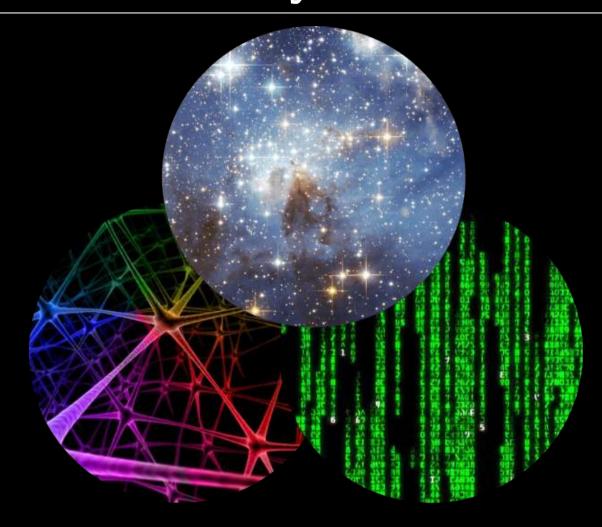
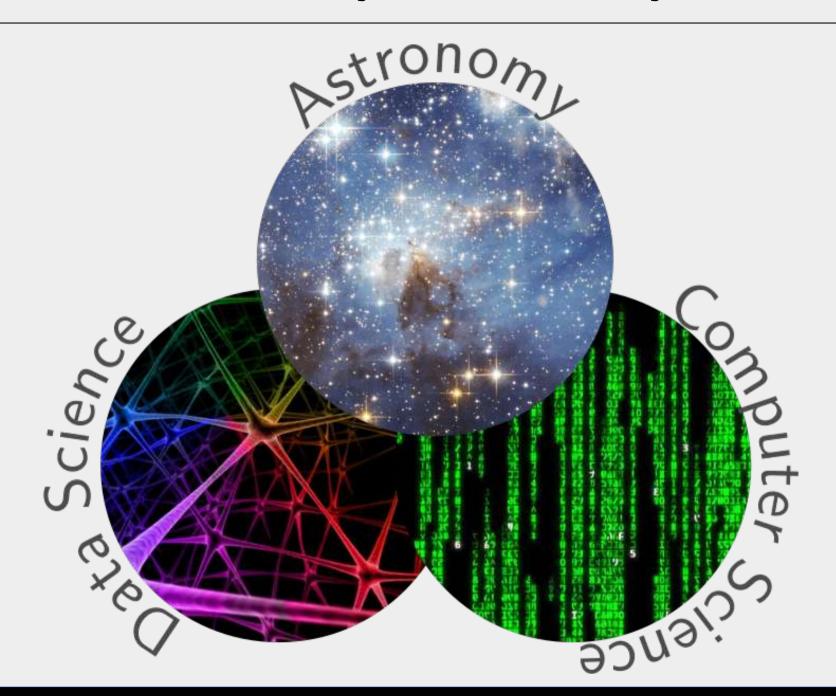
# Machine Intelligence in the Era of Survey Astronomy



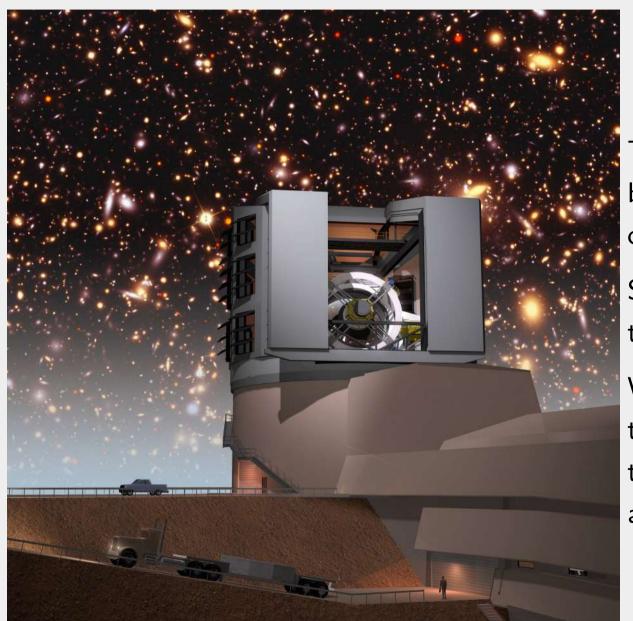




## The Era of Survey Astronomy



## The Large Synoptic Survey Telescope

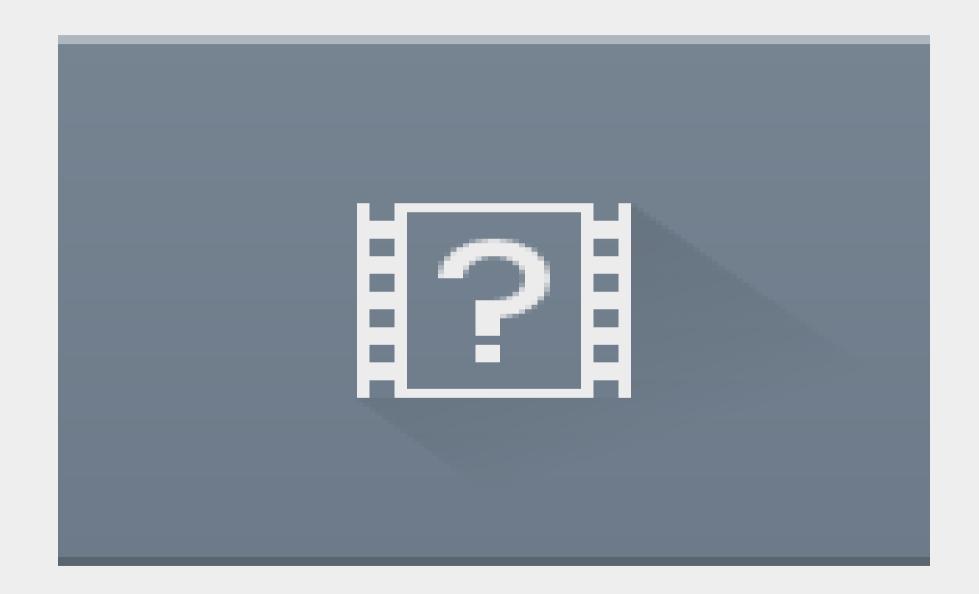


The 10-year LSST survey will be the widest, fastest, deepest optical survey ever done.

