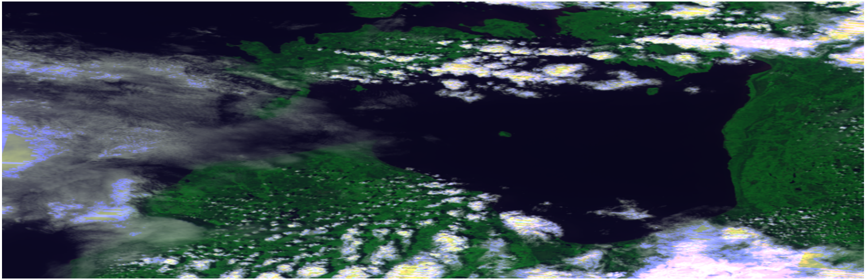
Proba-V Cloud Detection Round Robin Experiment



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ESA PV-CDRR Workshop – 1 March 2017 – ESRIN, Frascati, Italy

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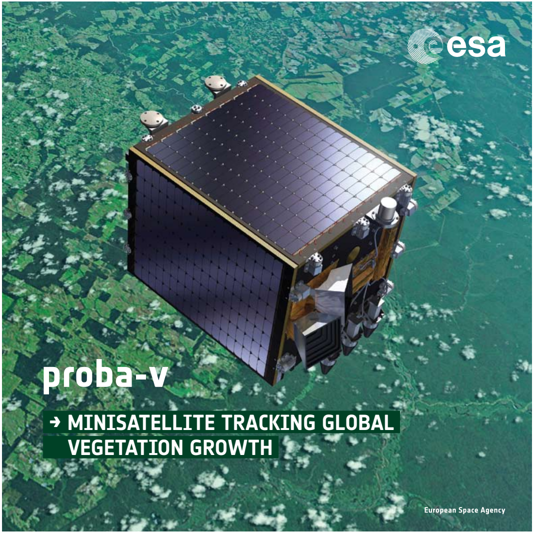
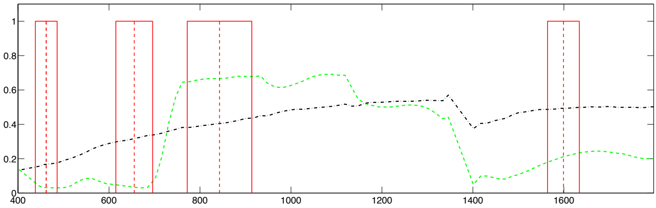
Proba-V

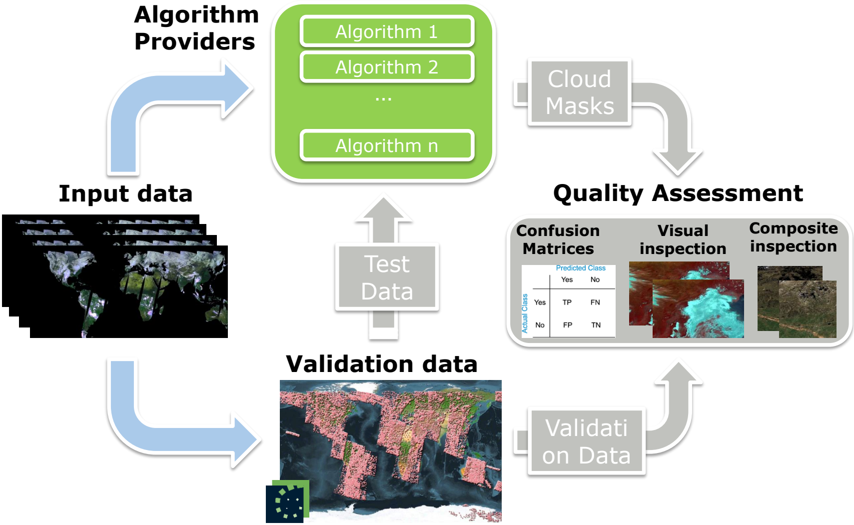

esa
proba-v
→ MINISATELLITE TRACKING GLOBAL VEGETATION GROWTH
European Space Agency

Motivation

- **Undetected clouds** still represent a major source of **uncertainty** for land (and atmosphere) applications, this was clearly highlighted during last Proba-V Symposium
- The operational Proba-V algorithm for cloud detection (thresholds-based), despite the clear improvements, part of the upcoming reprocessing, has still some drawbacks (e.g. over-detection in case of large sun/viewing angles)
- **Machine learning methods** allow optimal use of all information from the spectrum and may be the solution to overcome the intrinsic **limitations of Proba-V for clouds** (only 4 bands and no TIR)



ESA PROBA-V Round Robin Experiment (PV-CDRR)



Problem description

- 331 land images.
- 333m spatial resolution (nadir)
- 4 dates (4 seasons).
- 4 spectral channels.

