

# M2 Thesis Defense

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“Machine Learning for  
Photometric redshift estimation  
of LSST galaxies”

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# Structure

## Introduction:

- Vera Rubin Observatory - LSST
- Photometric redshift
- Machine Learning-Neural Networks
- Convolutional Neural Networks

## Results

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- Sequential CNN
- GoogleNet
- Comparison

## Conclusion and future prospects

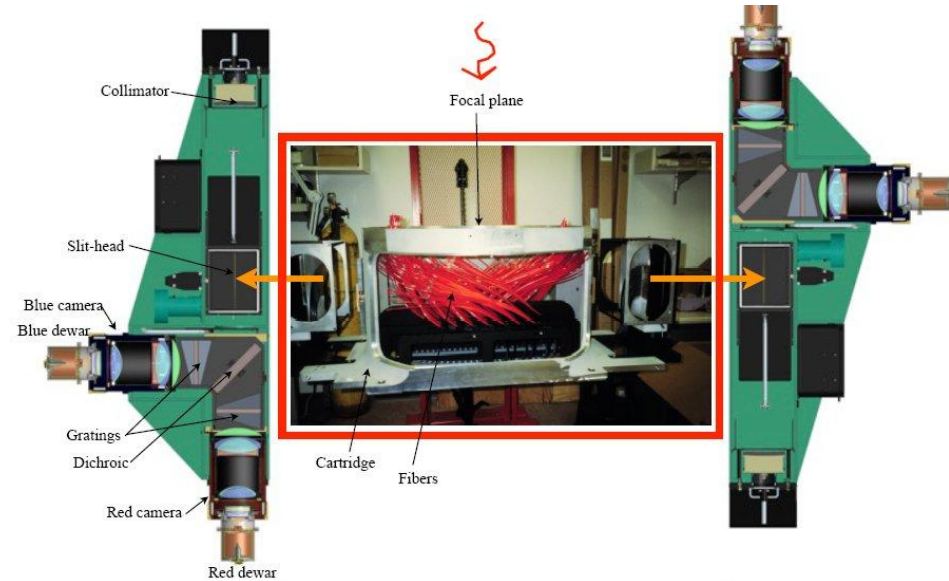
# Vera Rubin Observatory-LSST

- Legacy Survey of Space and Time (LSST) is a wide field survey that is going to observe galaxies in redshifts up to approx. 1.3-1.5, in 6 broad filters (ugrizy).
- It will use the Vera Rubin Observatory and its main goal is to probe Dark Energy and Dark Matter.
- It is anticipated to image around 20 Billion galaxies during its 10 years projected run.



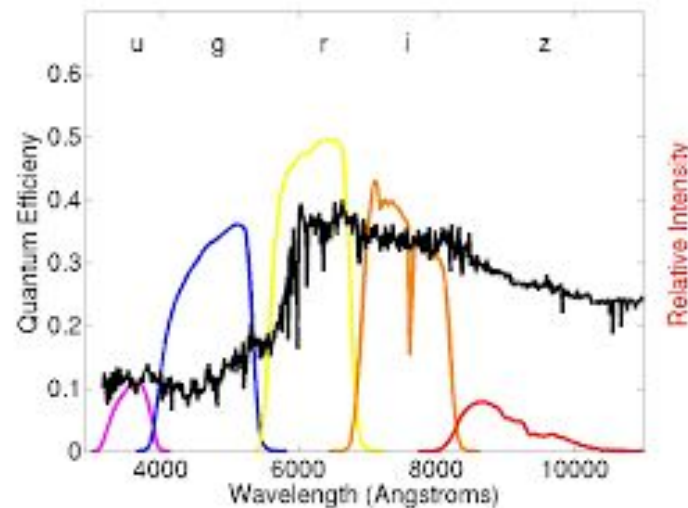
# Vera Rubin Observatory–LSST

- A typical spectrograph can produce spectra of 1000 galaxies each time.
- The spectroscopic measurement of all the galaxies in the LSST survey is not possible.
- Thus, photometric redshift estimation is the only option.
- What is a photometric redshift?



# Photometric redshift

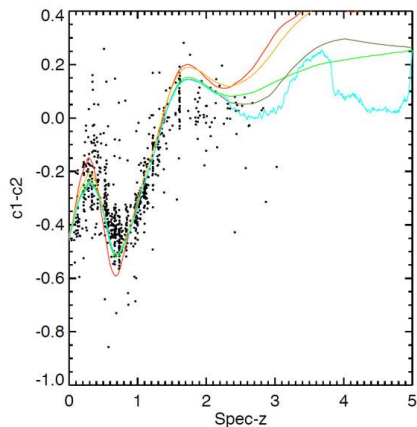
- When the redshift of an object is estimated through flux measurements in broader filters, like the ones used in imaging surveys, it is called a “Photometric redshift”.
- Essentially, it is just a mapping between the colour and the redshift.