Science ranges from asteroids to dark energy

Will detect  $\sim \! 10$  million transient events per night, thousands of which will be new astrophysical objects

## The Large Synoptic Survey Telescope



#### MeerKAT and the SKA



MeerKAT (64 dishes) under construction in the Karoo

First light ~2019

Huge range of science from transients to deep galaxy surveys

SKA phase 1 ( $\sim$ 200 dishes), first light somewhere in the 2020's

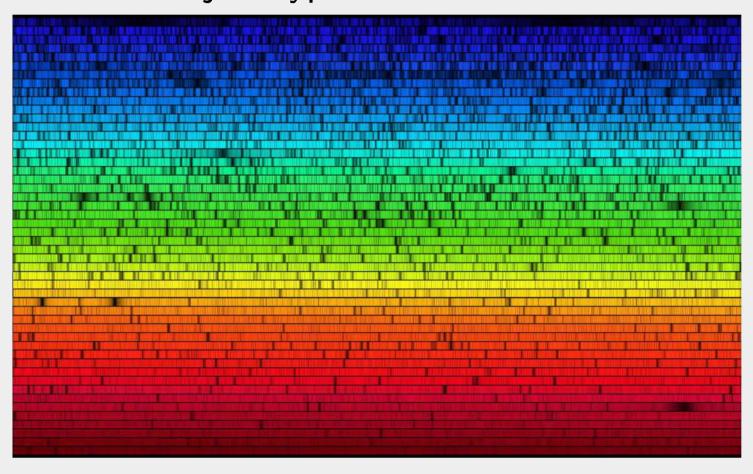
#### MeerKAT and the SKA



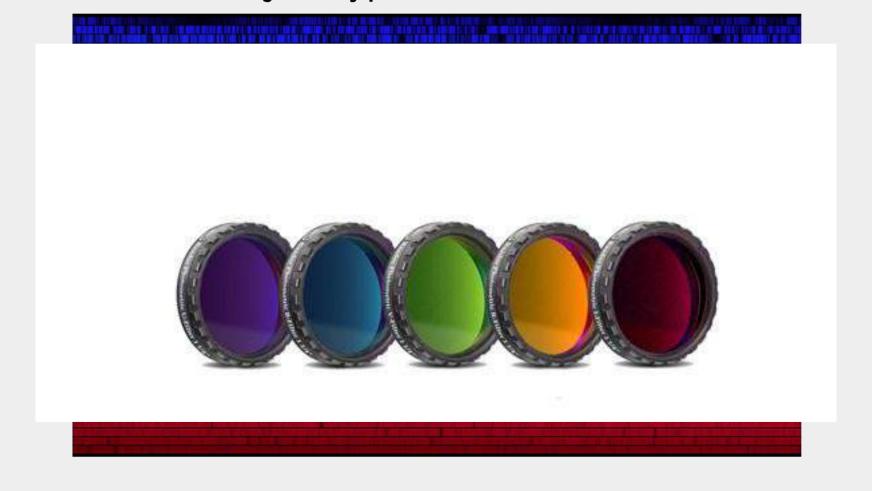
T. Abbott

LSST will be photometric only, very little spectroscopic confirmation of object types!

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LSST will be photometric only, very little spectroscopic confirmation of object types!



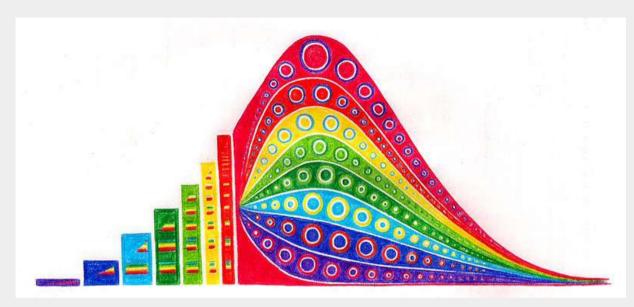
- LSST will be photometric only, very little spectroscopic confirmation of object types!
- > 10 million alerts per night to sift through

- LSST will be photometric only, very little spectroscopic confirmation of object types!
- > 10 million alerts per night to sift through
- SKA data rates will be equally nightmarish



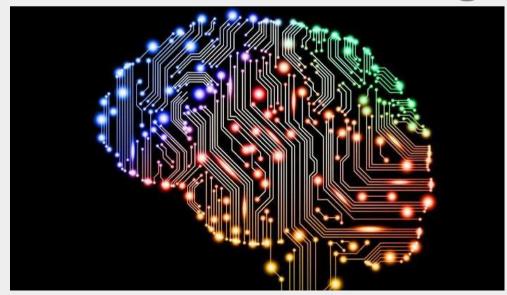
If you converted **one day** of SKA data to an audio file it would take two million years to play back

#### Two Pillars of Data Science



**Statistics** 

## Machine Learning



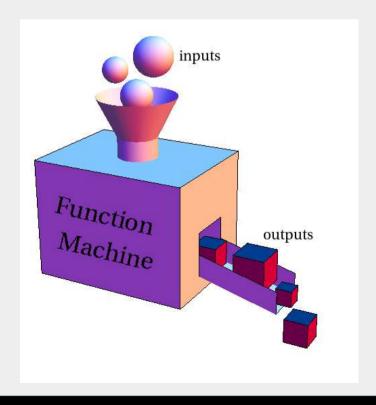
## What is machine learning?

## What is machine learning?

Essentially, automatically building a (usually highly nonlinear) model that maps a given input to output.

Different algorithms use different prescriptions for

building the model



#### When to use machine learning

For data exploration (unsupervised learning)

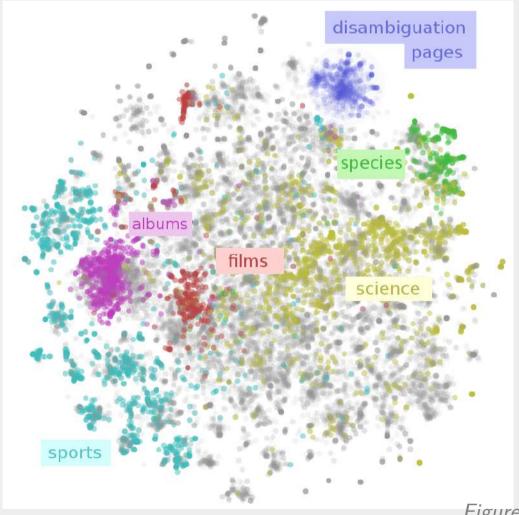
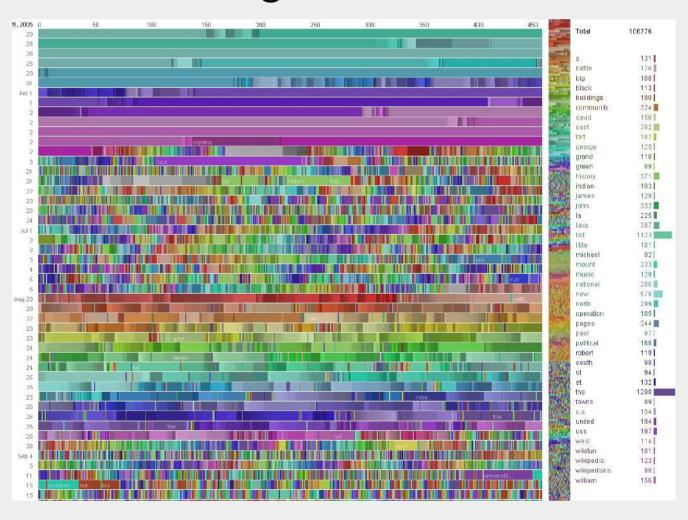


