# Automatic generation of magnification maps for lensed quasars and supernovae using deep learning

Somayeh Khakpash[1], Charles Keeton[1], Federica Bianco[2,4], Gregory Dobler[2], Giorgos Vernardos[3]

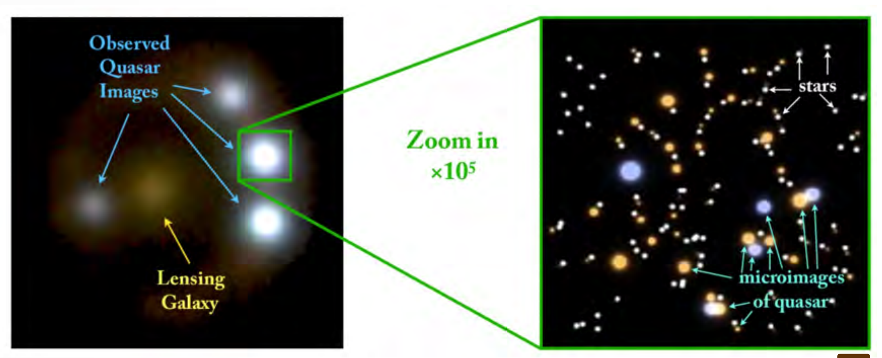
[1] Rutgers University, [2] University of Delaware, [3] CUNY Lehman College, [4] Rubin Observatory

## Extragalactic Microlensing

Images of multiply-lensed quasars and supernovae (SNe) are also affected by the microlensing effect of the stars' pattern within the lensing galaxy.
This phenomenon results in different microlensing variability observed in each of the quasar's images' light curves.
Modeling this microlensing variability is computationally demanding and automated algorithms are need when large surveys like LSST will find thousands of these events.

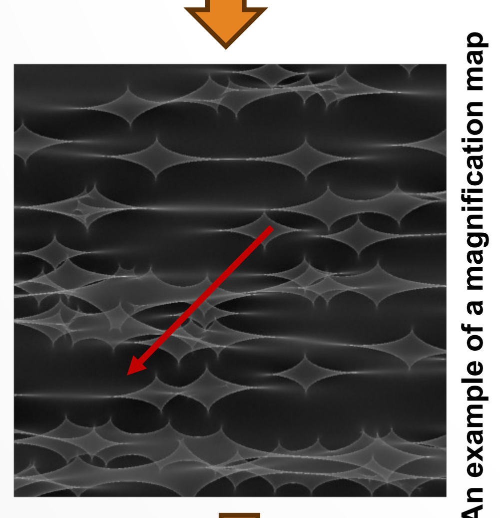
## Modeling Microlensing Variability in Lensed Quasars/SNe

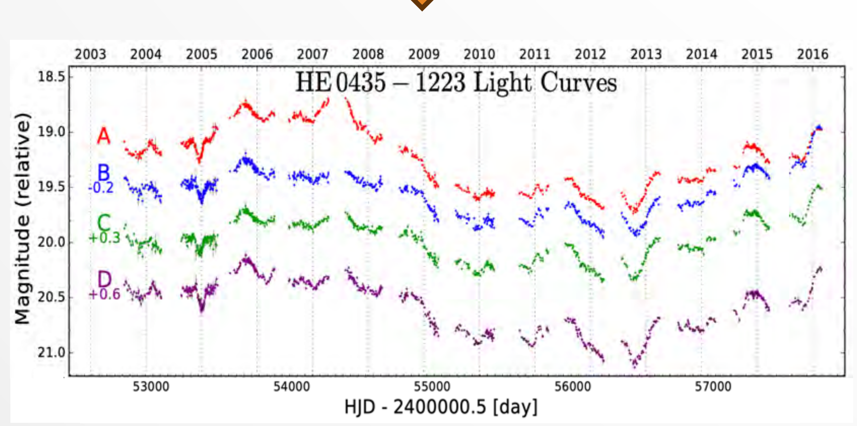
- A magnification map (from now on "map") is needed to model the observed light curve.
- Maps show theoretically the overall effect of a set of microlenses located in the lens galaxy on the source brightness on the source plane.
- The map covers only about 1 $\mu arcsec$ of the sky while a typical galaxy at low redshifts is $\sim 1\ arcsec$.
- Generating a map is a computationally very expensive task.




