6	0.73
UBW2	0.94	0.61	0.74
UD1BF0	0.91	0.6	0.73
UD1BDF0	0.97	0.65	0.78
URW1	0.94	0.59	0.73
URW2	0.98	0.59	0.74
UD1RF1	0.95	0.74	0.83
UD1RF2	0.92	0.63	0.75
Average	0.95	0.70	0.80

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BAD IMAGE IDENTIFICATION

- Thresholds are different for each image type.
- This quantity must to be set for each image type.

Method 3	
Image type	**Threshold**
UBB0	0.00012
URW1	0.00093
UD1RF1	0.00037

BAD IMAGE IDENTIFICATION

- The example shows an identification with F1=0.98, a recall of 1.0 and a precision of 0.95.
- All *_b labels mark the bad images (from Nicola's set).

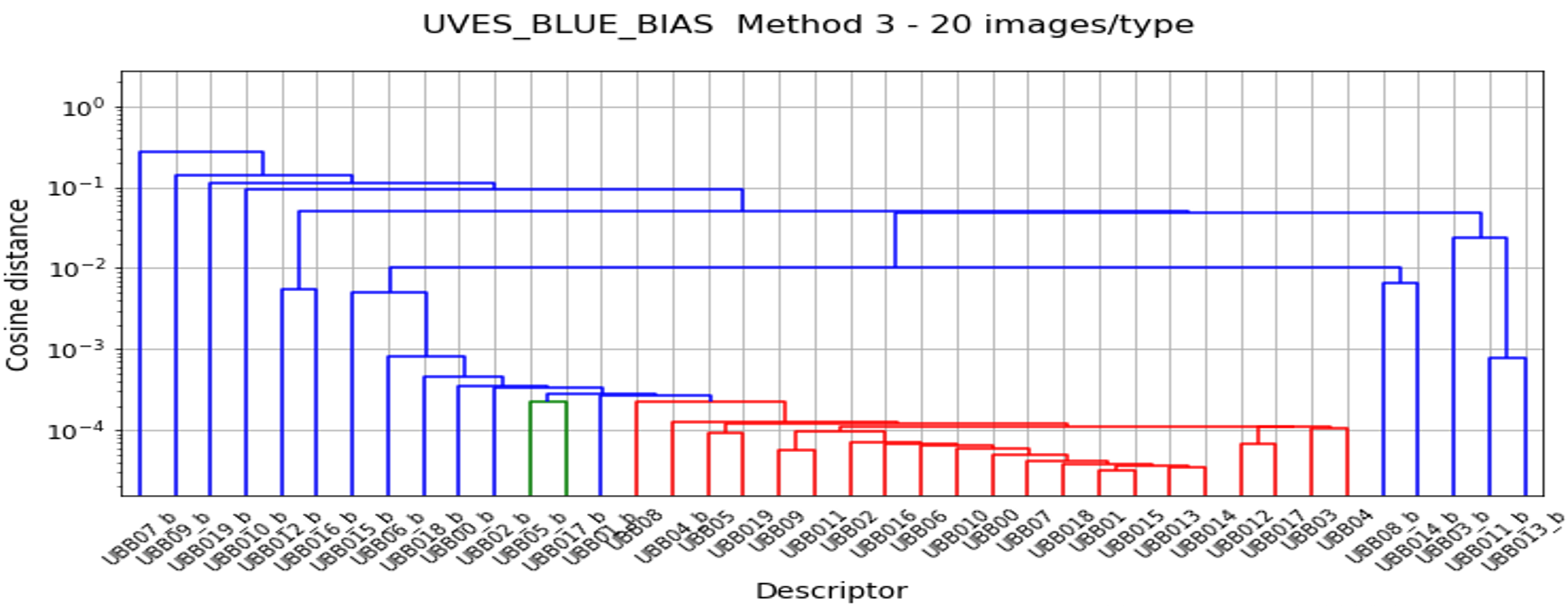

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IMAGE CLASSIFICATION

- ESO team image clasification results using ANN:
- UVES_BLUE_BIAS_ext0 :99.95
- UVES_BLUE_WAVE_ext1 :99.5
- UVES_BLUE_WAVE_ext2 :100.0
- UVES_DIC1B_DFLAT_ext0 :100.0
- UVES_DIC1B_FLAT_ext0 :99.3
- UVES_DIC1R_FLAT_ext1 :99.85
- UVES_DIC1R_FLAT_ext2 :99.85
- UVES_RED_BIAS_ext1 :99.9
- UVES_RED_BIAS_ext2 :99.75
- UVES_RED_WAVE_ext1 :99.95
- UVES_RED_WAVE_ext2 :99.05

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ACHIEVEMENTS

- Managed large datasets of astronomical images
- Developed a method to compute descriptors
- Trained one supervised and one unsupervised model to classify images using descriptors
- Models have recall higher than 95%
- MetricArts team developed tutorials for data processing and analysis

ACHIEVEMENTS

- ESO team learned how to connect to Azure and upload/download data from Azure Storage
- ESO team developed skills to explore and analyze data
- ESO team trained a supervised model to classify UVES calibration images
- ESO team applied method to SPHERE science images

ACHIEVEMENTS

- ESO team experimented with different data analysis tools, visualization techniques and clustering methods, like:
  - KMeans,
  - t-SNE
  - PCA
  - Dendograms.

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CONCLUSIONS

- The ResNet50 as feature extraction, combined with cosine_similarity clustering and Artificial Neural Networks gives enough information to classify images and detect outliers in the data.

- We think it is possible to use these ML techniques to build an automated image spotting system to help detecting calibration data anomalies.