Figure: http://colah.github.io/

#### When to use machine learning

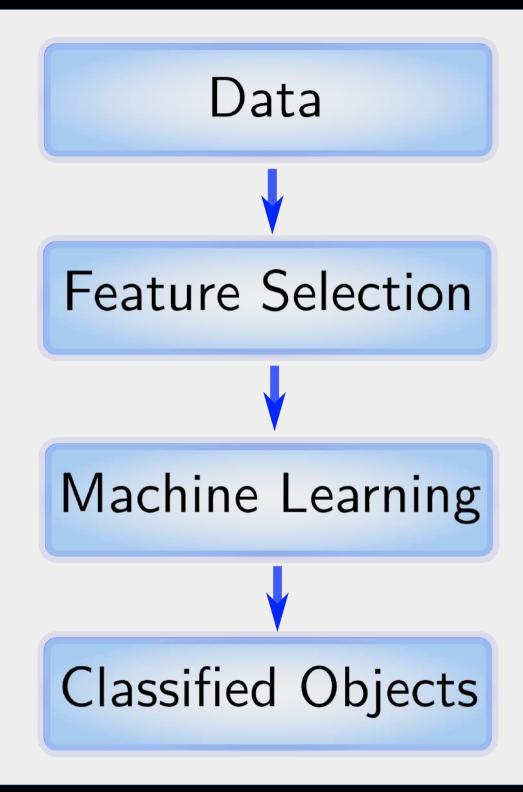
When your data are too complex for traditional model development and fitting with statistics