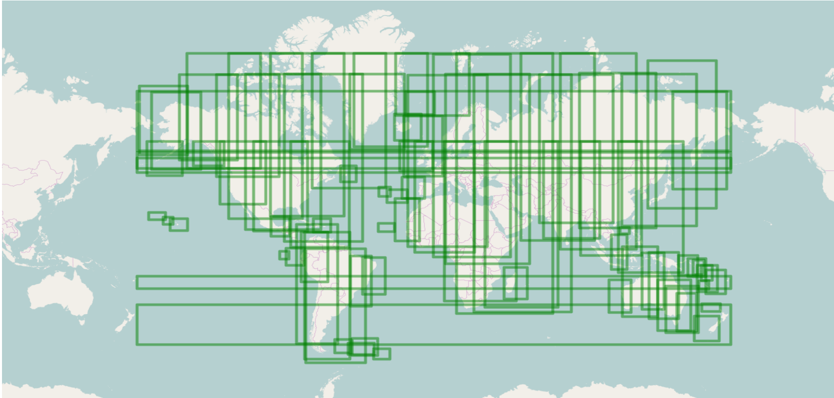


Figure : All images for a given date.

Training Set Generation

- **Cloud detection** can be tackled as a complex **binary classification**
  - Advanced machine learning methods for cloud detection
- **Statistical methods** learn directly from data
  - **Ground truth** required to train the models
  - $\longrightarrow$ Database of images/pixels **manually labeled** as cloudy/clear
- Approach: for each image we will cluster its pixels (GM model) and we will **manually label every cluster**.
  - **Pros** - Many pixels labeled (large training set).
  - **Cons** - *Some* pixel labels will be wrong.
- Afterwards we will **train a supervised classifier** using the (*pixel,label*) pairs.

