Deep Learning for Image Sequence Classification of Astronomical Events

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Joint work with Guillermo Cabrera-Vives, Francisco Forster, Rodrigo Carrasco , Pablo Huijse, Ignacio Reyes, Esteban Reyes, Nicolas Astorga et al.

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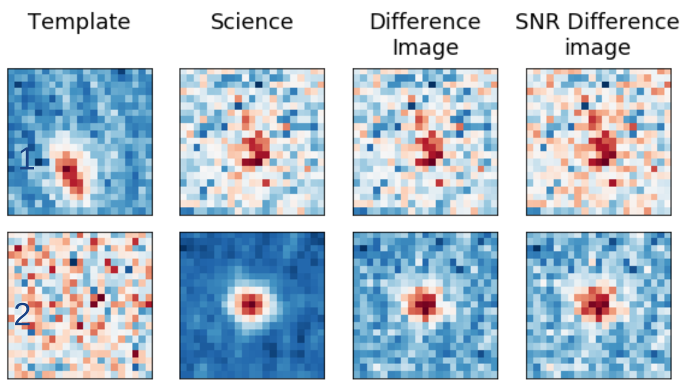
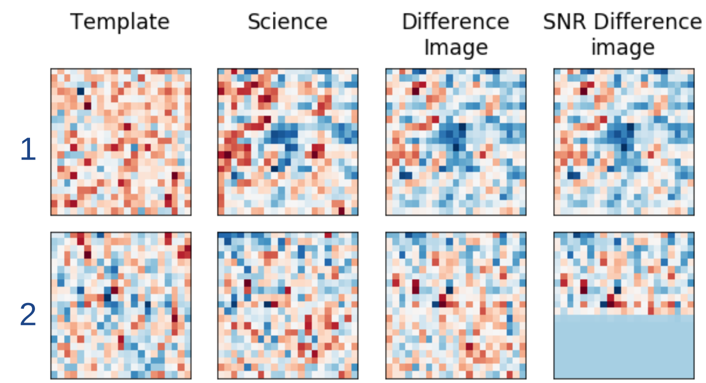
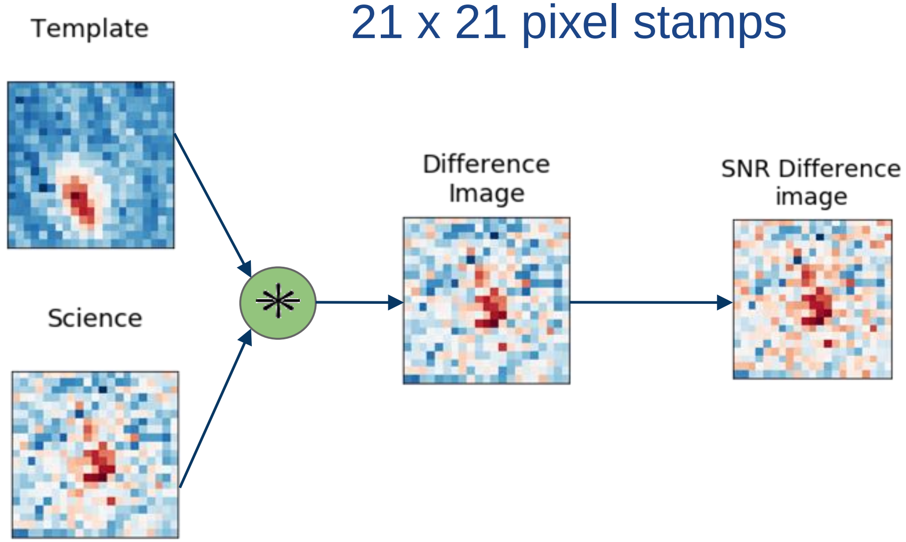
Contents