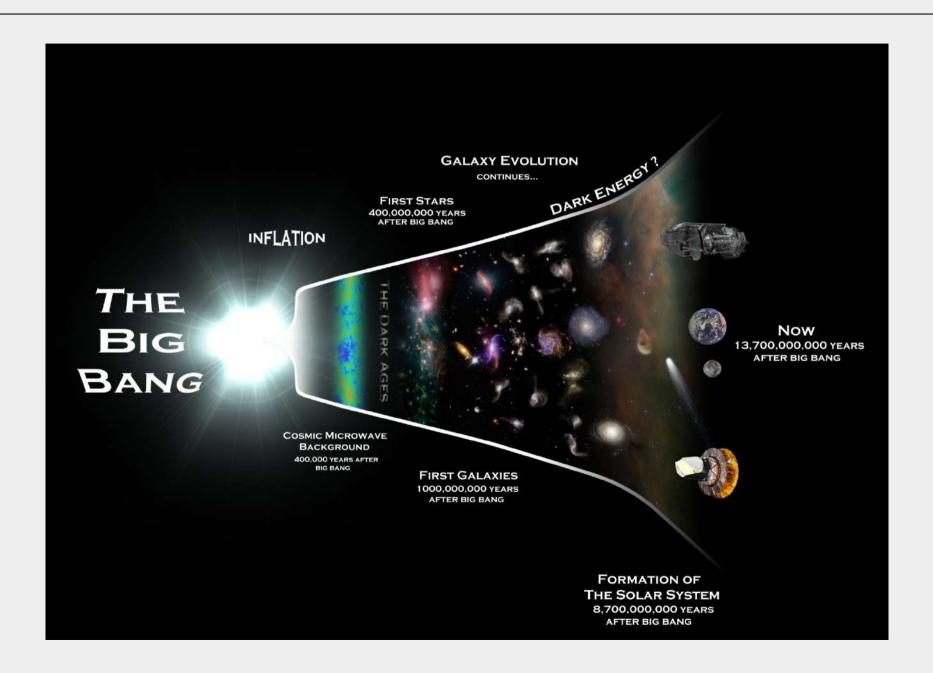
#### When to use machine learning

When you are too busy/ too lazy to perform a task repeatedly



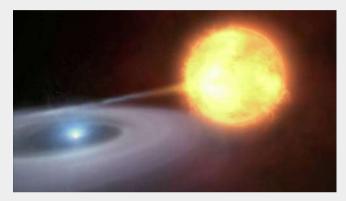


## Cosmology

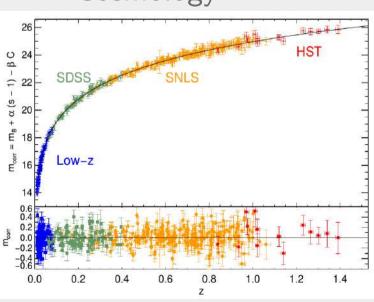


## LSST Problem 1 – Supernova Types

#### Type la supernovae



Cosmology

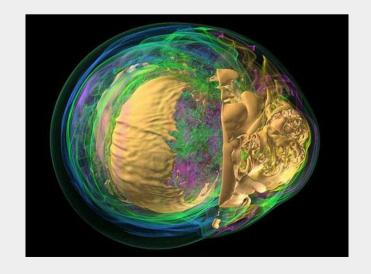


Conley et al. 2011

#### Core collapse supernovae

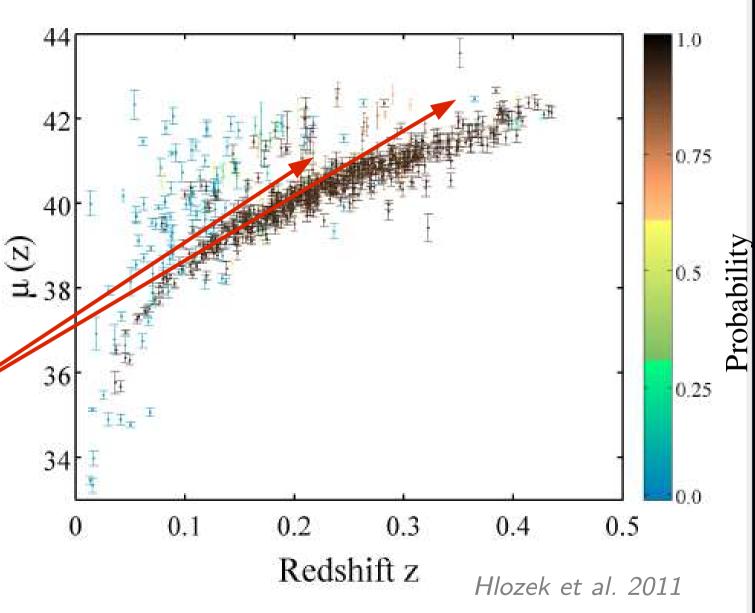


Supernova astrophysics

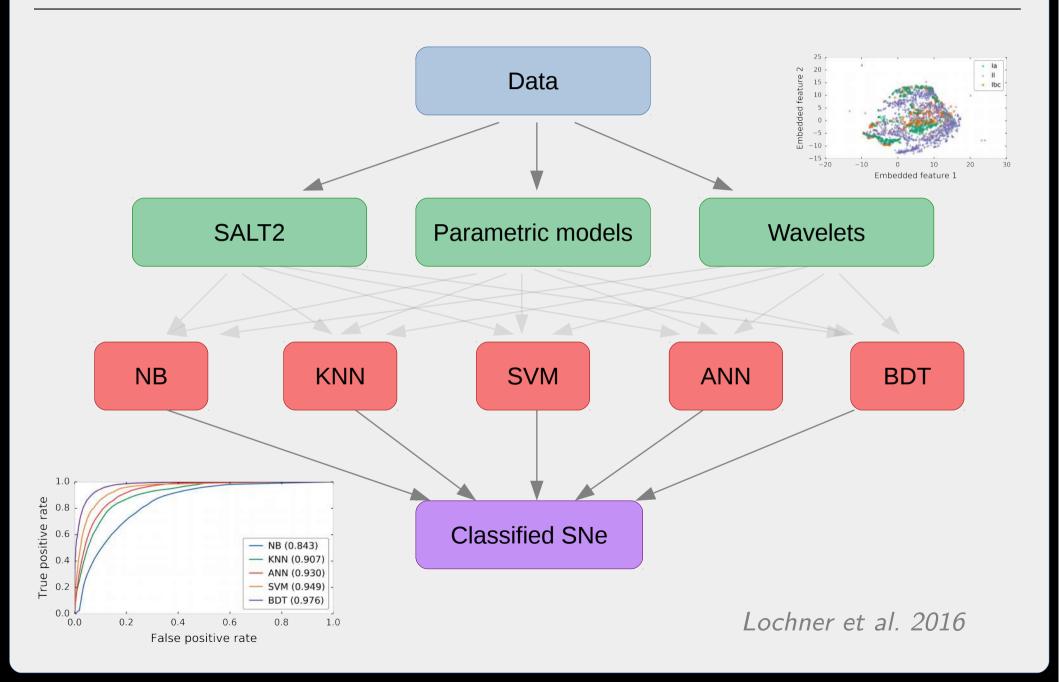


#### Non-la contamination is bad

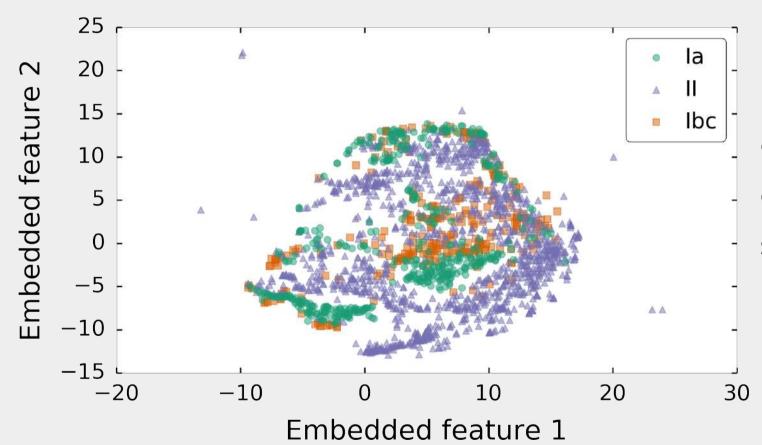
Non-la's tend to  $\frac{\mathbb{N}}{3.38}$  lie above the true cosmology  $\frac{36}{3.4}$  line and bias the best fit.