# Photometric redshift

- Template fitting

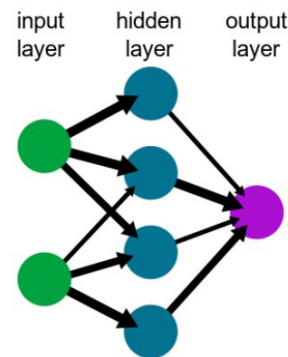
The redshift-colour mapping is based on previous physical knowledge, e.g. galaxy star formation histories, extended observed spectra.



- Machine Learning

The redshift-colour mapping is obtained each time using a representative training sample with both photometry and redshift measurements.

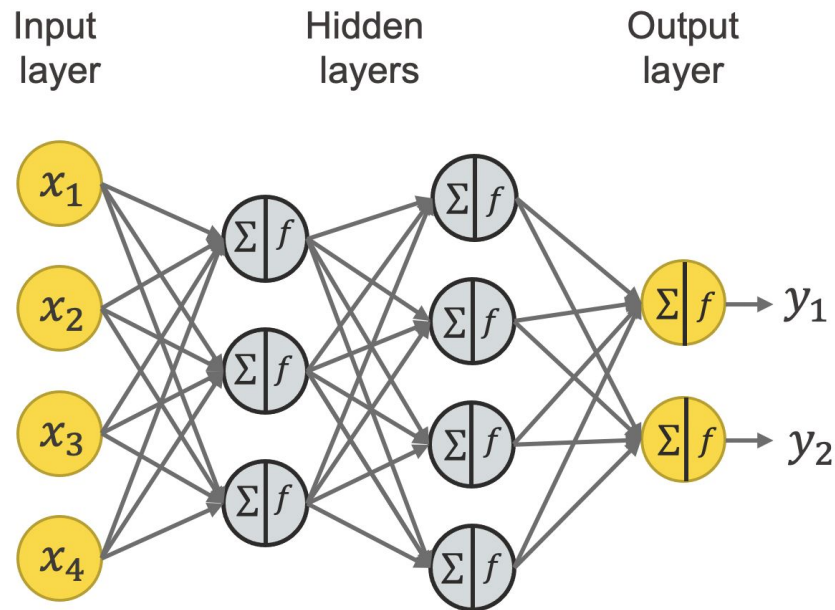
A simple neural network



# Machine Learning–Neural Networks

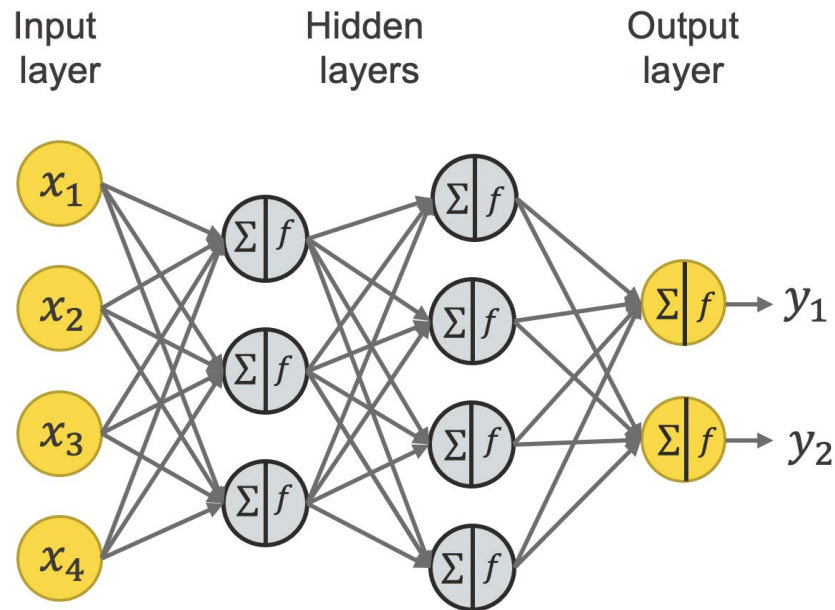
What is a Neural Network?

- An Artificial Neural Network is composed of artificial neurons which mimic the behavior of biological neurons.
- The structure consists of different layers.
- Each layer can be seen as a transformation of those which come before it.



# Machine Learning–Neural Networks

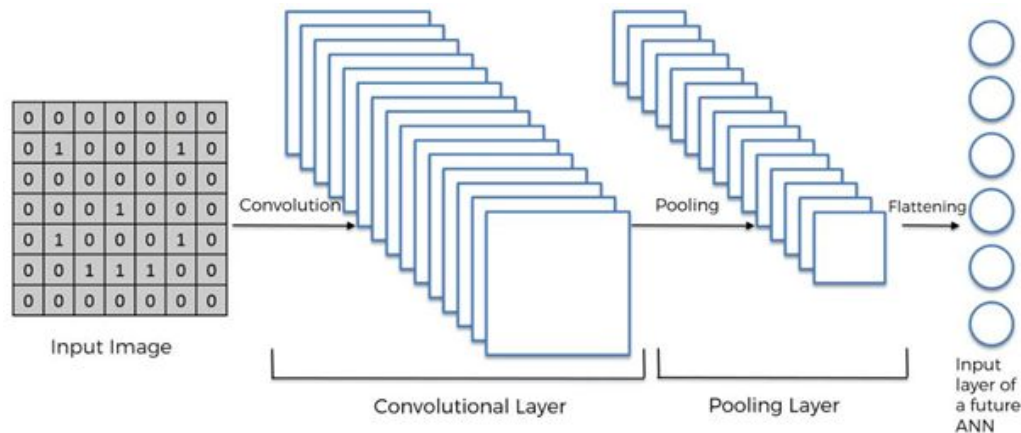
- The output of the NN is specified by the user and represents the target value of interest.
- The algorithm, using the training sample, tunes the transformations so that the output value minimises the residuals between the predicted and the true value.





