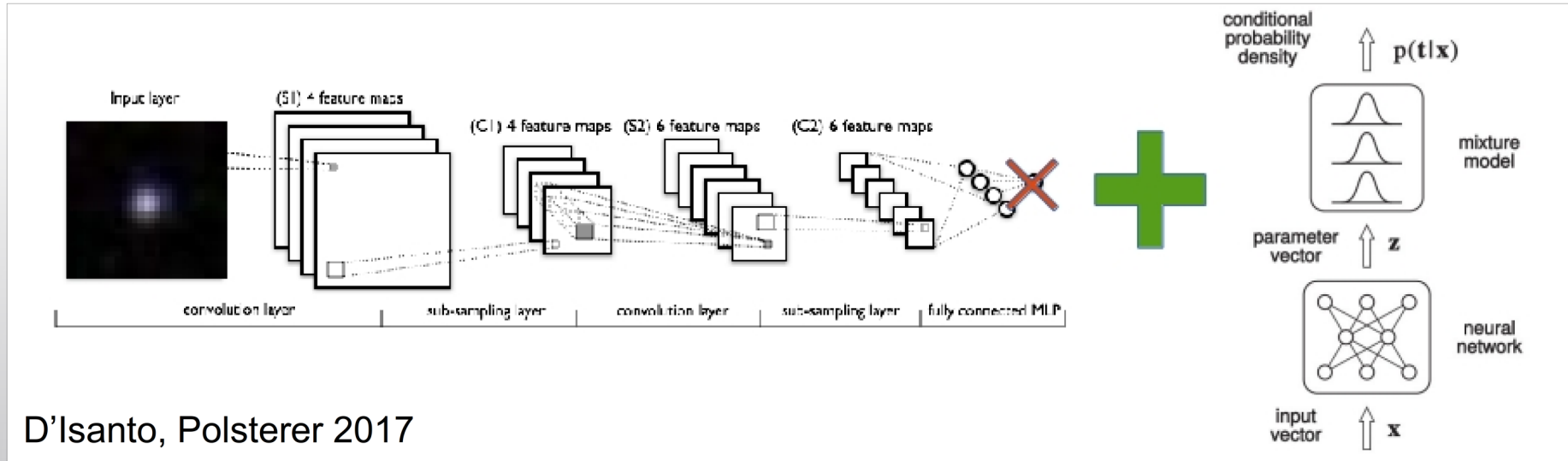


Code to the Data

a hard deep learning example

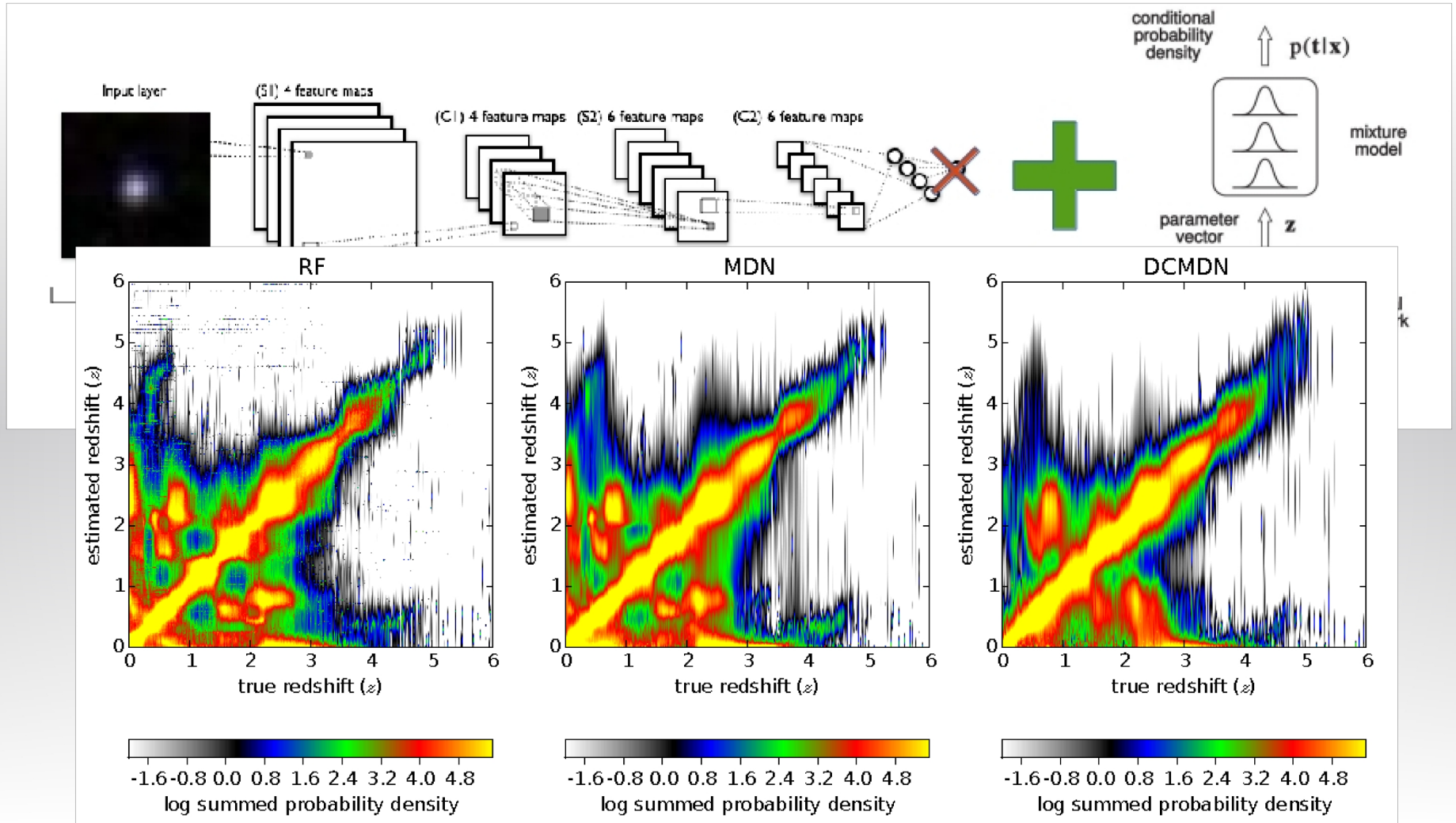
Deep Convolutional Network meets Mixture Density Network