#### Solution – Machine Learning

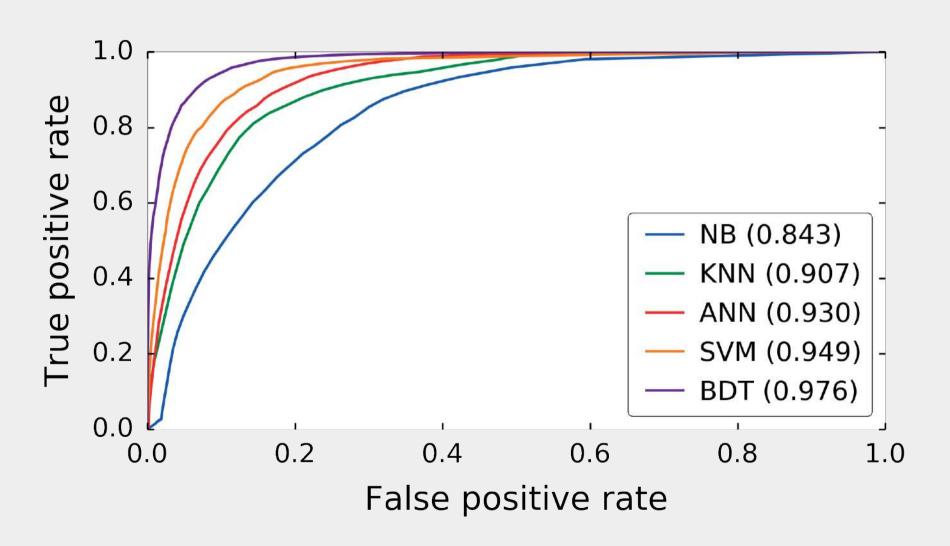


#### Results

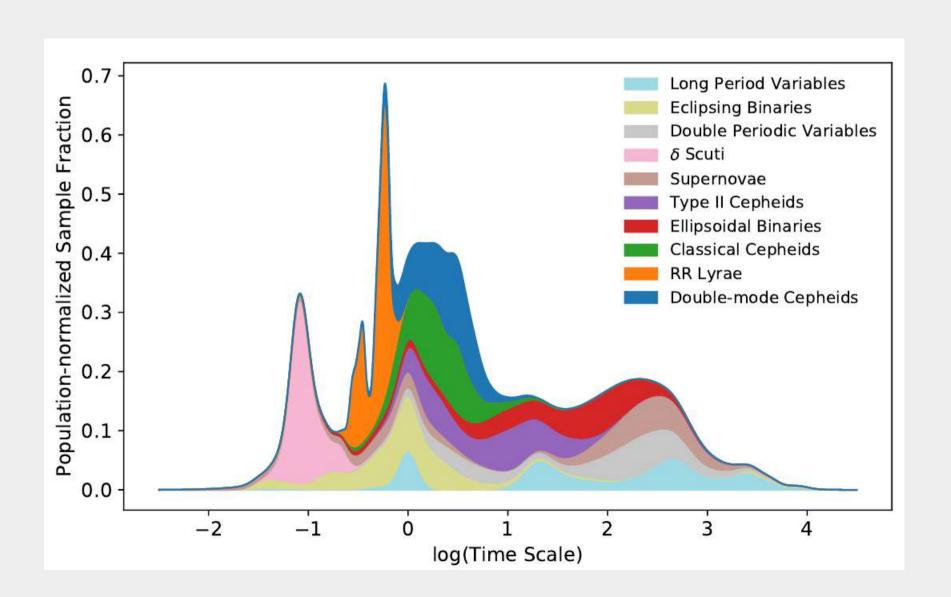


Machine learning can classify different types of supernovae with high accuracy

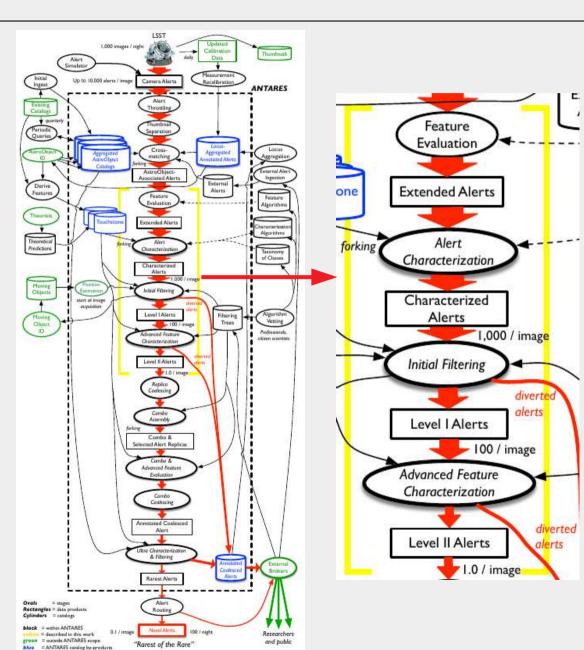
#### Results



#### LSST Problem 2 – 10 Million Transients

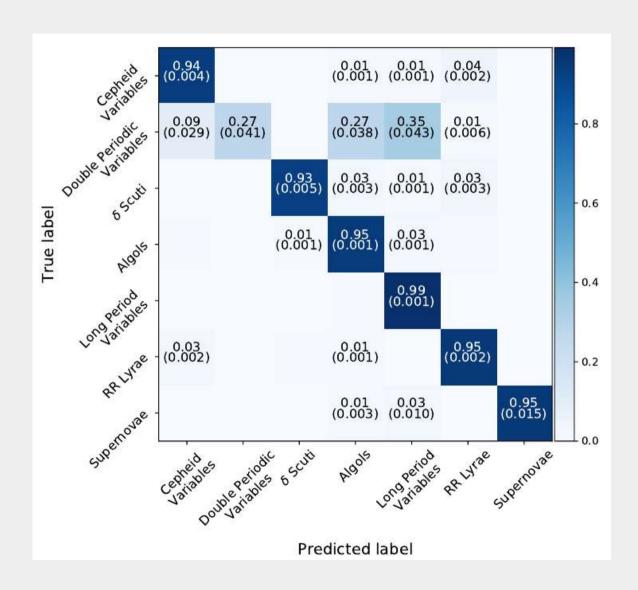


### Solution – Machine Learning



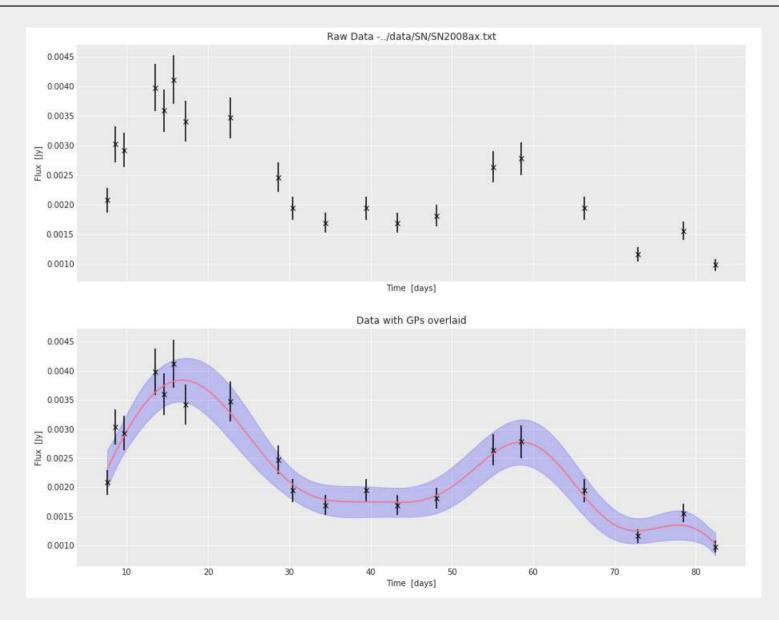
ANTARES is a transient broker and our algorithms form a central part of its classification pipeline

