Deep Learning on jovian decametric emissions

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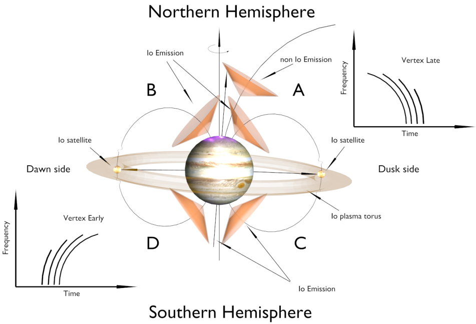
Direction Informatique de l'Observatoire

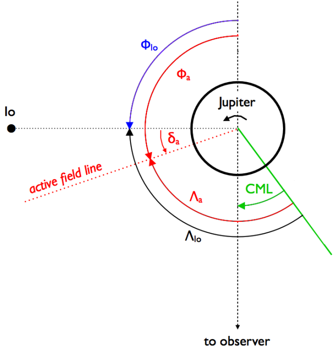
Semi-Hack-a-thon ASOV – March 24th 2021

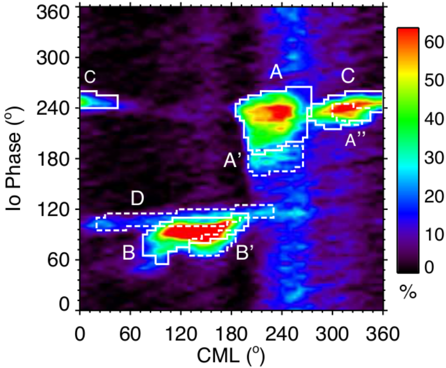
Jovian decametric emissions

Observed since the 50's, Jovian decametric emissions are produced by the cyclotron-maser instability, due to solar wind or by Jupiter-Io electrodynamic interaction.



Jovian decametric emissions

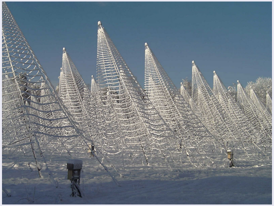




Probability of occurrence wrt. Jupiter rotation and Io ephemeris

Nançay Decameter Array

Built in the 70's
Numerical data since 1990
10 - 100 MHz
Daily observations of the Sun and Jupiter

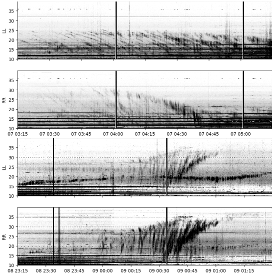


Receiver	# channels	Resolution (ms x kHz)	Data size (8 hours)
Routine	2	500 x 75	22 MB
New Routine	4	500 x 49	568 MB
JunoN	4	2.6 x 3.05	2.9 TB
		83.2 x 12.2	22.6 GB

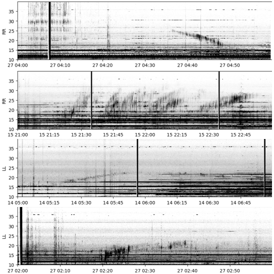
Observations with the NDA

J990807

J950509



Typical Io decametric emissions



J970627

J001115

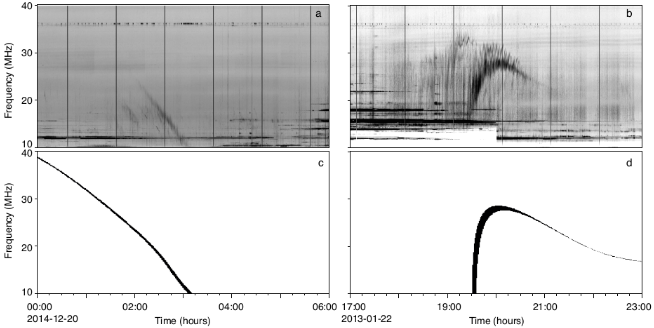
J041114

J001027

Typical non-Io decametric emissions

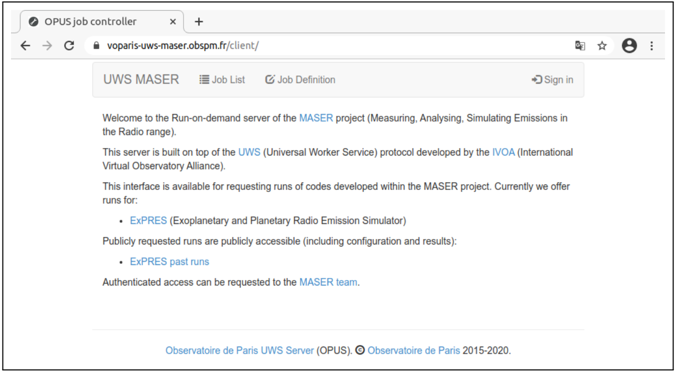
Simulations

ExPRES: an Exoplanetary and Planetary Radio Emissions Simulator (C. K. Louis et al)



https://maser.lesia.obspm.fr/task-2-modeling-tools/expres/

ExPRES : run on demand

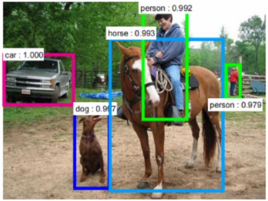


https://voparis-uws-maser.obspm.fr/

Neural networks: why?