Unsupervised clustering

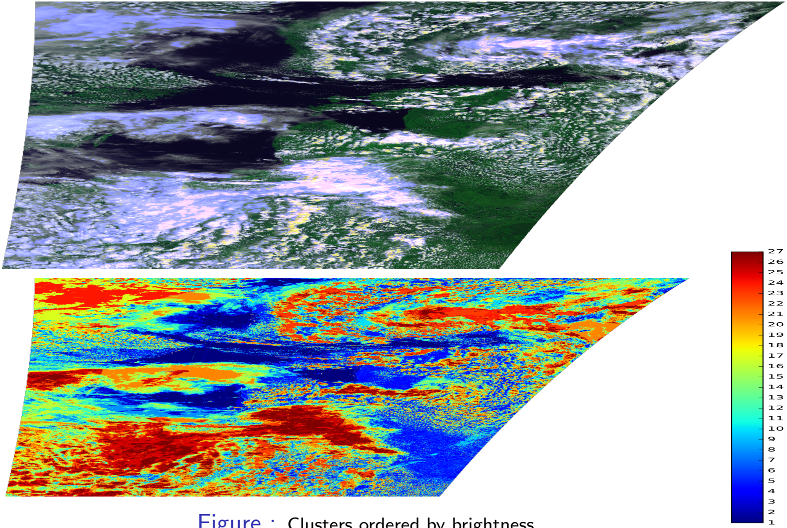
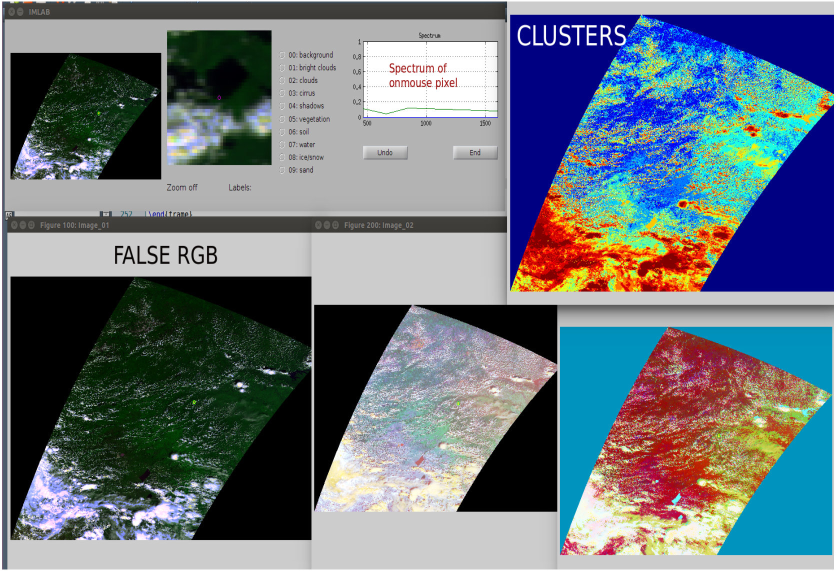
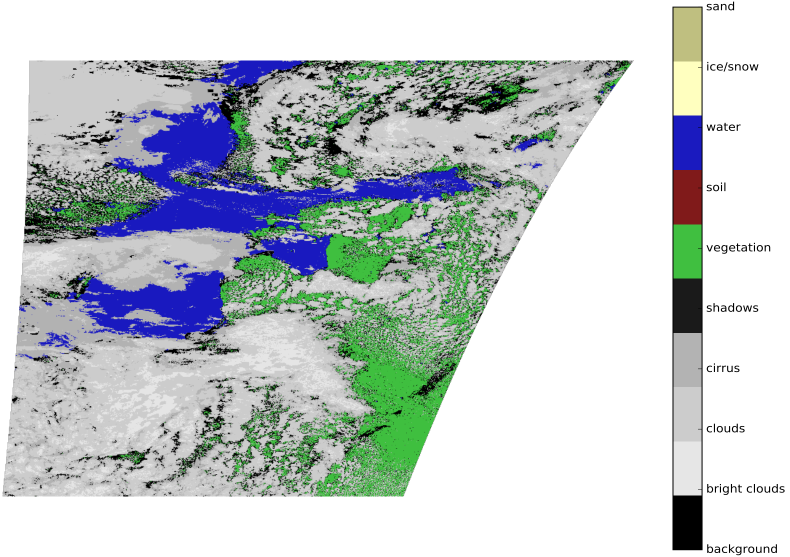


Figure : Clusters ordered by brightness.

Labeling process



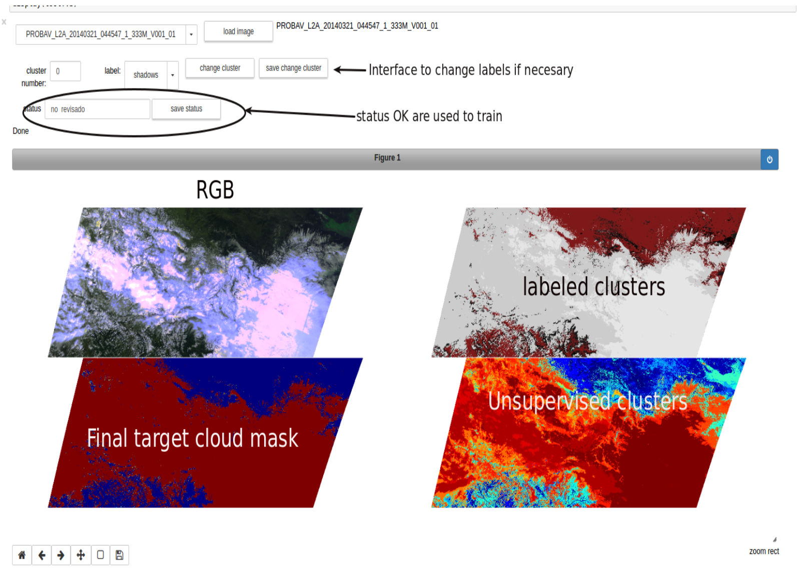
Manual labeling of the clusters



Labeled training set

- Clusters labeled in 10 categories to account for natural variability.
- *'background'* category means 'mixture of categories' and is rejected.
- Conversion of those categories into 1 for *'cloud'* and 0 for *'clear'*.
- Visual inspection of this ground truth mask.
- This binary mask is used for training a classifier.