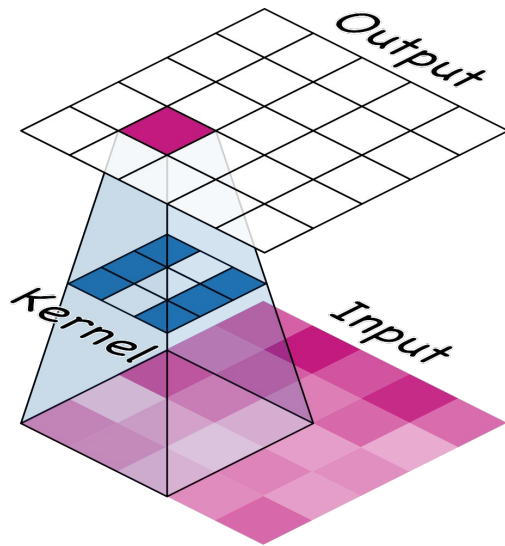
# Convolutional Neural Networks (CNNs)

- CNNs are a special type of multilayered NN composed of a number of convolutional and pooling layers followed by fully connected layers.



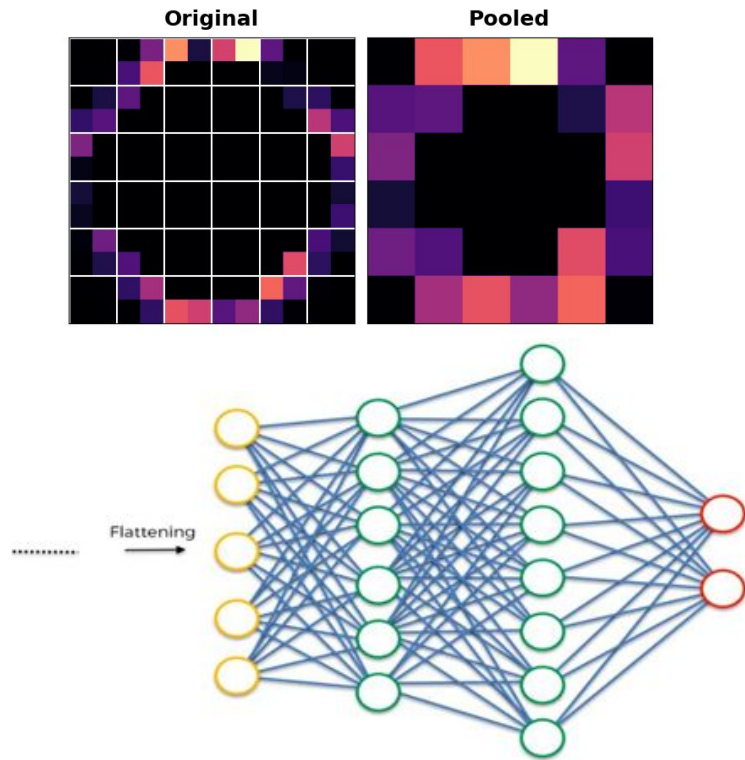
# Convolutional Neural Networks (CNNs)

- Convolutional layers use kernels and they operate on a datacube and compute several feature maps which emphasises regions that correlate with a specific pattern represented by the kernels.
- During the training process, the kernels' weights get updated to become relevant to the classification.



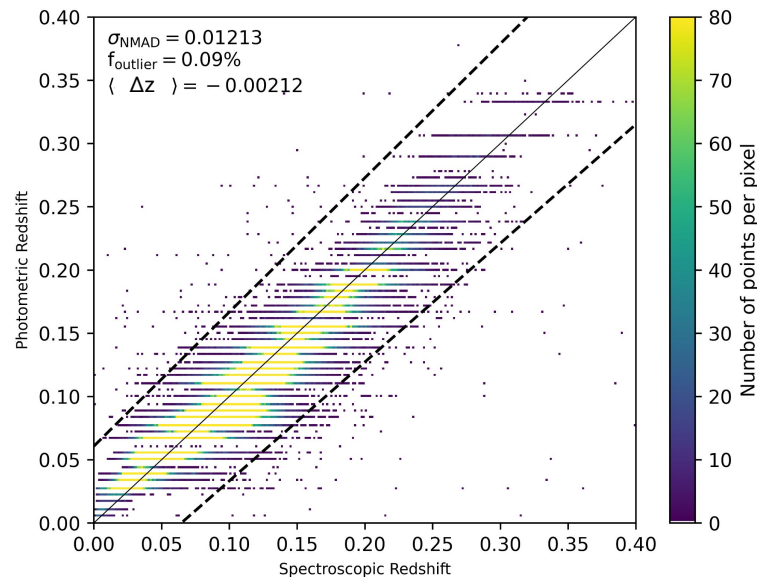
# Convolutional Neural Networks (CNNs)