(1)

$\kappa$: $Convergence$
$\gamma$: $External\ Shear$
$s$: $\dfrac{Smooth\ DM}{Total\ Matter}$



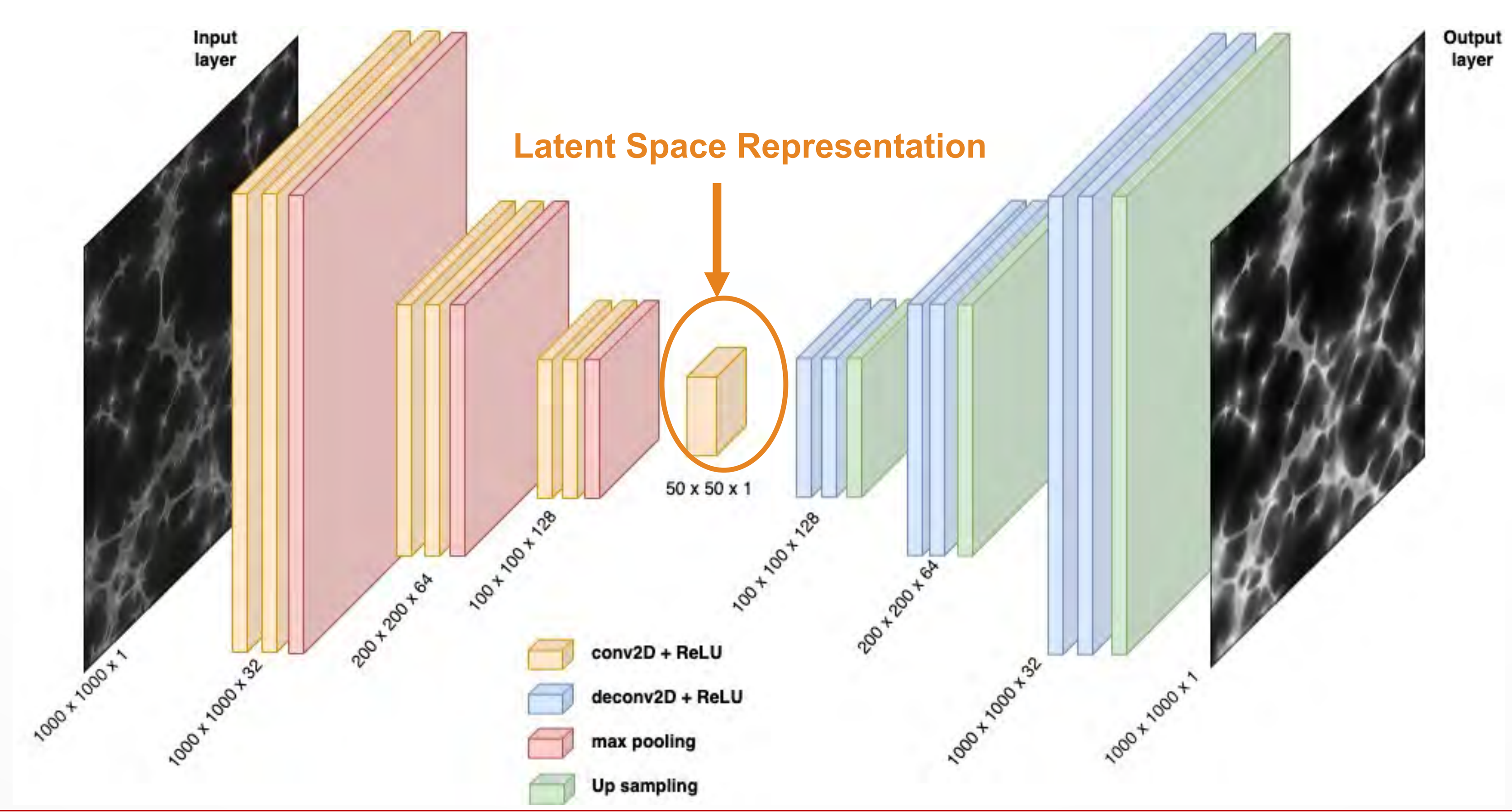

(2)