Manual examination of target masks



Labeled training set

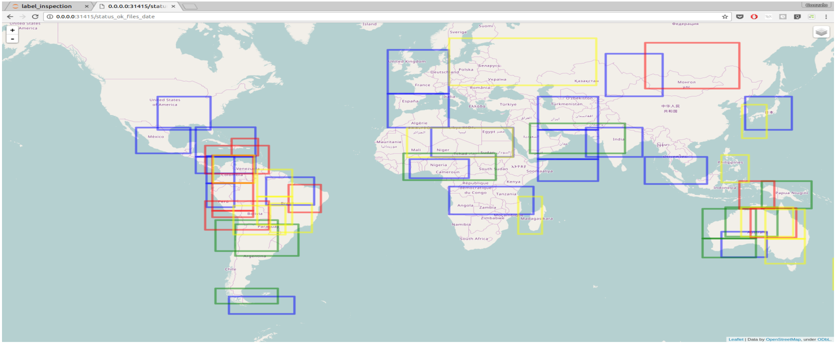


Figure : Labeled image set (colors correspond to different dates)

- 115 images manually labeled.
- 54 of those 115 have a reliable cloud mask (Figure).
- 48 of those 54 were used for training.

Methodology

Feature extraction + **supervised classification** approach:

- **Feature extraction**: Convert pixels from 4 dimensional space to D dim space ($\mathbb{R}^D$), in such D dimensional space clouds should be more *easily* identified.
- **Sample selection**: representative sample of training pixels
- Fit a **supervised classification model** on this samples.
- Apply the model to all pixels of all images.

Feature extraction

Basic spectral features:

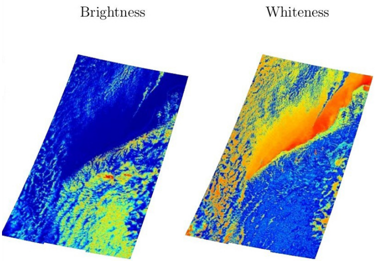


Table : Cloud features extracted from Proba-V.

Cloud Feature	Feature
Brightness	x_{Br}
Brightness VIS	$x_{Br,VIS}$
Brightness NIR	$x_{Br,NIR}$
Whiteness	x_{Wh}
Whiteness VIS	$x_{Wh,VIS}$
Whiteness NIR	$x_{Wh,NIR}$
Snow NDSI	$x_{(Blue-NIR)/(Blue+NIR)}$
Snow NDSI	$x_{(Blue-SWIR)/(Blue+SWIR)}$
Red-SWIR ratio	$x_{Red/SWIR}$
NDVI	$x_{(NIR-Red)/(NIR+Red)}$

Basic spatial features: mean and std at two scales (3×3 and 5×5).

- the four Proba-V spectral channels (4),
- the spectral features described in the Table (10),
- the mean (μ) and standard deviation at two different scales, which are computed for each pixel-based feature ($(4 + 10) \times 4$).

That results in a total number of 70 possible input features.

Feature Selection

In order to reduce the **complexity** of the trained classifiers, we define two sets of features with the first 20 and 40 **most relevant features**, which are selected using both filter and wrapper approaches.

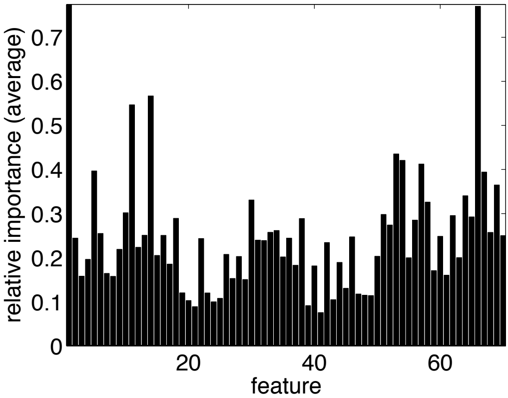


Figure : Ranking of the extracted features.