- Pooling layers are used to reduce the size of input of the feature maps through downsampling along the spatial dimensions.
- The Fully Connected layer uses the features extracted from the previous layers for classifying the input image into various classes based on the training dataset.



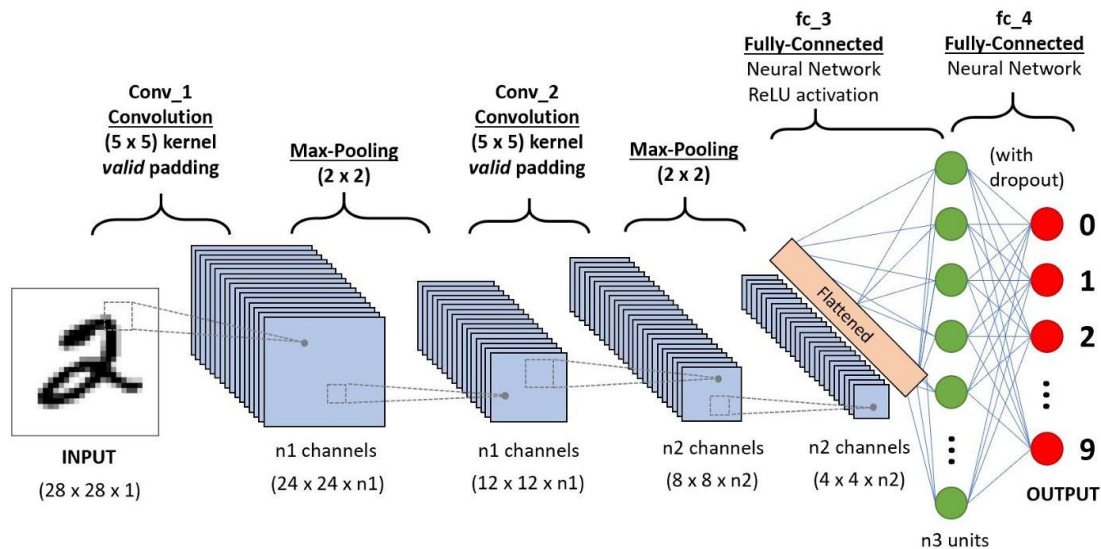
# Performance Metrics

- Residuals:  $\Delta z = \frac{z_{phot} - z_{spec}}{1 + z_{spec}}$
- Prediction bias:  $\langle \Delta z \rangle$
- MAD deviation:  $\sigma_{MAD} = 1.4826 \times MAD$
- MAD (Median Absolute Deviation):  
 $Median(|\Delta z - Median(\Delta z)|)$
- Outlier fraction:  
 $\eta = \text{outliers with } \Delta z > 0.5 \text{ or } (5 \times \sigma_{MAD})$