## Why modeling is this variability important?

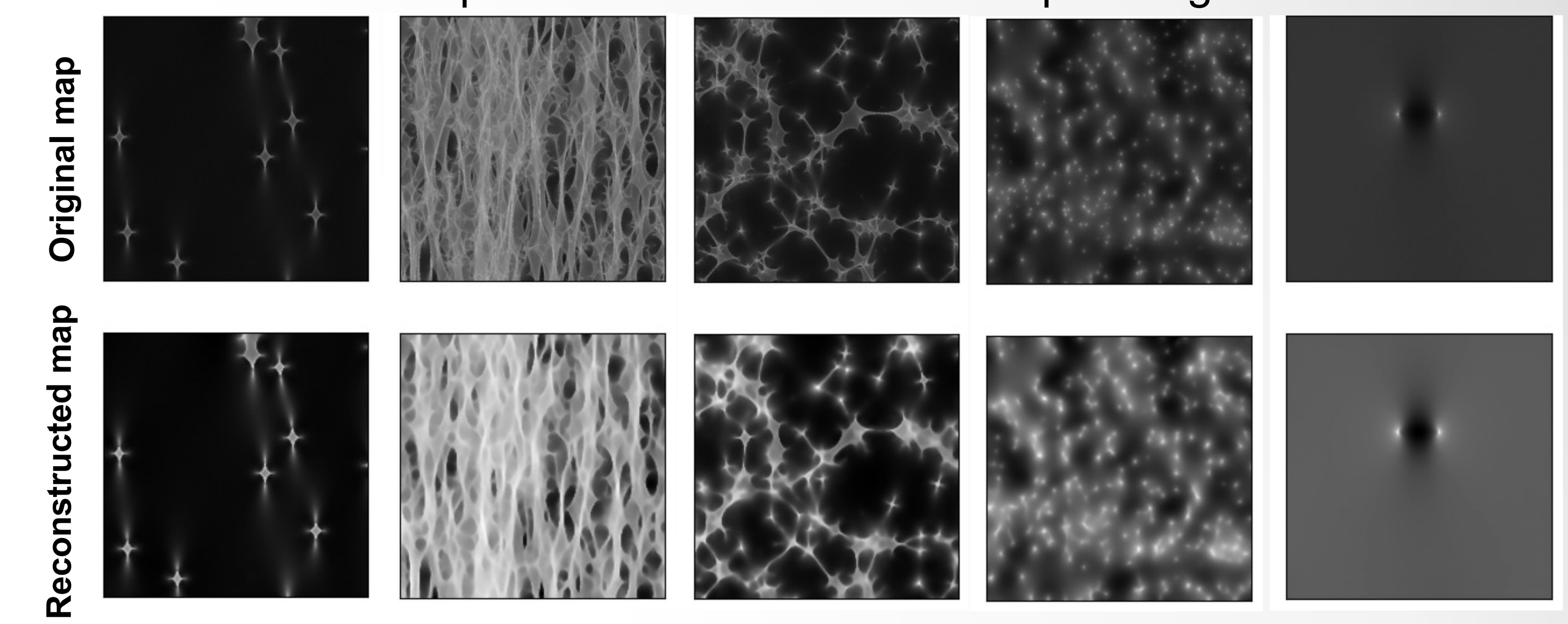
1. Enhanced modeling of the microlensing variation in lightcurves of strong-lensed multiply-imaged quasars leads to more precise measurements of the cosmological time delays and the Hubble Constant.[3]
2. We can study quasar's accretion disk and broad emission line region.[4]
3. We can study the distribution of mass in stars in distant galaxies.[5]

## Using an Autoencoder to generate maps

- The Autoencoder (AE) compresses the input unto a low dimension space called the latent space representation. Then it up-samples the latent space representation and reconstructs the input.
- The AE is trained on ~12300 pre-computed GERLUMPH[6] maps and compresses them from 1000x1000 to 50x50 and back to the original dimensions to regenerate the patterns in the maps.
- When the reconstruction is done well, the latent space representation will contain the most important information in a compressed format.