Classification methods

Standard ML classification methods are analyzed:

- Multilayer perceptron neural networks (MLP)
- Support vector machines (SVMs)
- Classification trees (TREE)

Pre-processing and Experimental setup

- Data converted to **TOA reflectance**
- Features **normalized** to be 0-mean and 1-std according to the mean and std of all (48) training images
- To train the classifiers we select **balanced training set** of pixels
  48 training images 1.573×10^9 labeled pixels $\rightarrow 10^5$ training pixels

bright clouds	clouds	cirrus	ice/snow	sand	shadows	soil	vegetation	water
3%	25%	21%	1%	1%	1%	16%	14%	18%

- We **compare** all methods for different number of samples (1, 2, 3, 4,6,10) $\times 10^4$ and with different combinations of features (`top20`, `top40`, `all`, `feat` and `spatial`).

Classification results

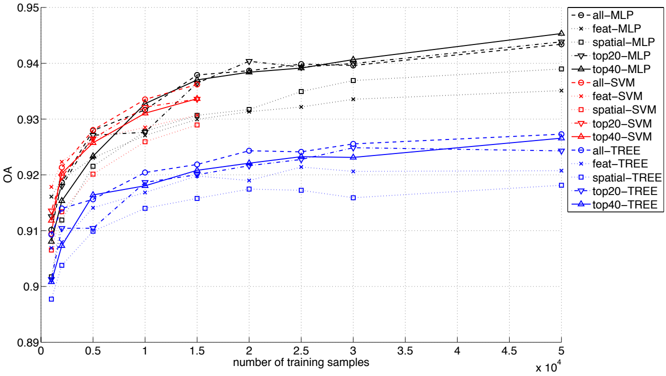


Figure : Overall Accuracy (OA%) over the test sets for the analyzed methods (TREE, SVM and MLP). The number of input features (spectral, spatial, and all features) and training samples per class vary for each test set.

Validation images (manually labeled)

Selected method: **multilayer perceptron (MLP) with top 40 features**.

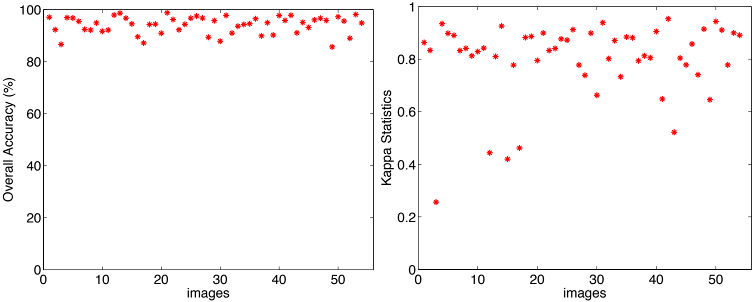
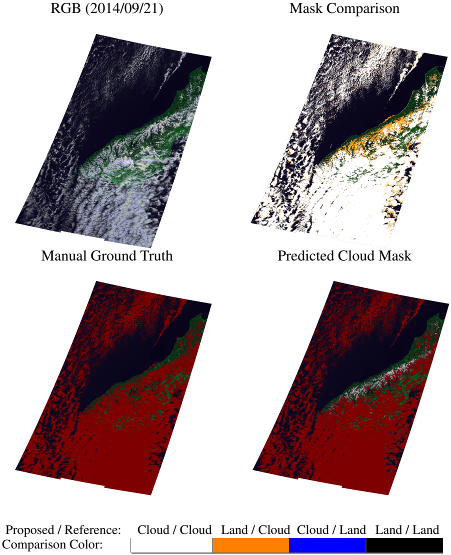


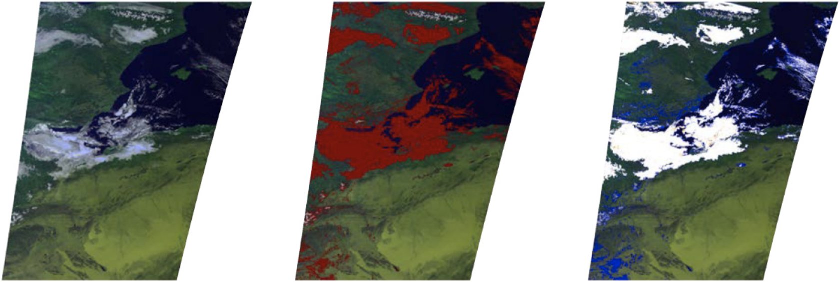
Figure : Overall Accuracy (%) for the 54 images, which were manually labeled in order to be used as reference (ground truth).