#### Results

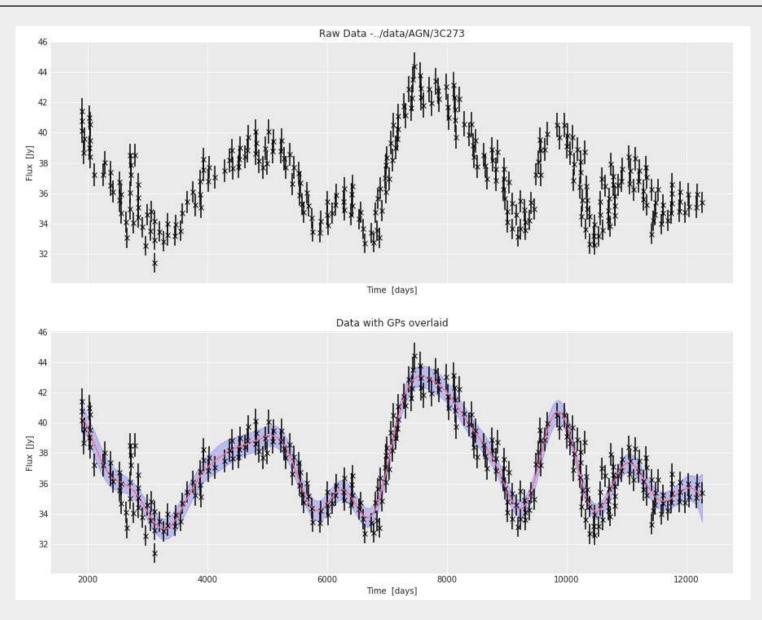


Once again, ML does a good job separating out different types of objects

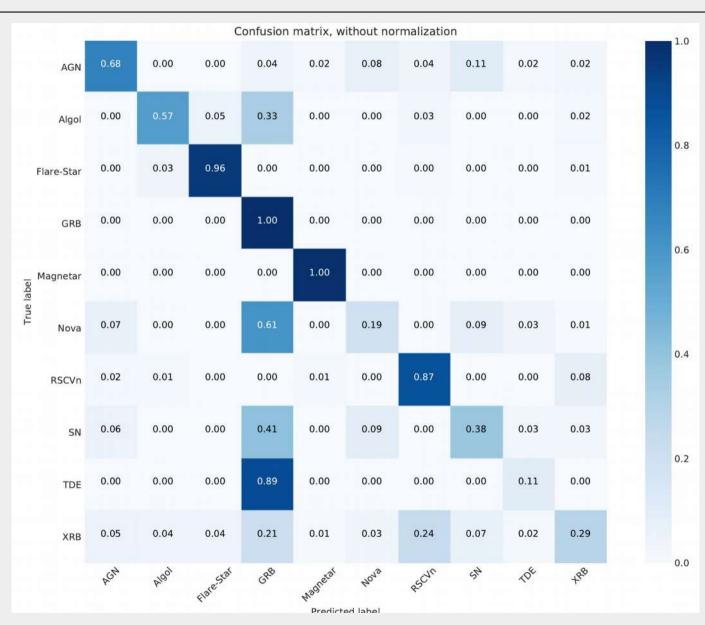
#### SKA Problem 1 – Radio Transients



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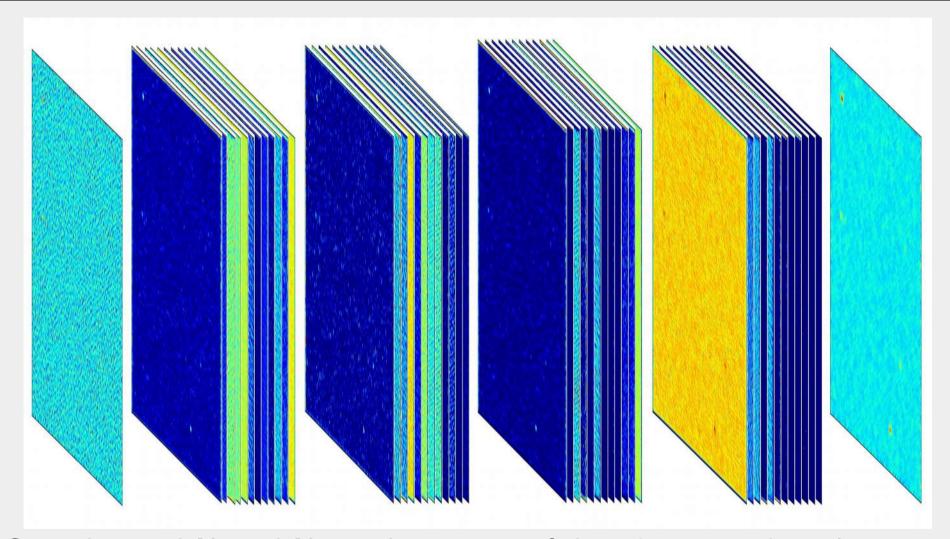
#### SKA Problem 2 – Source Finding



Need a fast, automated, reliable way to turn radio images into source catalogues

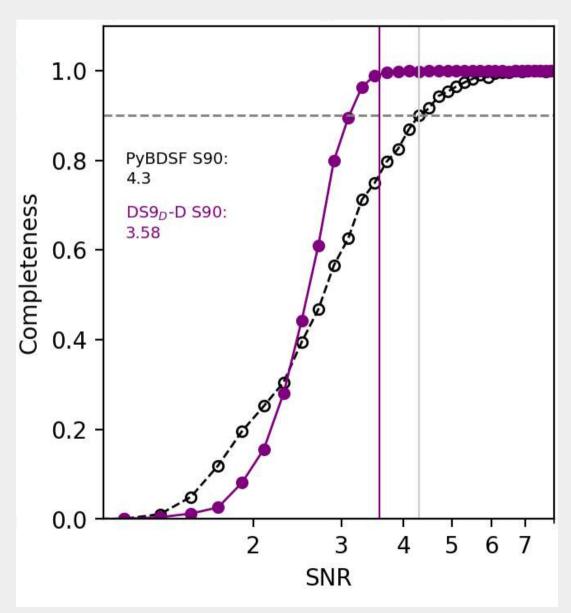
\*\*Vos et al. in prep

#### Solution – Machine Learning



Convolutional Neural Networks, a type of deep learning algorithm, can learn about correlated noise and instrumental effects

#### Results

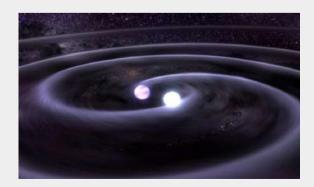


Our CNN can accurately detect more faint point sources than a commonly used source-finding algorithm

#### Other Astronomy Applications

Detecting gravitational waves

https://arxiv.org/abs/1711.07966



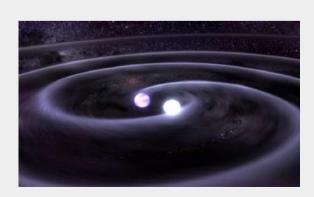
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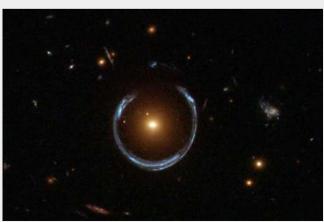


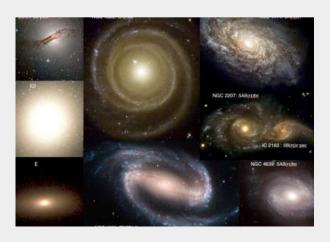
#### Other Astronomy Applications

Detecting gravitational waves https://arxiv.org/abs/1711.07966

- Finding strong gravitationally lensed galaxies https://arxiv.org/abs/1703.02642
- Combining humans and machines to classify galaxies https://arxiv.org/abs/1802.08713