Classify

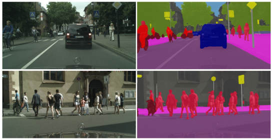
Generate



Localize

DeepL

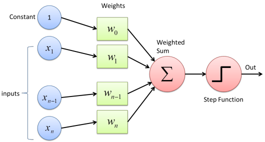
Translate



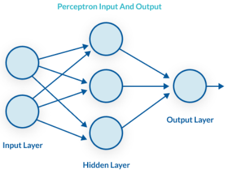
Segment

Play!

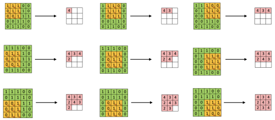
Neural networks: how?



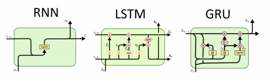
Perceptron (1957)



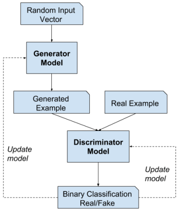
Multilayer Perceptron (1985)



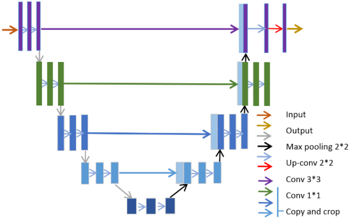
Convolutional Neural Network (1989)



Recurrent Neural Network (1995)



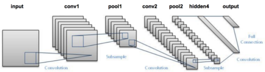
Generative Adversarial Network (2015)



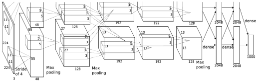
UNet (2015)

Convolutional networks

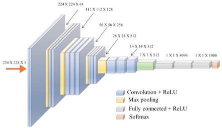
First tries :



LeNet (1989)

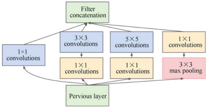


AlexNet (2012)

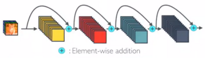


VGG (2014)

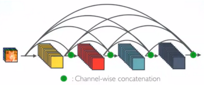
Then optimize convolutional block :



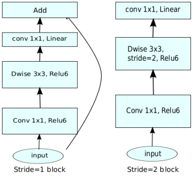
Inception module (2014)



ResNet sketch (2015)



DenseNet sketch (2016)



MobileNetv2 (2019)

Latest trends in CNN

Deeper networks (ResNet, DenseNet)

Wider networks (Wide ResNet, Pyramidal Net, ResNeXt)

Smaller networks (MobileNet, EfficientNet)

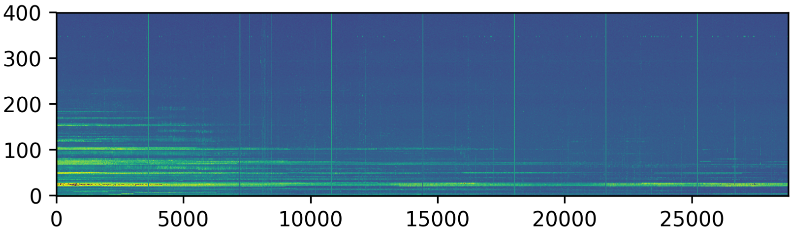
Learn best architecture instead of handcraft it! (NASNet, AmeobaNet, EfficientNet)

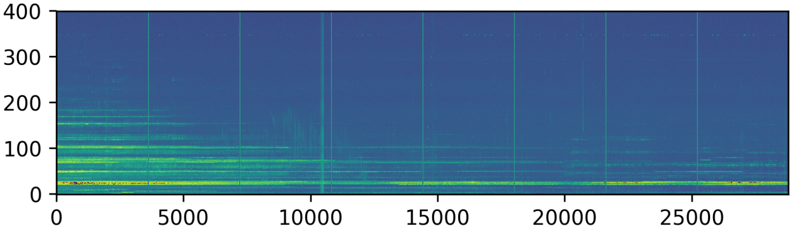
CNN Performance evolution

Net	Year	# params	FLOPS	ImageNet top 5
AlexNet	2012	60M	0.7B	80.4%
GoogLeNet	2014	6.8M	1.6B	90.8%
VGG19	2014	143M	19.6B	90.1%
ResNet-50	2015	26M	4.1B	92.3%
DenseNet-169	2016	14M	3.5B	93.2%
MobileNetV2	2019	3.4M	0.3B	90.5%
EfficientNet-B0	2019	5.3M	0.39B	93.5%
EfficientNet-B3	2019	12M	1.8B	95.6%