Cloud detection example



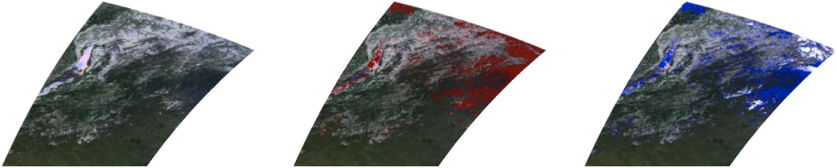
Cloud detection example II

20141221 (104105)	Cloud Mask	Agreement (93%, κ =0.78)



Cloud detection example III

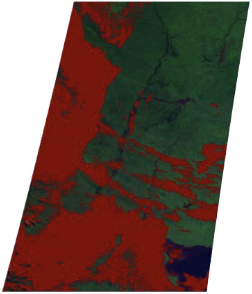
20140321 (044547) | Cloud Mask | Agreement (86%, κ =0.26)



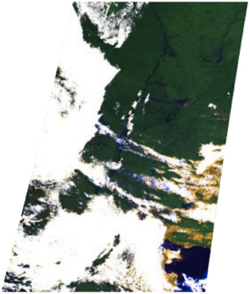
Cloud detection example IV

20140621 (144544)

Cloud Mask



Agreement (94%,κ =0.89)



Implementation

- SNAP
  - Read and split orbits in smaller subimages
  - Save subimages as DIMAP files
- Matlab
  - Manual labeling (ground truth generation)
  - Feature Extraction
  - Training of classification models
- Python
  - Visual quality check
  - Cloud mask HDF5 file generation
- Ground segment implementation (advantages/drawbacks)
  - No ancillary data required (*vs. reference reflectance maps*)
  - No multitemporal information (*vs. cloud change detection*)
  - Single global model (*vs. combination of classifiers*)
  - Simple inputs as small patches (*vs. advanced spatial features*)
  - Fast and parallel implementations for NN predictions

Summary

- Cloud detection for Proba-V images.
- Simple spatio-spectral physically-based features.
- A supervised classification (training samples).
- ML methods and scenarios have been compared.
- MLP trained with manually labeled real data.

Criticism/Open issues

- **Quality Assessment**: accuracy over bright surfaces (ice, snow, sand, sun glint), detection of thin clouds (cirrus, dust), validation over different world regions (arctic regions)
- **Oversimplified labels**: cloud mask (1-0)
- **Oversimplified spatial features**: mean and std
- **Coupling between cloud and shadow** detection neglected:
    - The method does not provide a shadow mask
- **Available training set** determines the quality of the results:
    - Number of samples, accurate labels, comprehensive cases, ...
    - To merge available labeled sets from all PVCDRR teams?

Parallel Activities

- Convolutional Neural Networks for cloud classification:
  - Automatic learning of advance spatial features
  - Improvement of +1% in accuracy
- IGARSS2017 presentations (submitted):
  - ‘Cloud detection machine learning algorithms for Proba-V image cloud masking’
  - ‘Convolutional neural networks for image cloud masking’
- Related Projects:
  - Google Earth Engine Award (2016-2017)
  - Spanish National R+D+i project (2017-2019)

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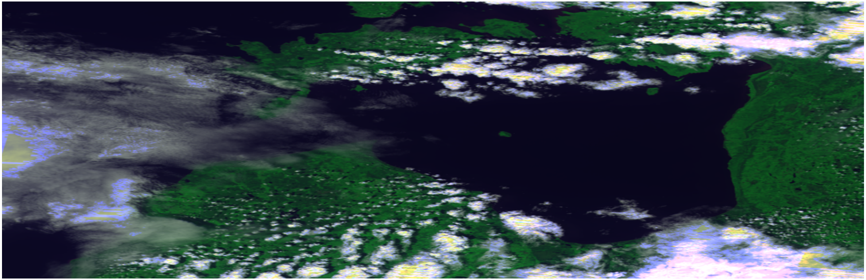

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