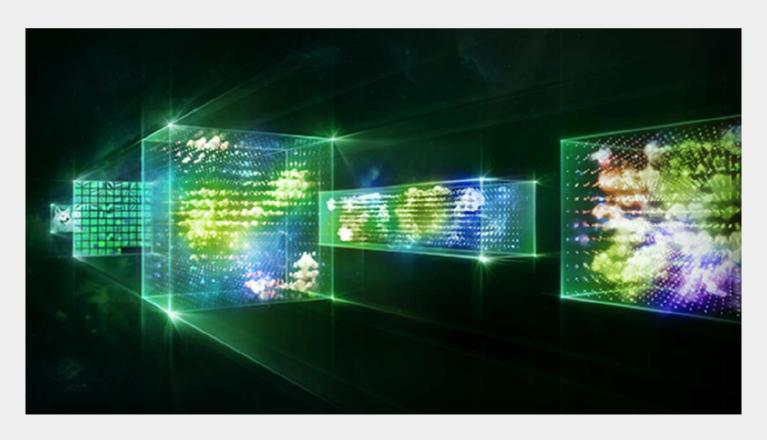






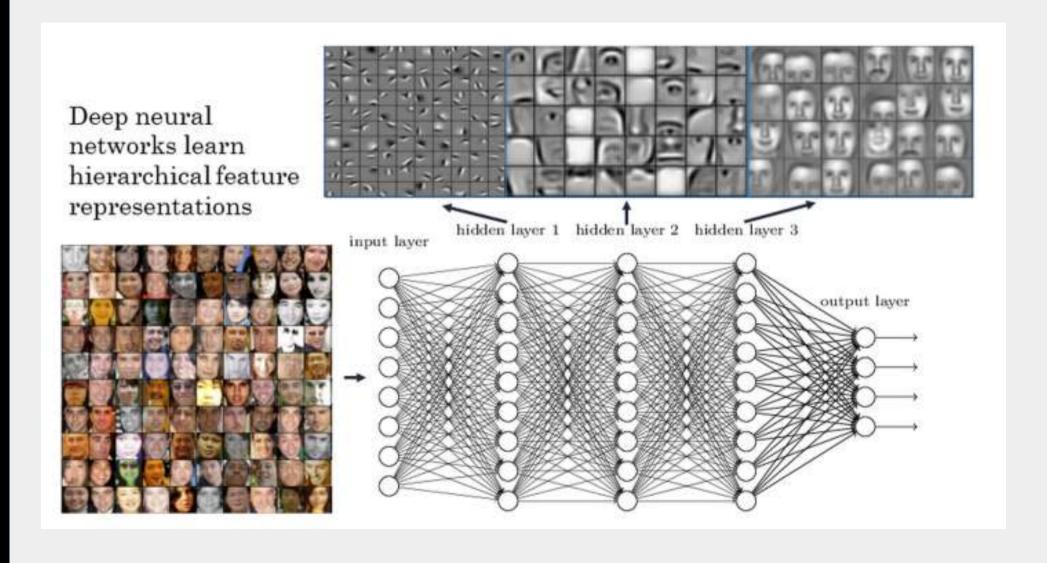
#### Going Deep

Deep learning has revolutionised machine learning in recent years, solving problems that have baffled computers for decades



### Going Deep

#### Convolutional neural networks



### Why Deep Learning is hard

You need a huge amount of training data

You need a GPU, unless you're very patient

It's an art to get the right architecture

Hard to interpret

### Making Deep Learning Easier

You need a huge amount of training data

Use data augmentation

You need a GPU, unless you're very patient

Get a GPU

It's an art to get the right architecture

Use existing architectures known to work. Also look at

Dufourq & Bassett (https://arxiv.org/abs/1709.09161)

Hard to interpret

### The Deep Learning Revolution

Convolutional neural networks for image classification, recurrent neural network for image descriptions



construction worker in orange safety vest is working on road.



two young girls are playing with lego toy.

#### Towards AI



Technically, the Turing Test was passed in 2001...













Elgammal et al. (2017) 1706.07068

### Music

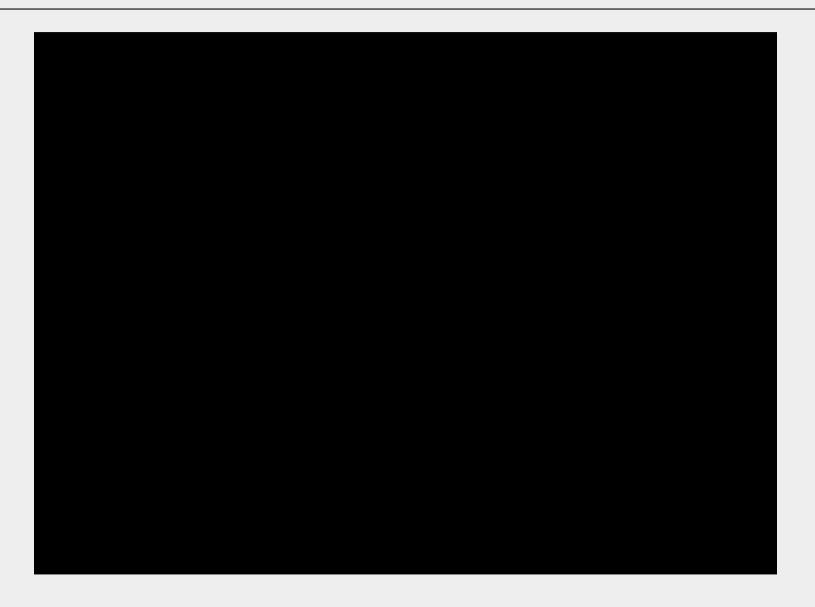
#### Music

# Chopin Music Generation

with Recurrent Neural Networks and Deep Learning

## Sci-Fi

#### Sci-Fi



#### Sci-Fi

INT. SHIP

We see H pull a book from a shelf, flip through it while speaking, and then put it back.

H

In a future with mass unemployment, young people are forced to sell blood. That's the first thing I can do.

H2

You should see the boys and shut up. I was the one who was going to be a hundred years old.

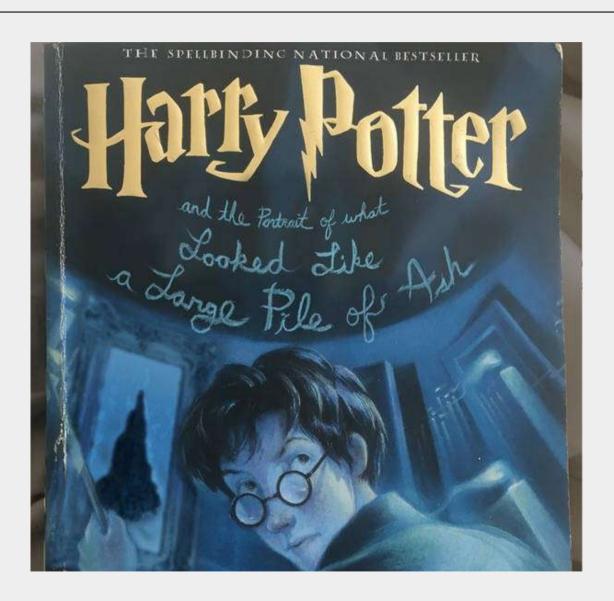
H

I saw him again. The way you were sent to me... that was a big honest idea. I am not a bright light.