predict redshifts photometrically,
purely based on images

→ find new high redshift objects

Deep Convolutional Network meets Mixture Density Network



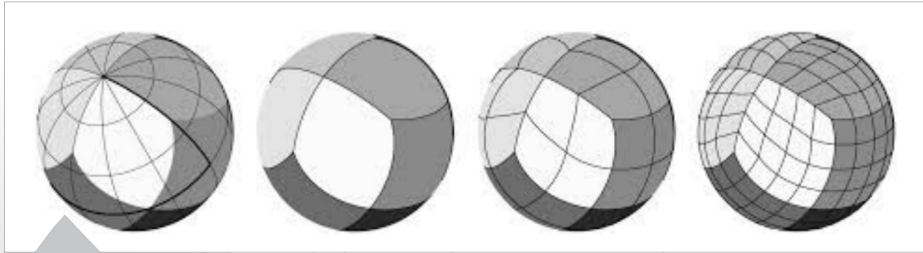
Code to the Data: a story of failures



Creating training data

- find all objects in CFHTLS wide with SDSS spectra + redshift
 - merge Schneider et al. 2010 & Paris et al. 2017
 - crossmatch with CFHTLS wide
 - no MOC at CADC → CDS
 - Aladin Beta → 1.000 objects, too few
 - problem with coordinate columns fixed → 3.000 objects, too few
 - all SDSS objects with spectra + other → CSV 5 mio. objects
 - Aladin Beta → out of memory
 - Topcat → 60.000 objects + augmentation (480k = enough)