2013 HiTS dataset





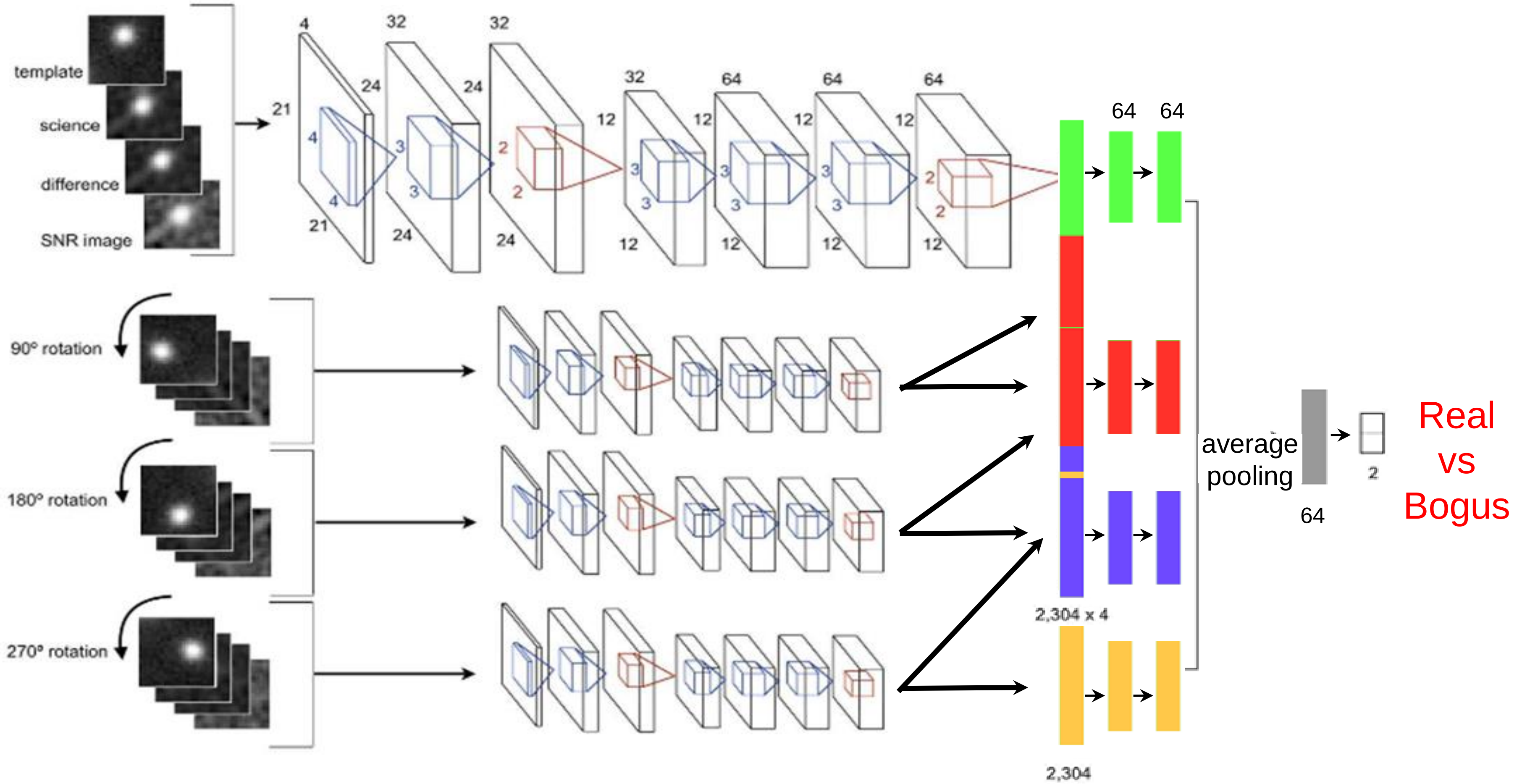
21 x 21 pixel stamps



- ❑ Training set -> 1,250,000 samples
- ❑ Validation set -> 100,000 samples
- ❑ Test set -> 100,000 samples

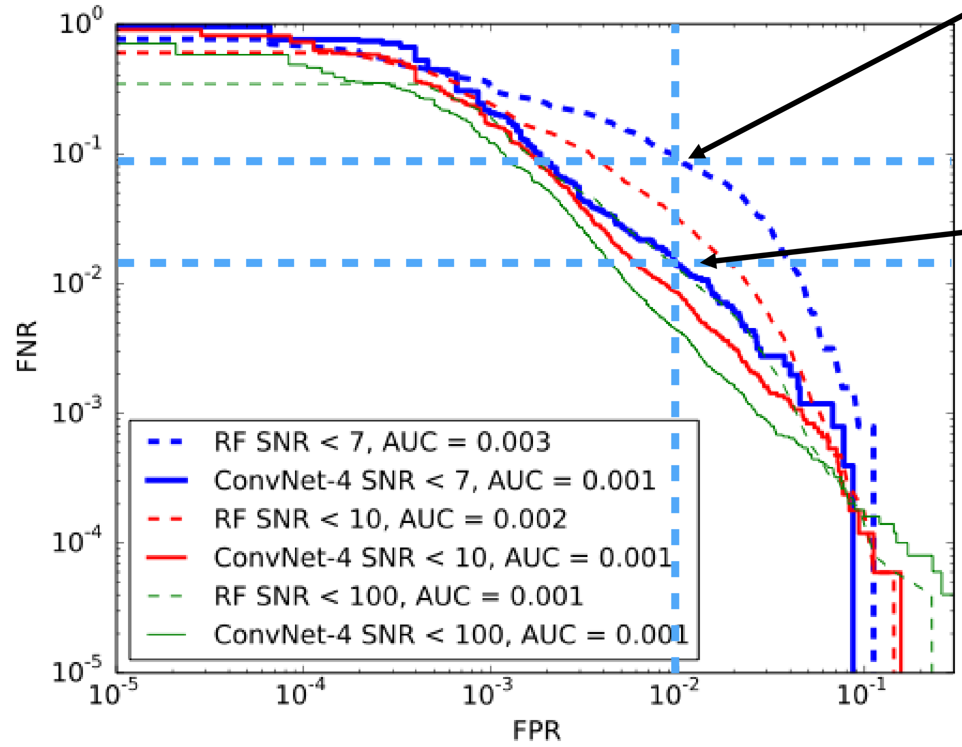
To discriminate between real transients and bogus events with low FPR, FNR

Deep-HiTS Real/Bogus Classifier: Supervised Approach



Cabrera-Vives, G., Reyes, I., Forster, F., Estevez, P.A., Maureira, J.C., “Deep-HiTS: Rotation Invariant Convolutional Neural Network for Transient Detection”, Astrophysical Journal, Feb. 2017.
Reyes, E., Estevez, P.A., Cabrera-Vives, G., Forster, F. “Enhanced Deep Neural Network Model”, 2018 International Joint Conference on Neural Networks, IJCNN 2018, Rio de Janeiro, July 2018.

Detection Error Tradeoff (DET)



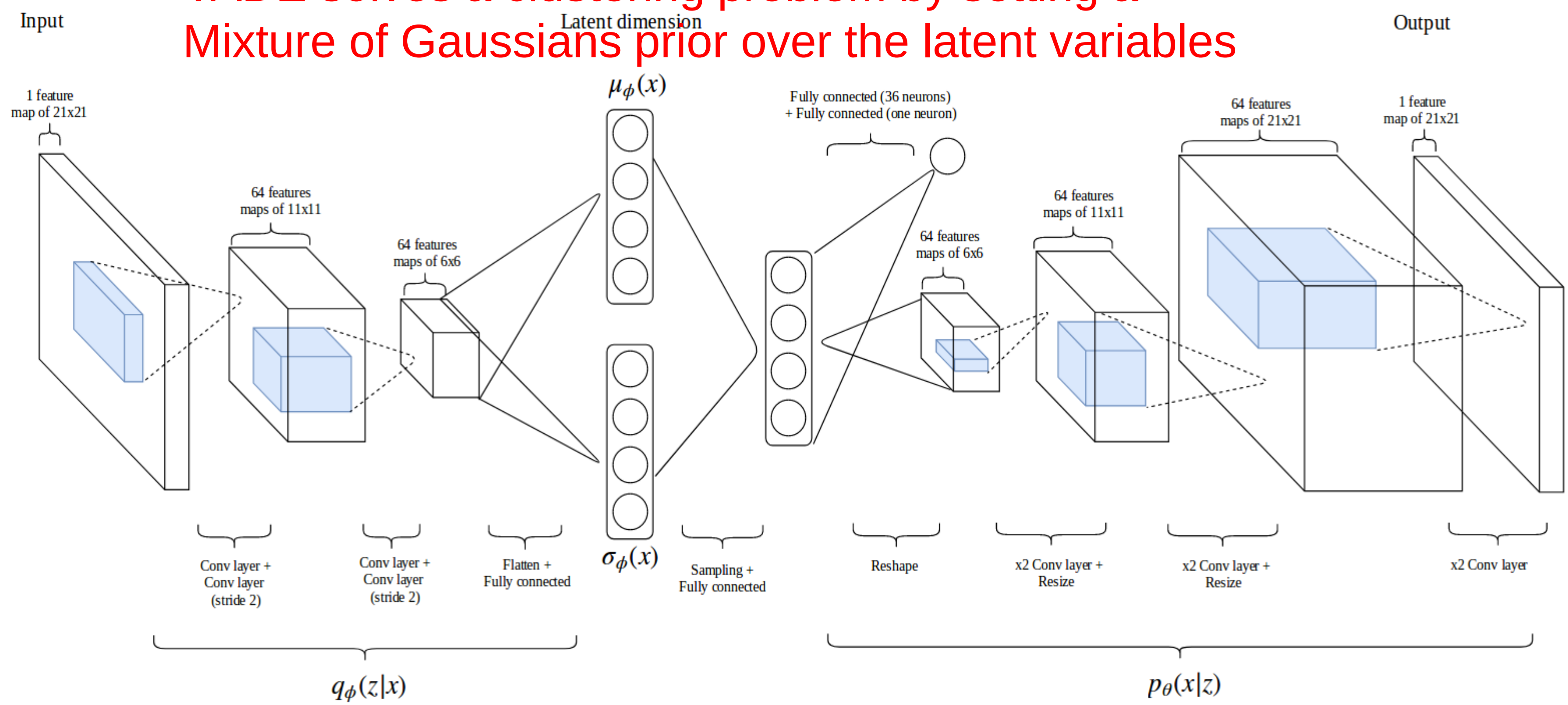
RF: random forests +feature engineering approach (56 handmade features)