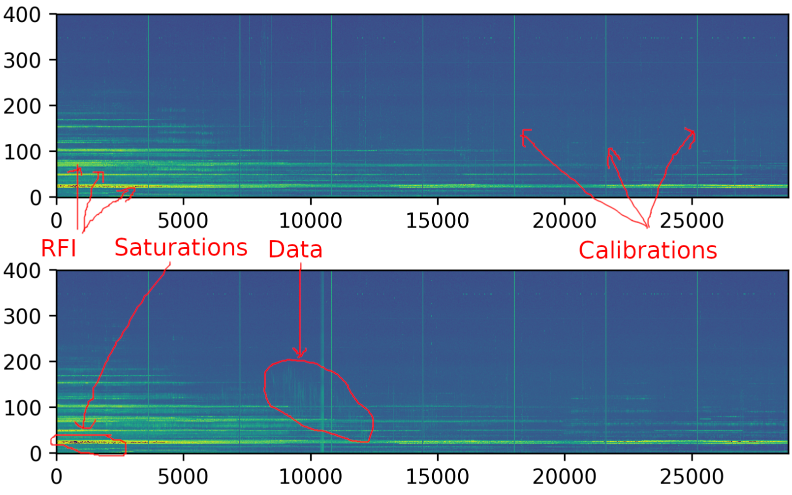
Pretrained models are freely available. Using them speeds up training.

Data exploration





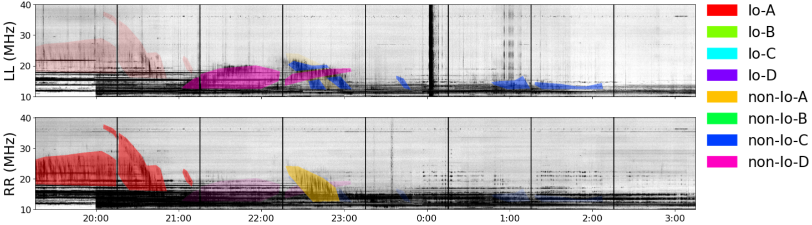
Data exploration



Catalog

Marques et al (2017) built a catalog of 26 years of jovian decametric emissions.

8163 observations ($\sim$ 8 hours), 11463 emissions (type, polarization, time range, freq. range, polygon)



Data preparation

Cut samples of 4000 s into observations.

Clean calibrations, background, filters.

Normalize data wrt mean, sigma.

Reduce (mean) to samples of size 400 (time) x 400 (freq) x 3 (channels = LH, RH, Circular pol)

Output = segmentation into 9 types (nothing, Io-A,B,C,D and Non-Io-A,B,C,D) reduced to 100x100.

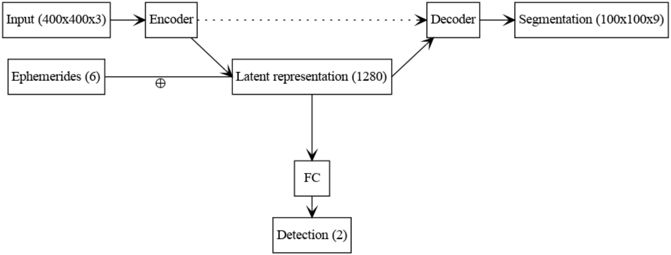
17968 samples in training set, 1998 samples in validation set (balanced wrt presence of emission)

Convolutional Network

Unet architecture, with EfficientNetB0 as encoder and a simple convolutional decoder.

Probability of detection obtained via a fully connected network connected to the latent space.

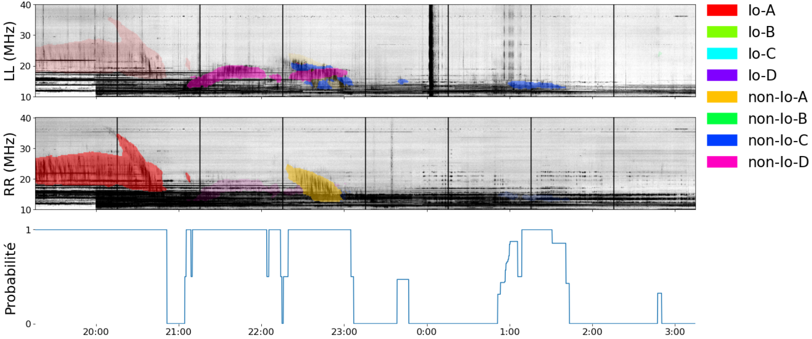
14 M parameters, 10 M in the decoder.



Results

Detection of emission : $>$ 97 % success

Segmentation : $>$ 92 % IOU.



Visualization portal

Visualization of the catalog and neural network predictions:
https://voparis-minerva-jupiter.obspm.fr/

Validation of the predictions

Probability check for an emission:
https://jupiter-probability-tool.obspm.fr/

- Check if Io emission is probable
- Compare with ExPRES simulation and observation

Perspectives

Reduce decoder parameters to speed up training and infering.

Apply to emissions due to Ganymede and Europa.

More validations

Build a TAP service with the original catalog and the automated predictions. Use B. Cecconi's TFCAT to describe polygons.

Detection in real time and signaling with VoEvents.

Thank you!