Download images via Healpix / HiPS



J2000 23 31 7.416 -54 54 31.56

Base image layer

WTF

Color map: nati Reverse

Overlay layers

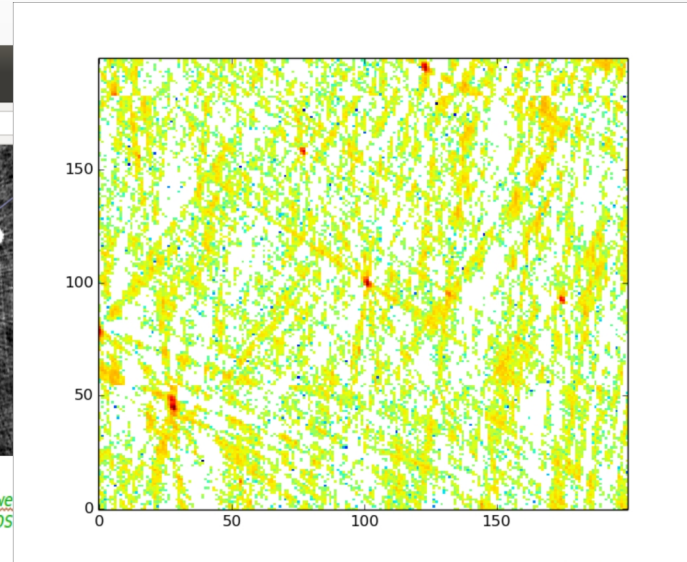
Reticle

HEALPix grid

Tools

Export view as PNG

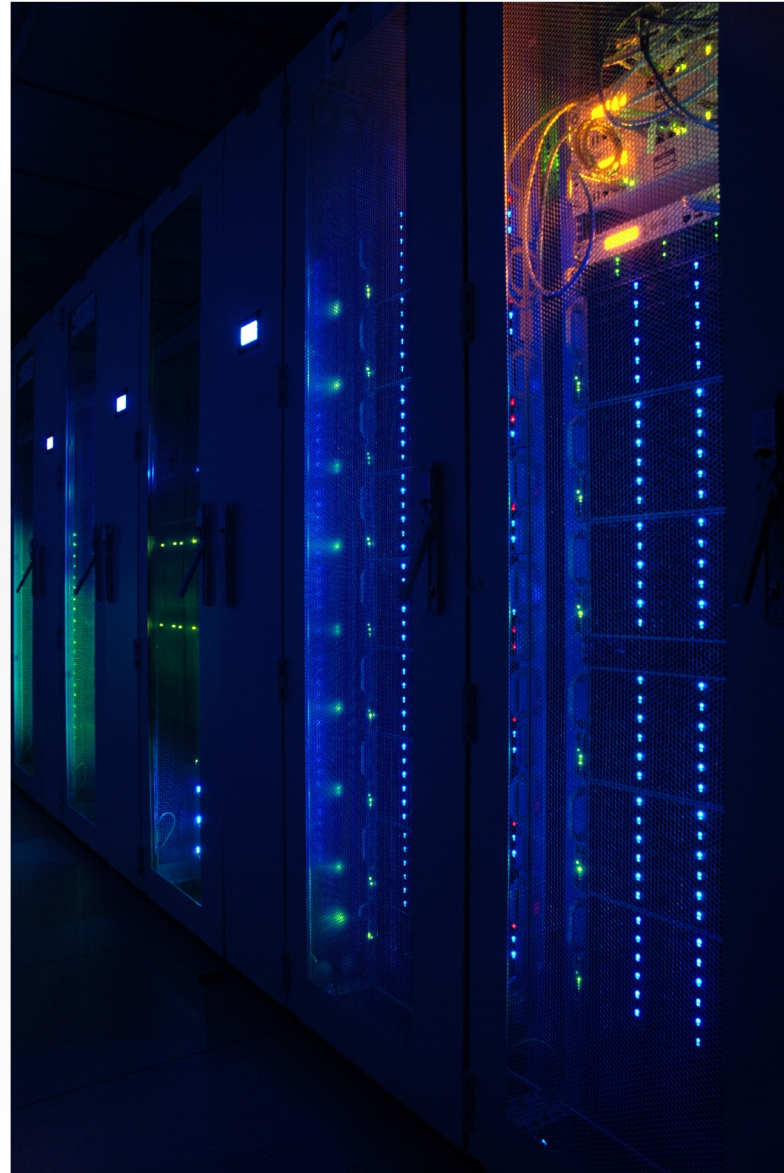
```
230 if __name__ == "__main__":
231     surveyAddress = "atlas-spt-hips-2.s3-west-1.amazonaws.com"
232     surveyAddress = "alasky.u-strasbg.fr/DS"
233
234     coordinate = [350.86, -55.225]
235     size = [200, 200]
236     resolution = 0.002
237
238     myHiPSfs = HiPSfs(surveyAddress) # create access!
239
240     image = myHiPSfs.extractCoordinate(coordinate, size, resolution, nested=True) # extract data array!
241
242     pyplot.figure()
243     pyplot.imshow(image, aspect='auto', interpolation="nearest")
244     pyplot.gca().invert_yaxis()
245     pyplot.show()
```



Training Model

on local GPU – Cluster

- several days
- exclusive hardware



KD Schema

provide the necessary tools to access the data and transfer only the required parts

consider the usage of optimized hardware

provide the data for processing & schedule, optimize and distribute the workload

transfer / post-process data / collect, generate provenance

provide analysis capabilities