ConvNet-4: using all 4 images.

Model	Accuracy	Precision	Recall	F1-score
Deep-Hits (DH)	99.45±0.02	99.37±0.04	99.55±0.06	99.45±0.02
Deep-Hits + ReLU	99.47±0.02	99.44±0.04	99.52±0.06	99.47±0.02
Cyclic Avg. Pool (CAP)	99.52±0.01	99.45±0.01	99.61±0.02	99.52±0.01
Cyclic Avg. Pool Ensemble (CAPE)	**99.53±0.01**	**99.45±0.02**	**99.63±0.03**	**99.53±0.01**

Deep Variational Embedding (VADE) Autoencoder: Unsupervised Approach

VADE solves a clustering problem by setting a Mixture of Gaussians prior over the latent variables



<u>Original SNR diff image 21x21 pixels</u>

Encoder: Encodes data X into latent variables

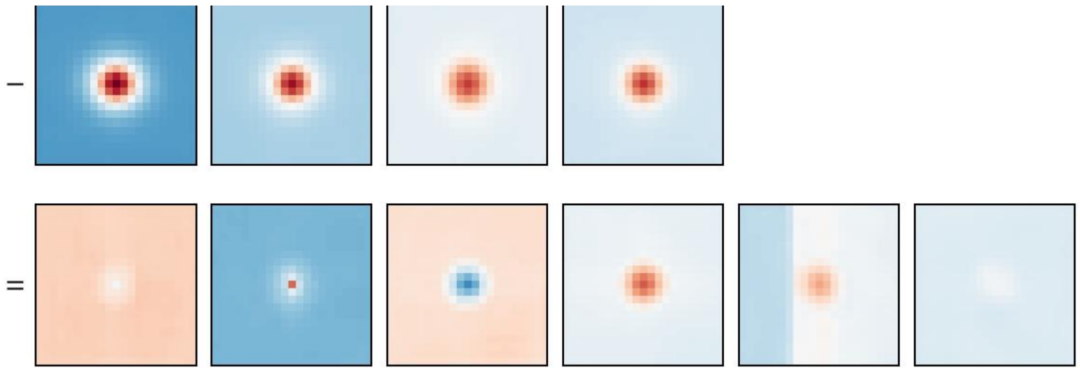
<u># neurons: dimensionality of latent space</u>

Decoder: generative model to reconstruct data X

<u>Reconstructed SNR diff image 21x21 pixels</u>

VADE Results on Real/Bogus

Method	Accuracy
Incremental PCA + GMM	93.43 ± 1.25 %
Online DL + GMM	90.79 ± 0.22 %
VAE + GMM	87.06 ± 0.69 %
VADE	95.33 ± 0.11 %



Cluster Centroids

Positive class

Negative class

Fig. 6. Reconstruction obtained by sampling from the VADE centroids μ_c. The first and second rows correspond to clusters associated to the positive class (stellar transient) and the negative class (artifacts), respectively.

[1] Astorga, Huijse, **Estévez, Förster**, "Clustering of Astronomical Transient Candidates using Deep Variational Embedding", IJCNN 2018
[2] Huijse, **Estévez, Forster,** Pignata, "Latent representations of transients from an astronomical image difference pipeline using VAE", ESANN 2018

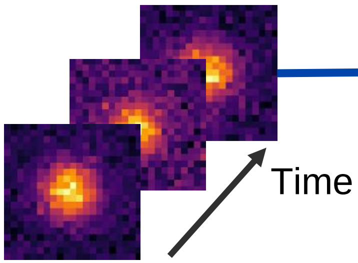
Deep Learning for Image Sequence Classification of Astronomical Events

- We propose a sequential classifier based on a recurrent convolutional neural network (RCNN)
- It uses sequences of images as inputs
- This approach avoids the computation of light curves or difference images
- A basic assumption is that there is more information in the original images than in the light curves, e.g. spatial information.
- We use synthetic datasets to train the models, and real data from the HiTS survey to test them.

Carrasco-Davis, R.; Cabrera-Vives, G.; Forster, F., Estevez, P.A., Huijse, P., Protopapas, P., Reyes, I., Martinez-Palomera, J., and Donoso, C. “Deep Learning for Image Sequence Classification of Astronomical Events”, submitted to PASP, 2018.