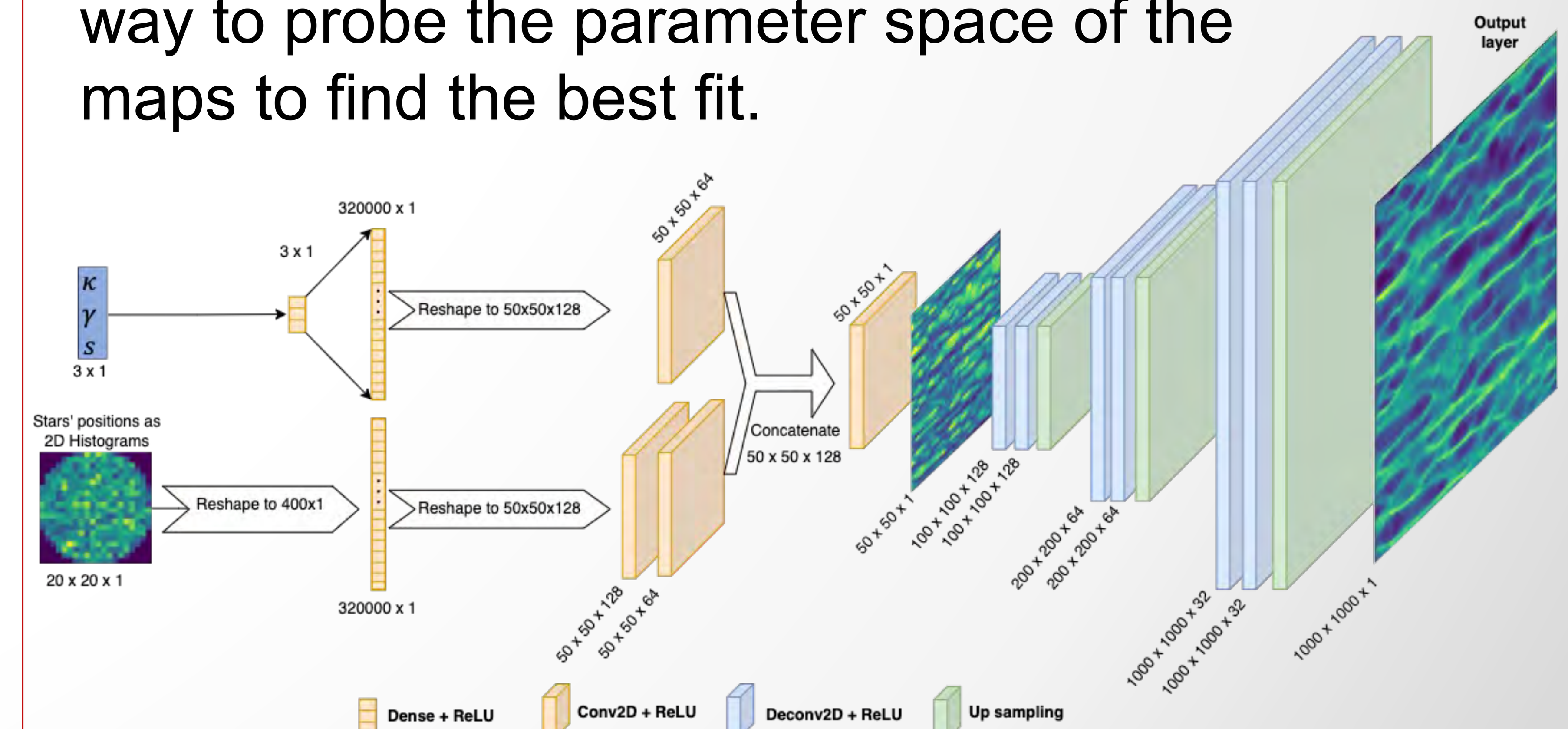



Examples of the reconstructed maps using VAE




## Automated Generation of Maps

- We need an algorithm that can generate maps given the three parameters $\kappa$, $\gamma$, and $s$.
  1. A network that generates the latent space representations given the parameters.
  2. The trained VAE will decode the generated latent space representation into a map.
- The random stars' locations can result in maps that are statistically the same but visually different. We include these locations as a 2D histogram as input to the network in step 1 and use Convolutional Neural Networks CNNs to carry on this task.
- With this approach, we can generate a map in less than a second and use that as a fast and efficient way to probe the parameter space of the maps to find the best fit.




## References

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