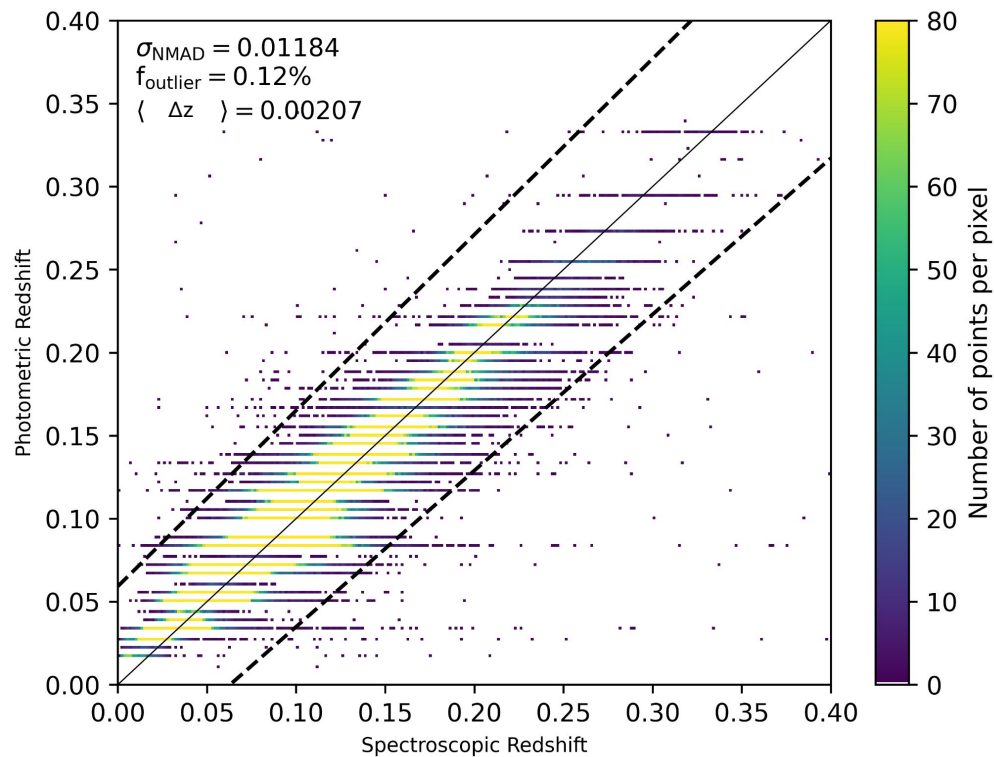
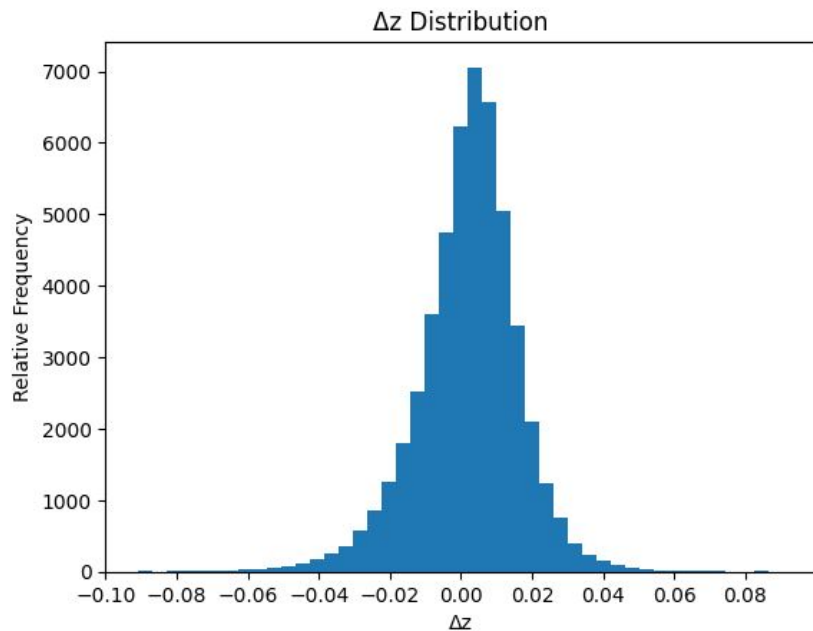


# Sequential CNN

- The simplest possible CNN.



# Sequential CNN – Results

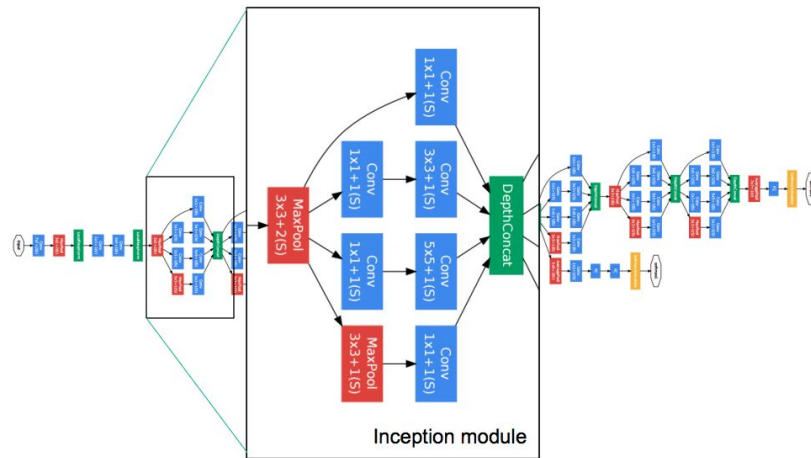


# GoogleNet

- Introduced in 2015 by Szegedy et al.
- It is based on the construction of Inception modules.

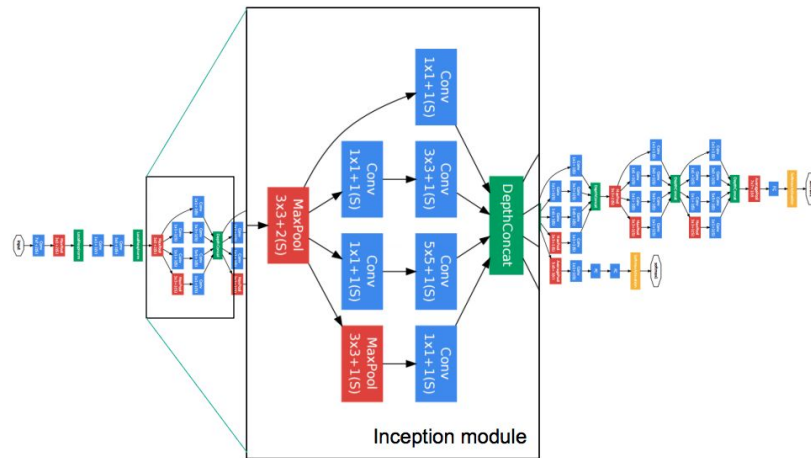
Each inception module is organised in two stages:

- At first, the feature maps are convolved by three “1x1” convolutional layers.
- Thus, they are being combined and reduced in number.