Basic Idea

Synthetic

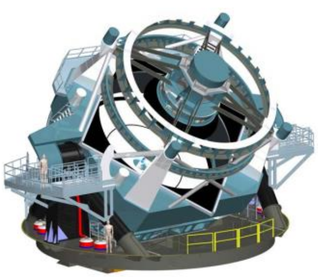


Train with synthetic data

Machine Learning Classifier Model

- Sequence of Images > Images > Light Curve
- Without differencing images

Real Data



After training
Predict class with real data

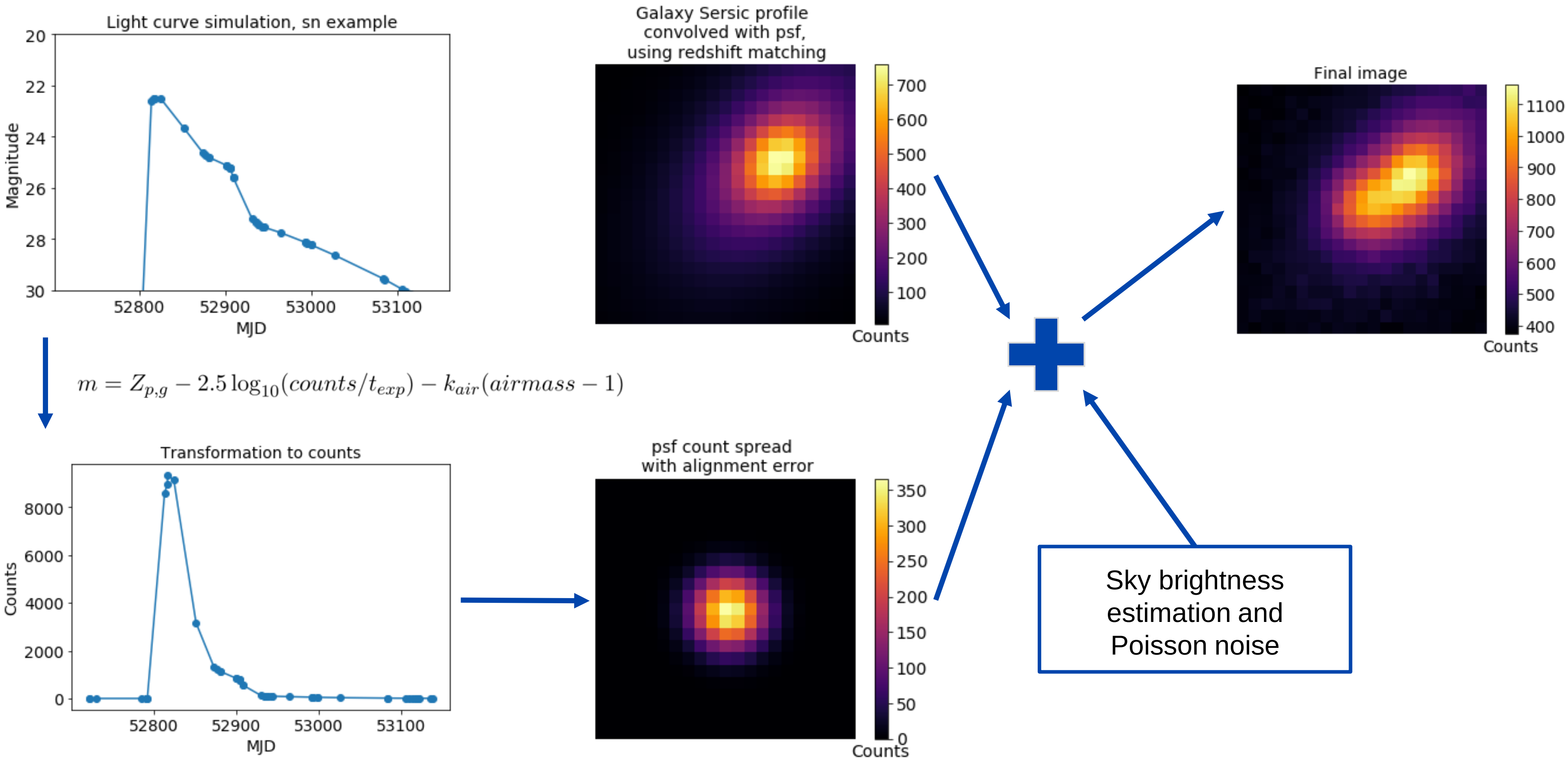
Machine Learning Classifier Model

List of supernovae candidates

Synthetic Dataset

- First we simulate light-curves based on physical and empirical models, and sample them using the observation times.
- Each point in a light curve is transformed to an image by taking into account:
  - Instrument specifications
  - Exposure times
  - Atmospheric conditions
- A given PSF (point spread function) is assumed, which is sampled from a collection of empirical PSFs.

Example of Image Simulation



Synthetic Dataset (7 classes)

Table 2 Class description, astronomical sources simulated in this work.

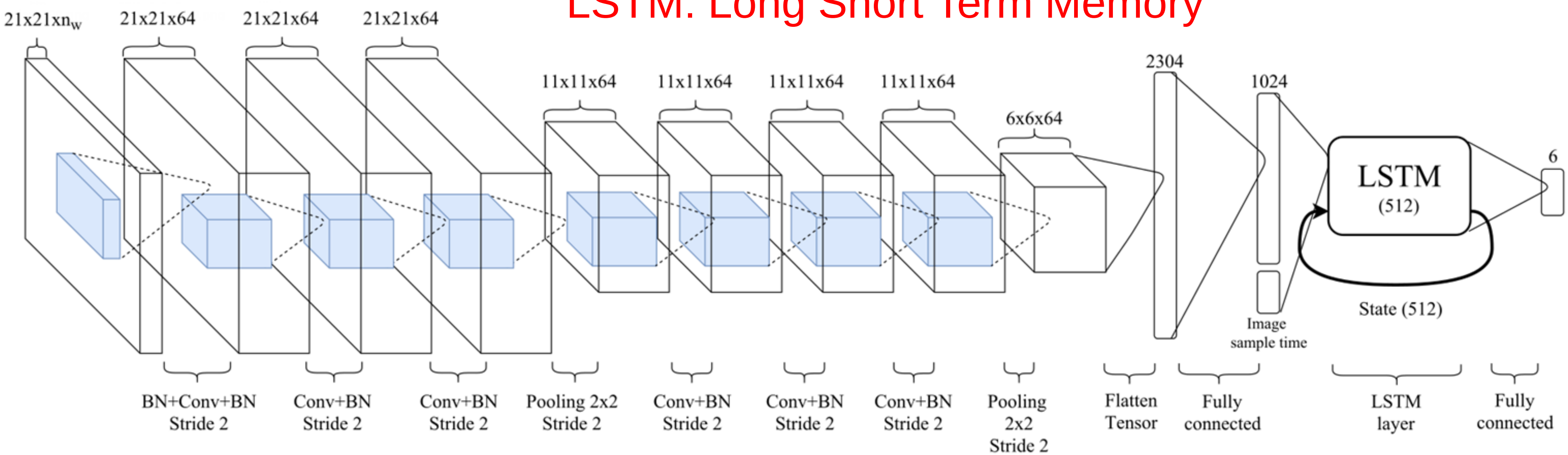
Astronomical Object	**Generation model**
Supernovae	Simulations based on physical models of SNe II from (Moriya et al., 2017) and SN Ia spectrophotometric templates from (Hsiao et al., 2007)
RR Lyrae	483 light curve templates, sampling a random phase and average magnitude (Sesar et al., 2010)
Cepheids	600 real cepheids light curve Hartman et al. (2006) fitted with a Gaussian process for interpolation (Rasmussen & Williams, 2005)
Eclipsing Binaries	375 Eclipsing binaries templates from CatSim[1], part of the LSST simulation tools
Non-Variable objets	Constant brightness value for each time of observation
Galaxies	Exponential and De Vaucouleur's luminosity profile using parameters from SDSS galaxy catalog (Blanton et al., 2017)
Asteroids	Simulated as a bright source in just a single time of observation

Synthetic and Real Datasets

- We simulated 686,000 objects for the training set, 85,750 for the validation set and 85,750 for the test set.
- In this work, the observing conditions were sampled from real observations from the 2015 HiTS survey.
- Five classes are available for real image sequences: supernovae (73), RR Lyrae (111), eclipsing binaries (76), non-variables (255) and asteroids (51).