C

Well, I have to go to the skull. I don't know.

### Harry Potter



### Harry Potter

Harry could tell that Voldemort was standing right behind him. He felt a great overreaction. Harry tore his eyes from his head and threw them into the forest. Voldemort raised his eyebrows at Harry, who could not see anything at the moment.

"Death Eaters are on top of the castle!" Ron bleated, quivering. Ron was going to be spiders. He just was. He wasn't proud of that, but it was going to be hard to not have spiders all over his body after all is said and done.

### Games

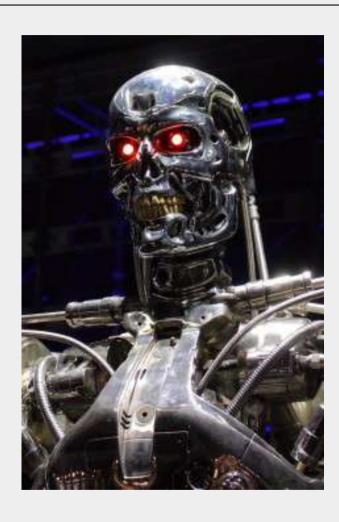


#### The Future



Does the future look like this?

#### The Future

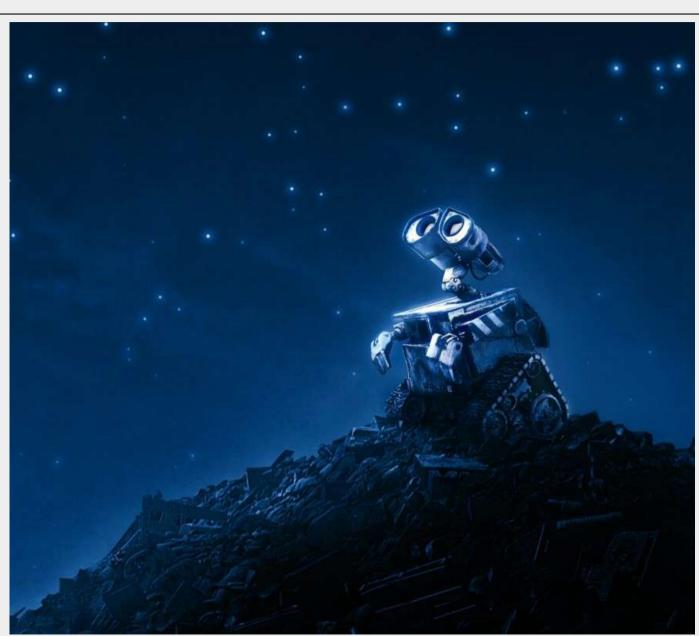


#### Or this?



#### The Future

Or this?



dr.michelle.lochner@gmail.com

#### References

https://www.coursera.org/learn/neural-networks-deep-learning

http://cs231n.github.io/convolutional-networks/

http://colah.github.io/posts/2014-07-Conv-Nets-Modular/

http://playground.tensorflow.org

Email me at: dr.michelle.lochner@gm

#### References

- SN classification https://arxiv.org/abs/1603.00882
- Transient classification

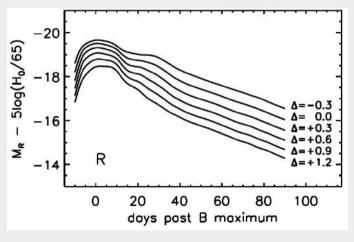
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https://arxiv.org/abs/1801.07323
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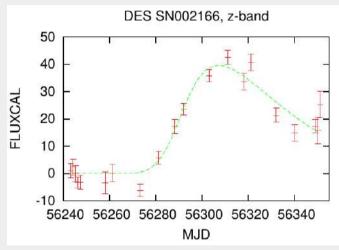
- SN cosmology https://arxiv.org/abs/1704.07830
- HI spectral line fitting

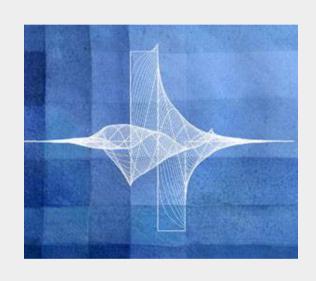
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https://arxiv.org/abs/1704.08278
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#### Feature selection

So far, we've identified three promising approaches:





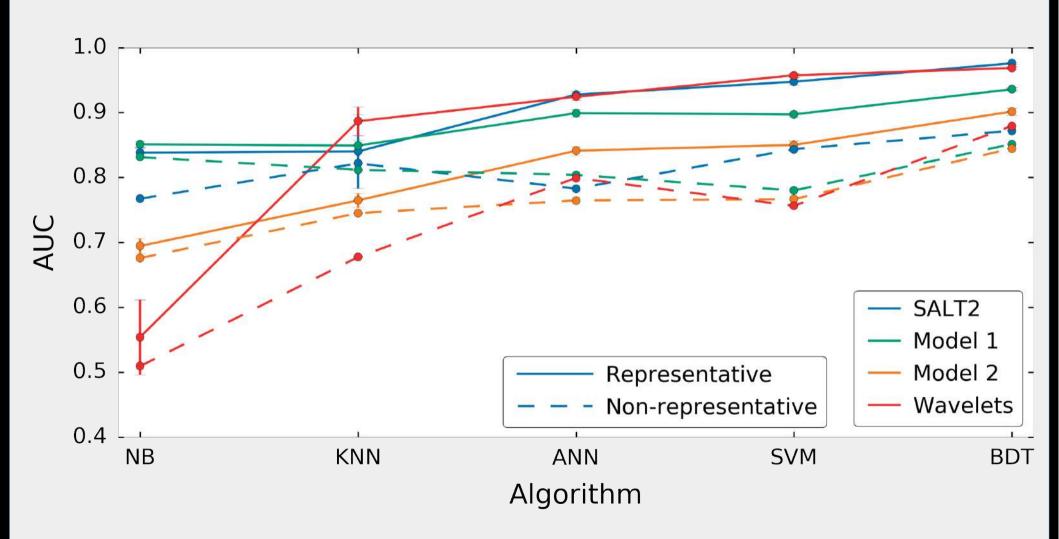


1) Template fitting

- 2) General light curve parameterisations
- 3) Wavelets

Model independence

#### Results



Lochner et al. 2016

#### Receiver Operator Characteristic (ROC) curves