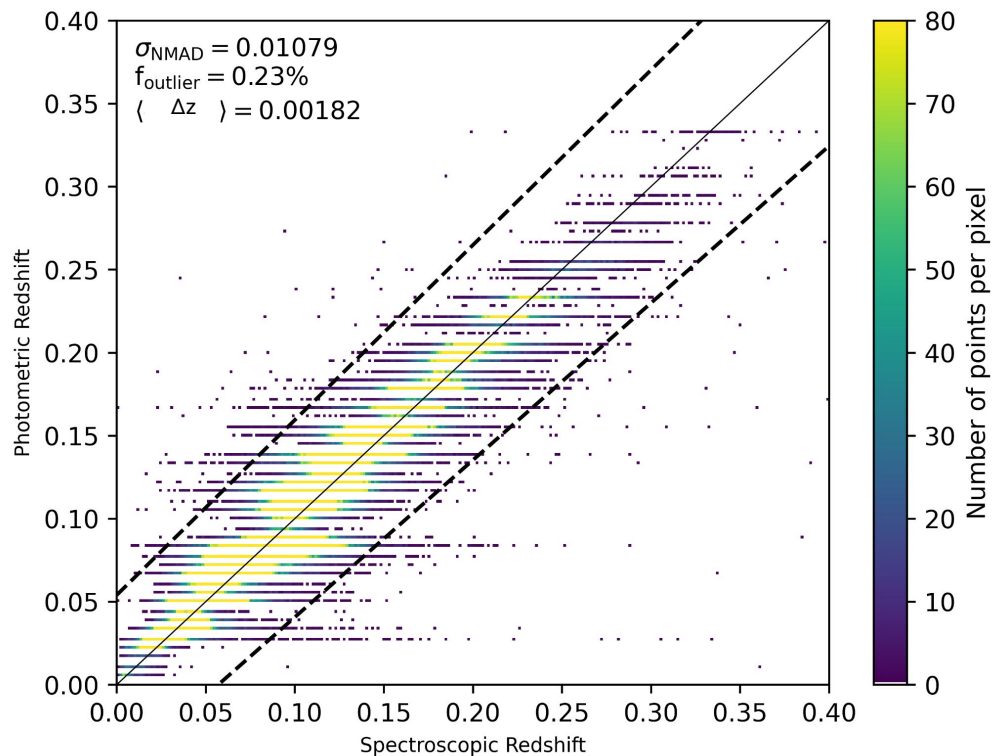
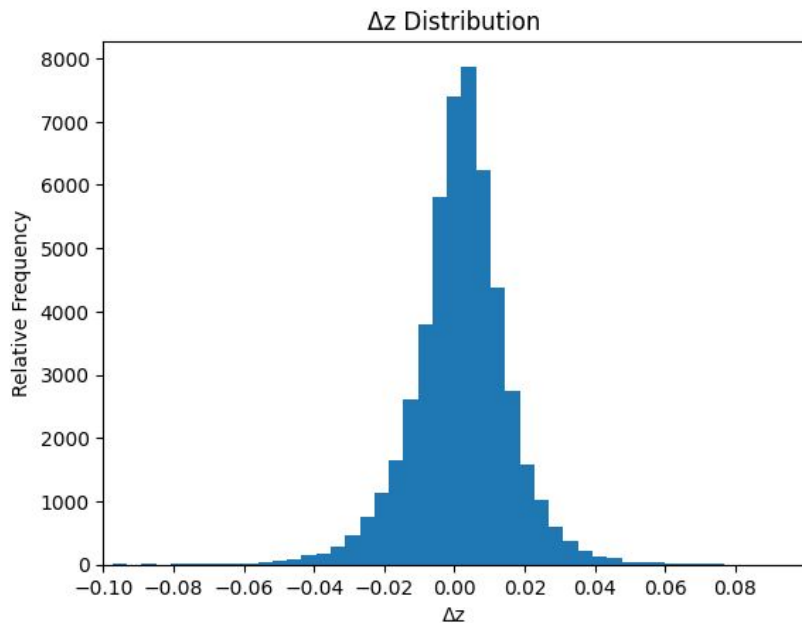
# GoogleNet

- Then, they are processed in parallel in a pooling layer and a pair of larger convolution layers, such as: “3×3” and “5×5”.
- These layers help the network identify larger patterns.
- Lastly, the resulting feature maps are concatenated along the depth dimension before going to the fully connected layer.