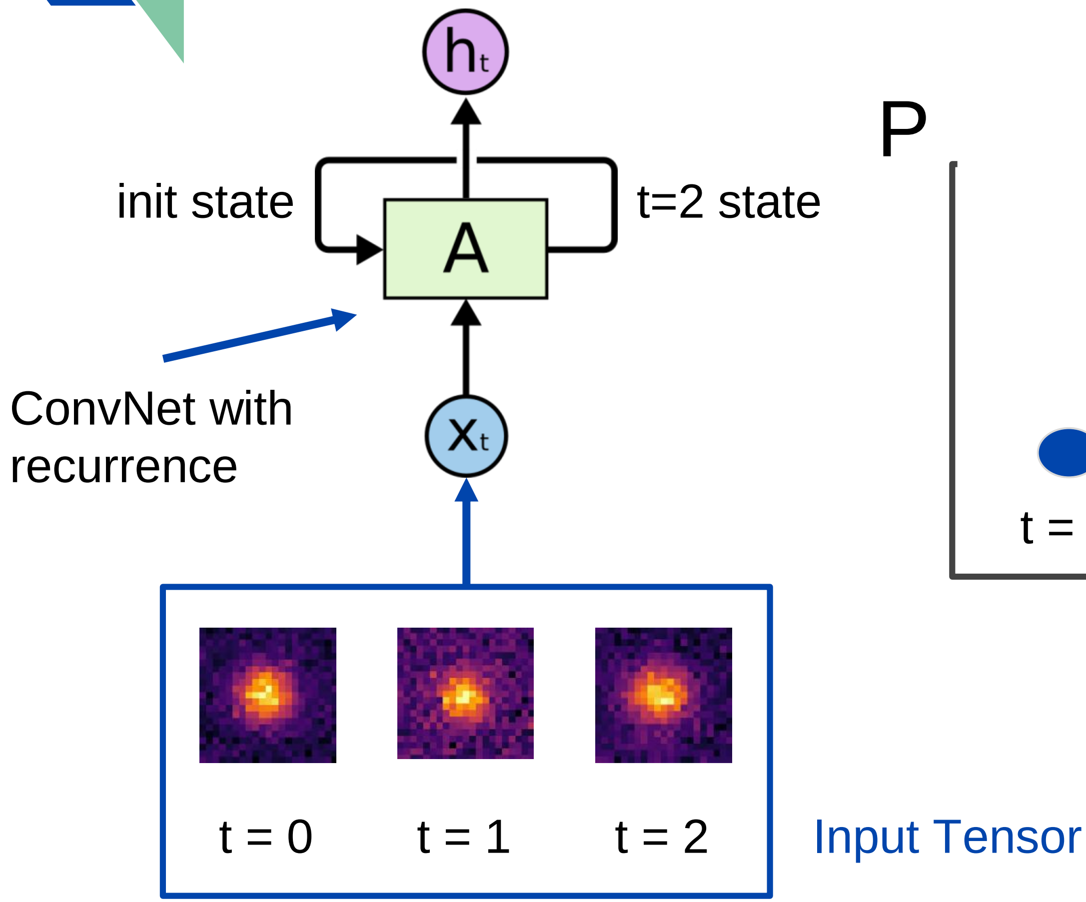
Recurrent Convolutional Neural Network

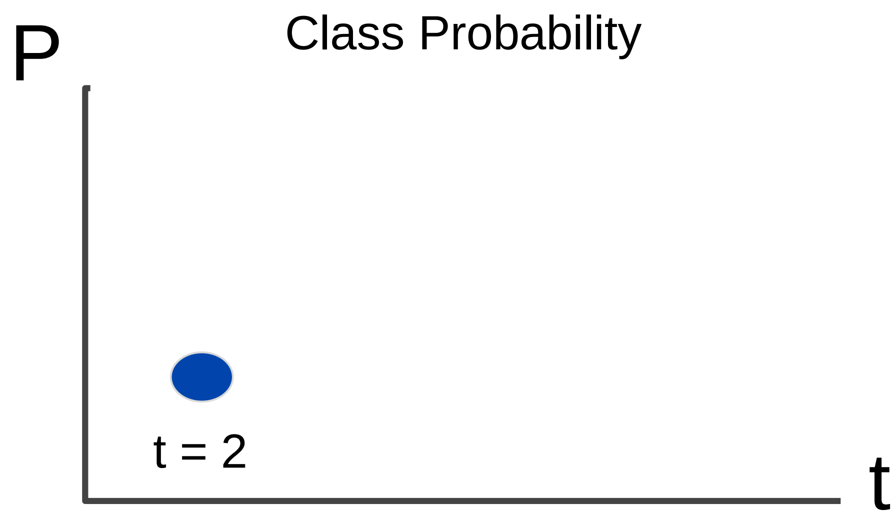
LSTM: Long Short Term Memory

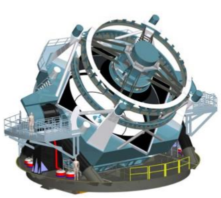


- Convolutional layers are able to automatically learn the spatial correlation among pixels in the input images and extract high-level features.
- A LSTM recurrent layer is used to learn time dependencies among images at irregular times.