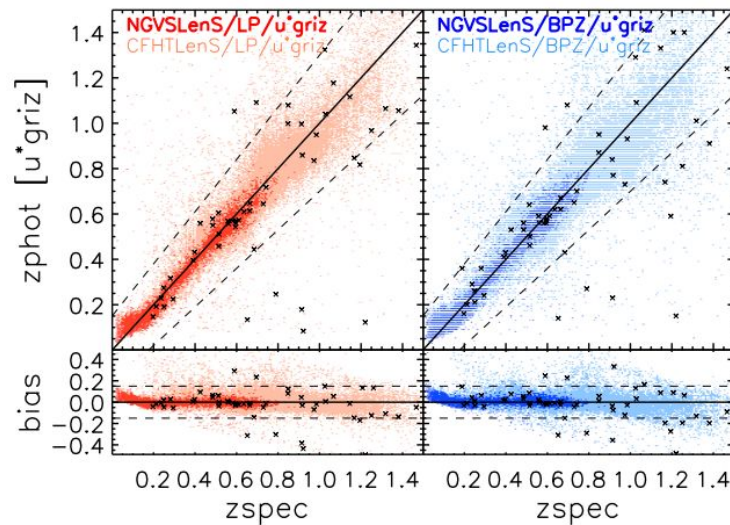
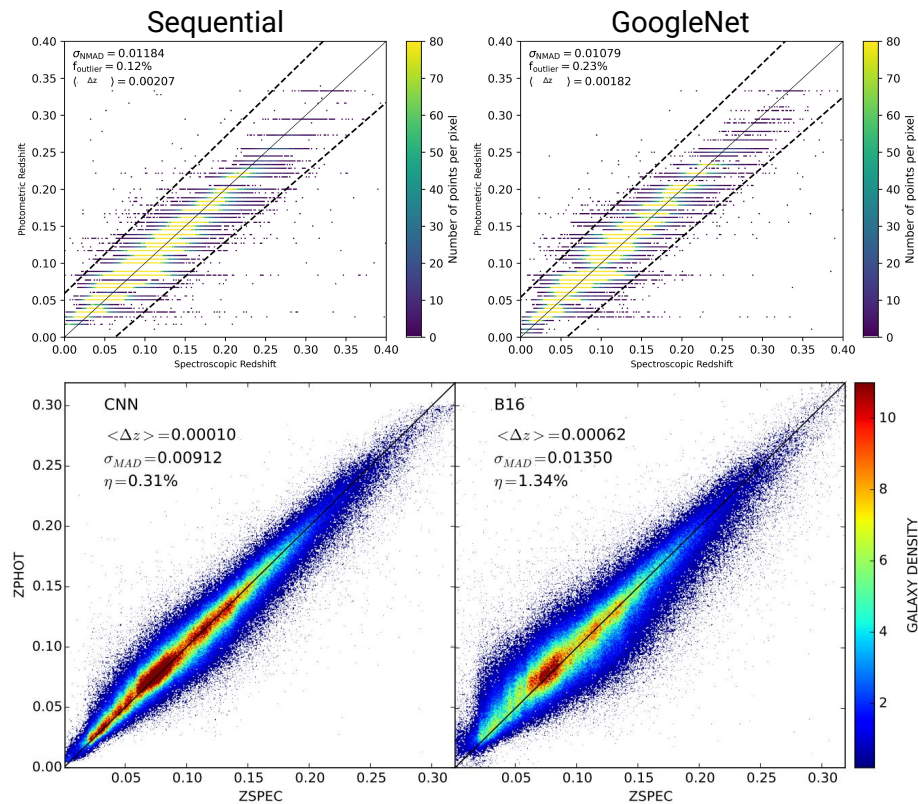




# GoogleNet – Results



# Comparison



# Conclusion

- In this work, I present the use of two types of CNNs in photometric redshift estimation of galaxies.
- Essentially, the information present in the images is being exploited without the need of pre-extracted spectral or image features.
- The value of  $\sigma_{\text{MAD}}$  I obtained is comparable with the best models published so far.
- Even when using the simplest possible CNN, the MAD deviation does not worsen to a great extent, staying comparable to the best performing models, while having much less trainable parameters.

# Conclusion–Future prospects

- The bias appears to be one order of magnitude higher.
- A possible explanation is due to a trade-off between higher dispersion and lower bias as we continue the training of the models.
- The first possible extension of this work is the use of data coming from simulations of the LSST data, and also the first real data.
- Also, another possible extension is the use of current state-of-the-art networks such as RNNs and EfficientNets for Photometric Redshift estimation and the comparison with current models.

# Thank you for your attention!

The code, along with the plots, produced during this internship are publicly available in my github [page](#)

# References

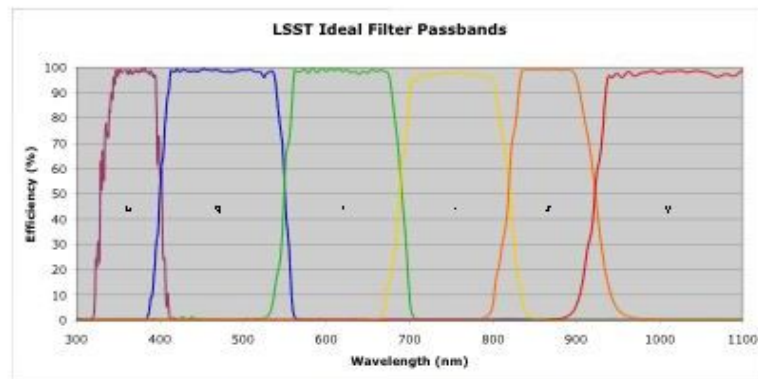
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# Extra Slides–LSST Filters

## Specs

Half-Maximum Transmission Wavelength			
	Blue Side	Red Side	Comments
U	350	400	Blue side cut-off depends on AR coating
G	400	552	Balmer break at 400 nm
R	552	691	Matches SDSS
I	691	818	Red side short of sky emission at 826 nm
Z	818	922	Red side stop before H <sub>2</sub> O bands
Y	948	1060	Red cut-off before detector cut-off

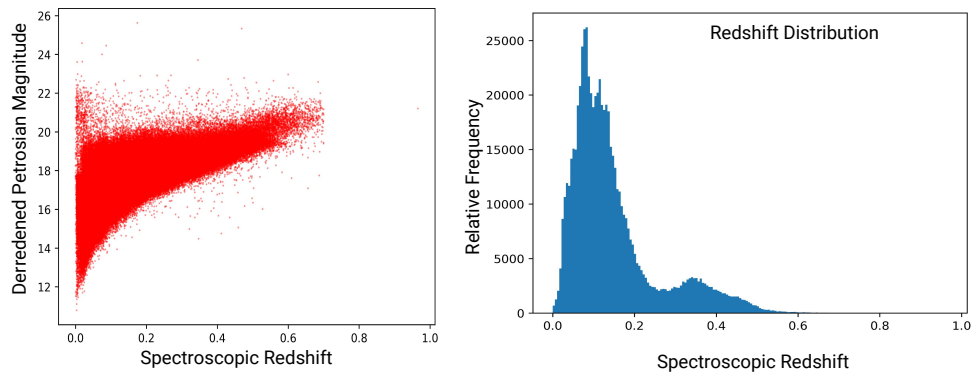
- 75 cm dia.
- Curved surface
- Filter is concentric about the chief ray so that all portions of the filter see the same angle of incidence range, 14.2° to 23.6°



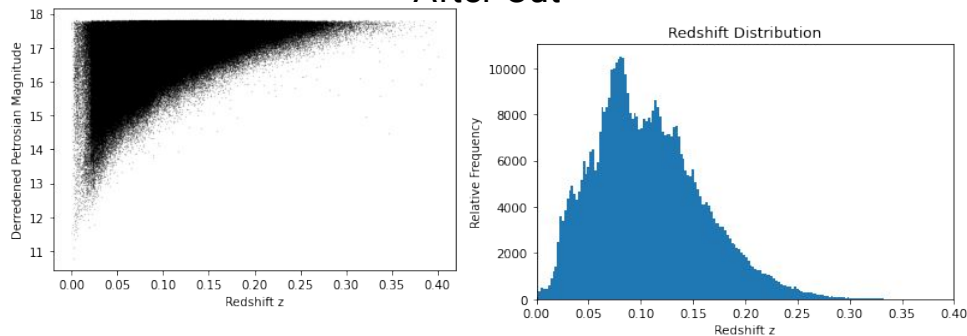
Uniform deposition  
required at 1% level  
over entire filter

# Extra Slides–Raw Data

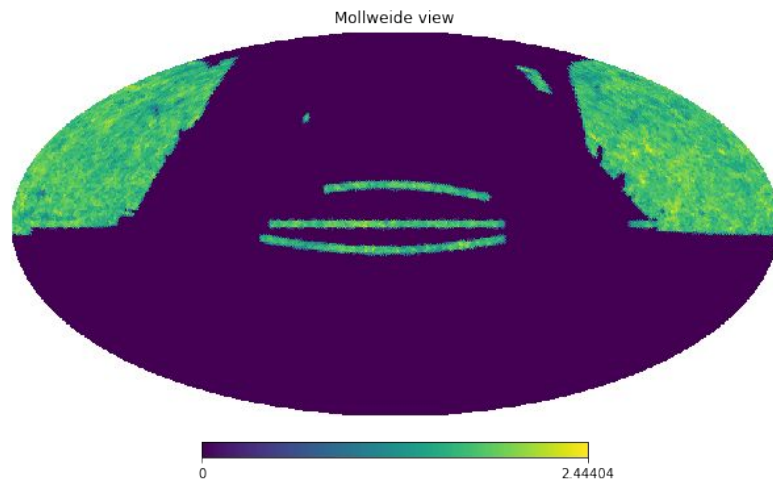
Before Cut



After Cut



Coordinates of the data





# Extra Slides–Models Comparison