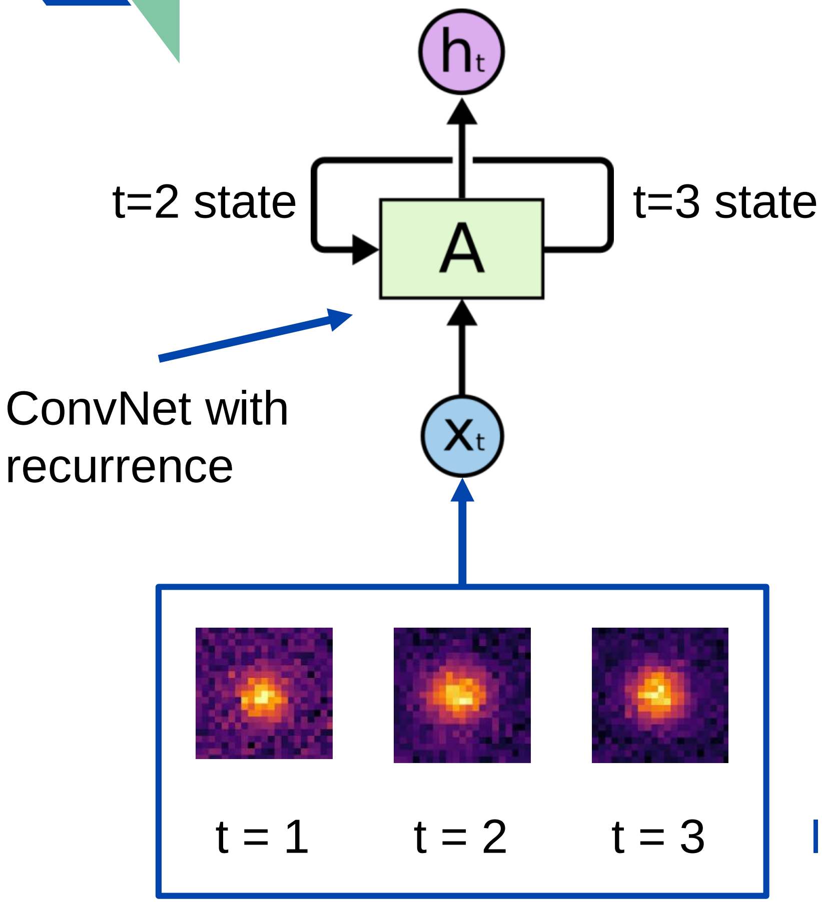
Classification Process

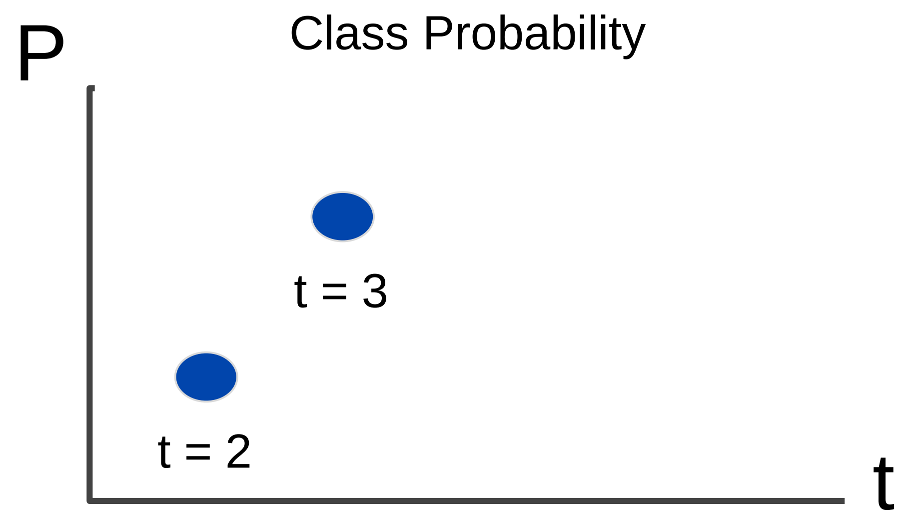




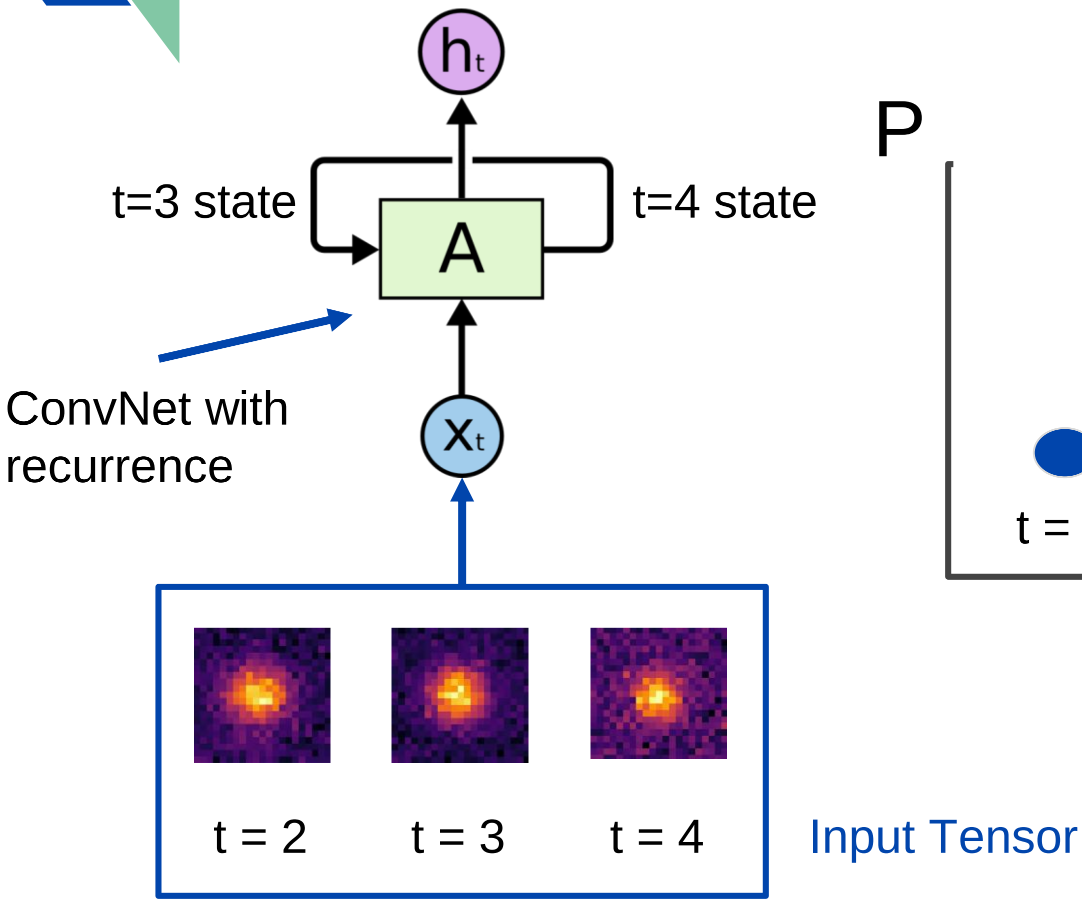


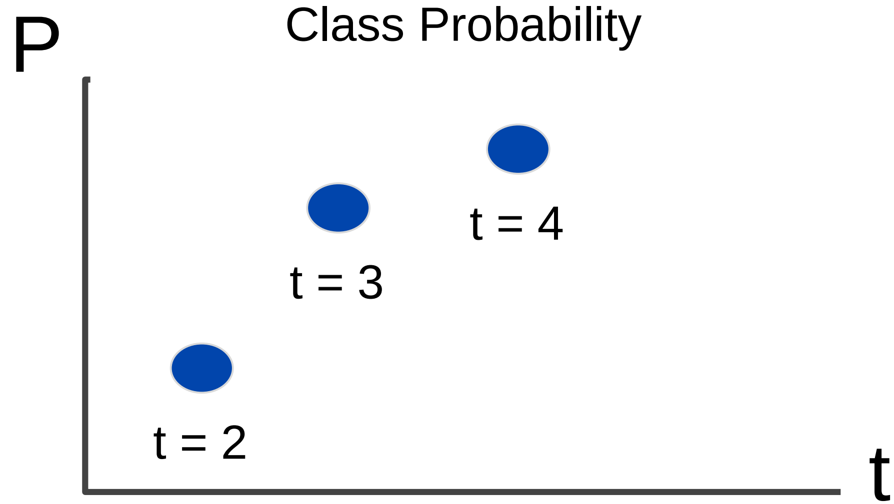
Classification Process



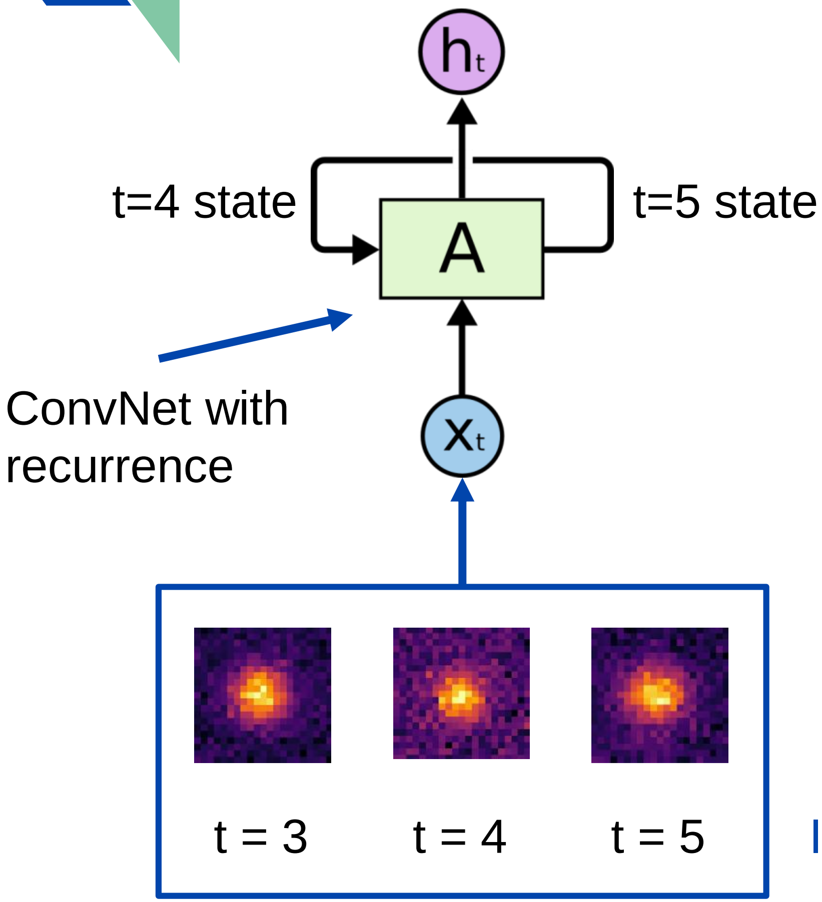


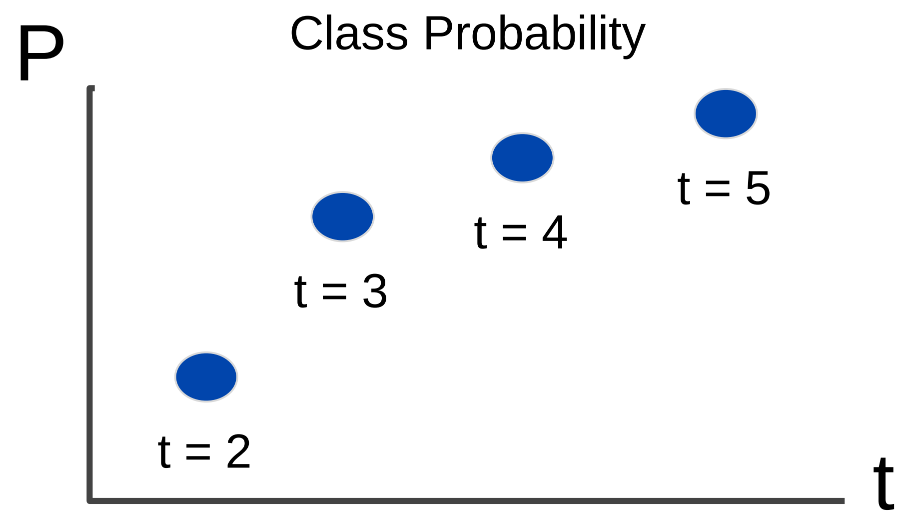
Classification Process





Classification Process

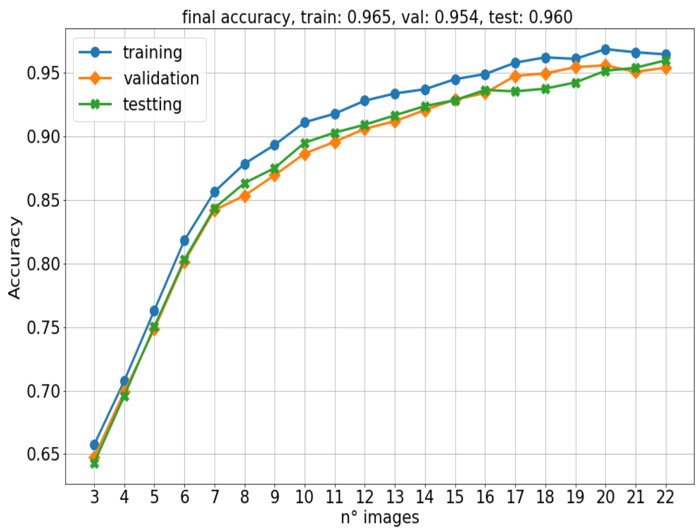


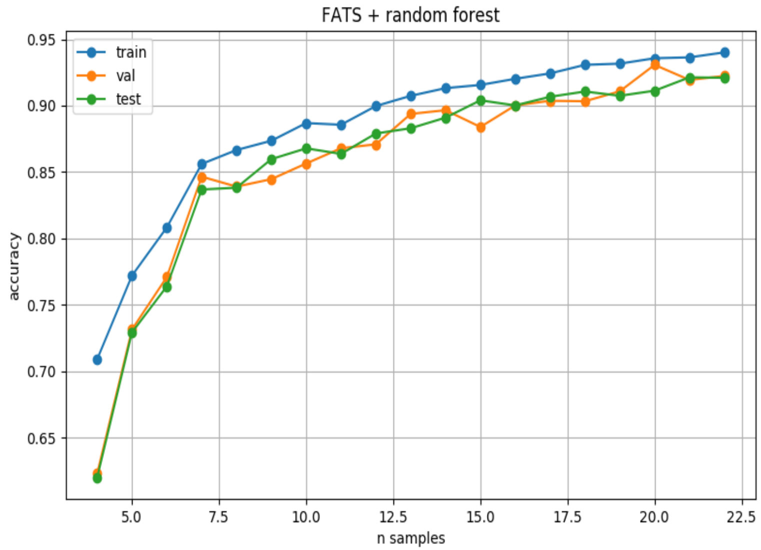


Model performance on synthetic data

- RCNN model

FATS (58 features) + RF (Random Forests)

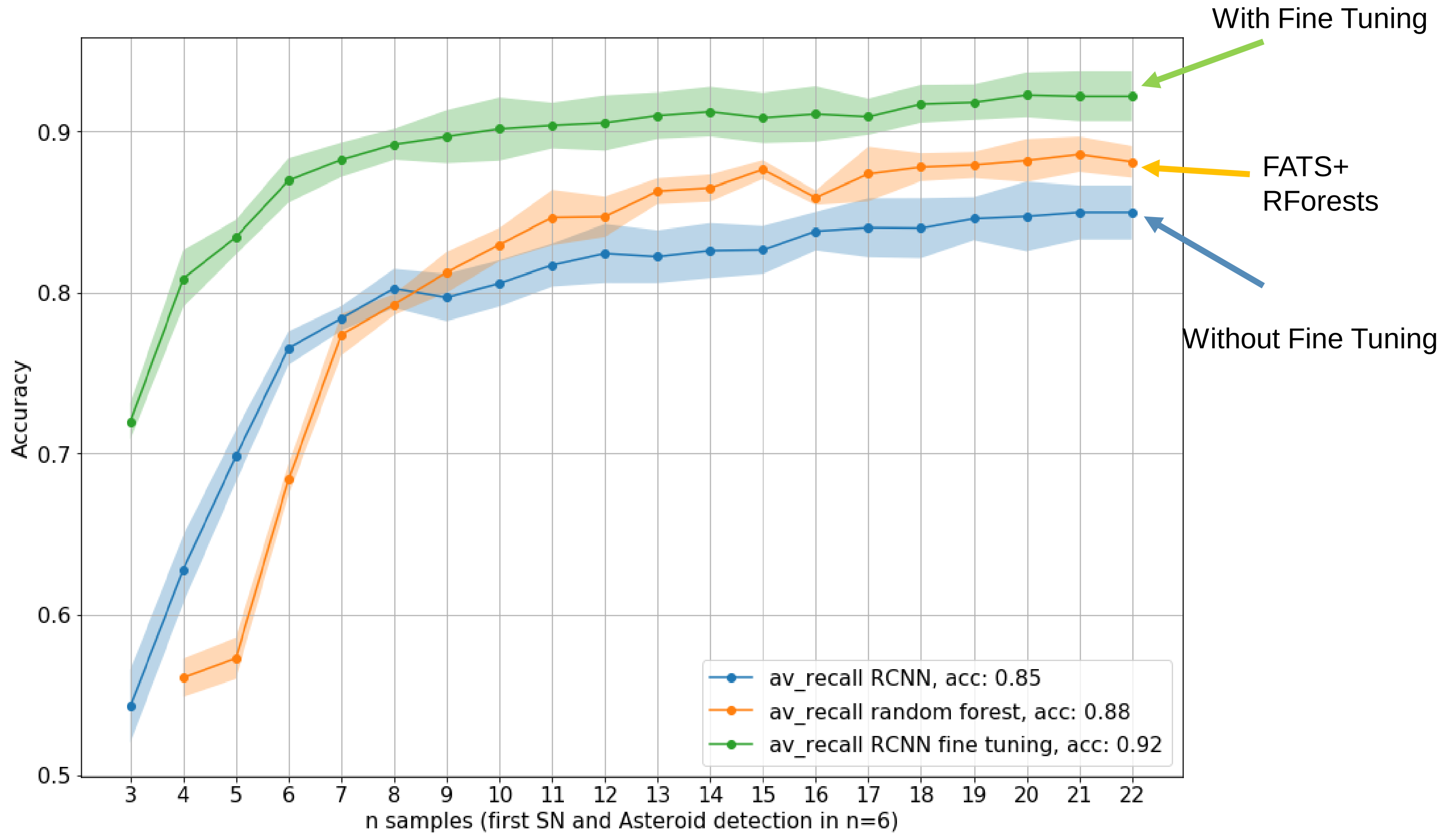




Our model uses sequences of images as inputs directly

Light curves in count units were extracted from the simulated images using optimal photometry.

Model evaluation on real data: average results



Conclusions

- The proposed RCNN model uses sequences of images. Scales well since it has a constant computational cost.
- Domain adaptation is an important area of research. Our model gets a very high performance on the real dataset after fine tuning. Just after presenting a few real samples.
- The proposed approach allows us to generate datasets to train and test our RCNN model for different astronomical surveys and telescopes.

Any Questions?

Here
We love
Deep Learning
to death!

References

- Carrasco-Davis, R.; Cabrera-Vives, G.; Forster, F., Estevez, P.A., Huijse, P., Protopapas, P., Reyes, I., Martinez-Palomera, J., and Donoso, C. “Deep Learning for Image Sequence Classification of Astronomical Events”, submitted to PASP, 2018.
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- P. Huijse, P. Estevez, P. Protopapas, JC Principe, P. Zegers, “Computational Intelligence Challenges and Applications on Large-Scale Astronomical Time Series Databases”, IEEE Computational Intelligence Magazine, August 2014.