Model-independent Cosmology

(and a little on Spectral Classification using Deep Learning)

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Supervisors: Dr David Parkinson, UQ

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About me…

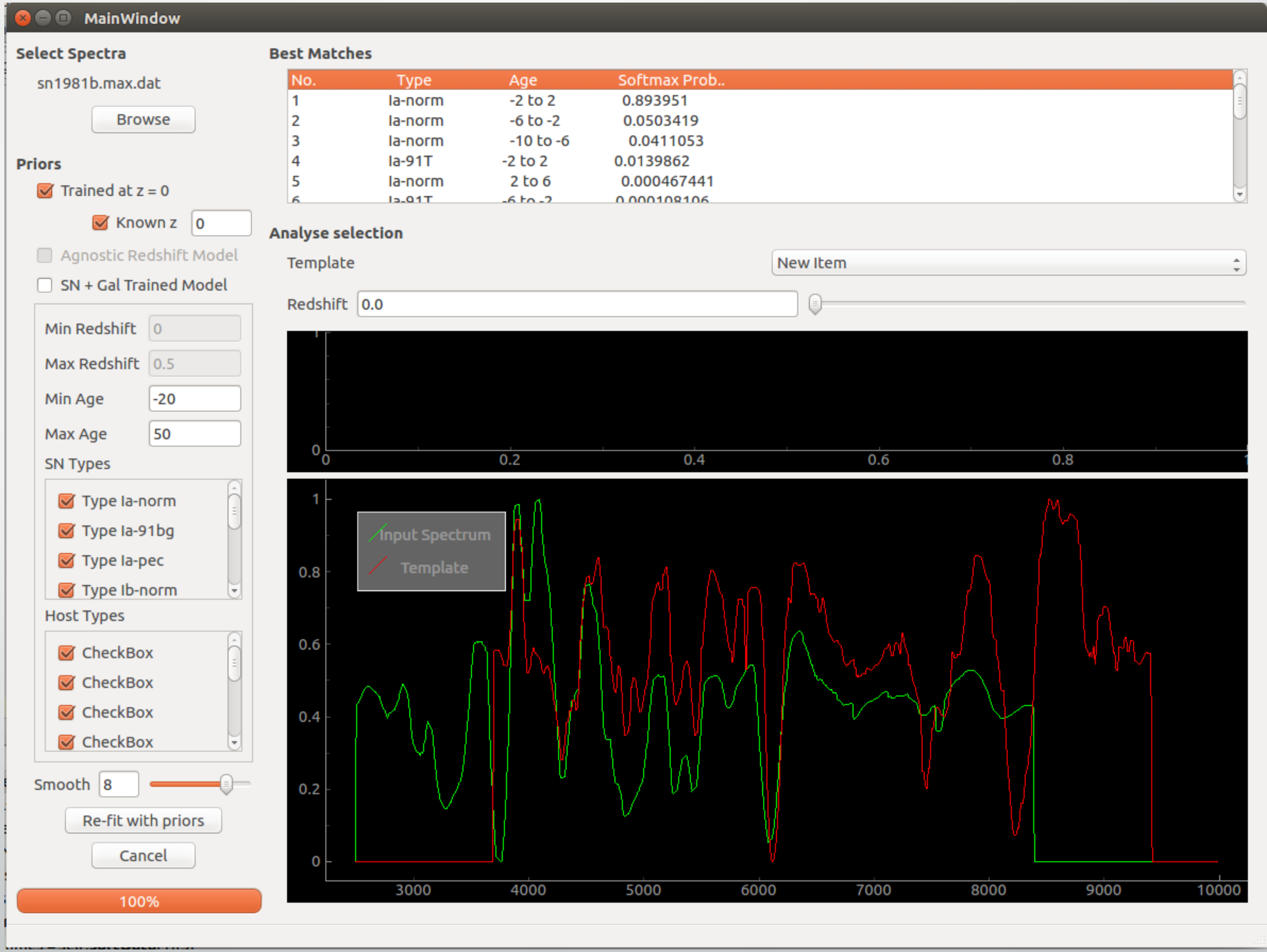
- Final year Honours Student at the University of Queensland
  - BSc (Physics)
  - BEng (Electrical & Aerospace)
  - Prospective ANU PhD student
- Main Research Areas
  - Supernova spectral classification
    - Machine learning
  - SN and BAO Cosmography
    - *A cosmographic analysis of the transition to acceleration using SN-Ia and BAO*, **Muthukrishna, D.**; Parkinson, D., Journal of Cosmology and Astroparticle Physics, submitted. https://arxiv.org/abs/1607.01884
  - GHIIR (Giant HII Regions)
    - Gemini South Observatory, Chile

Outline

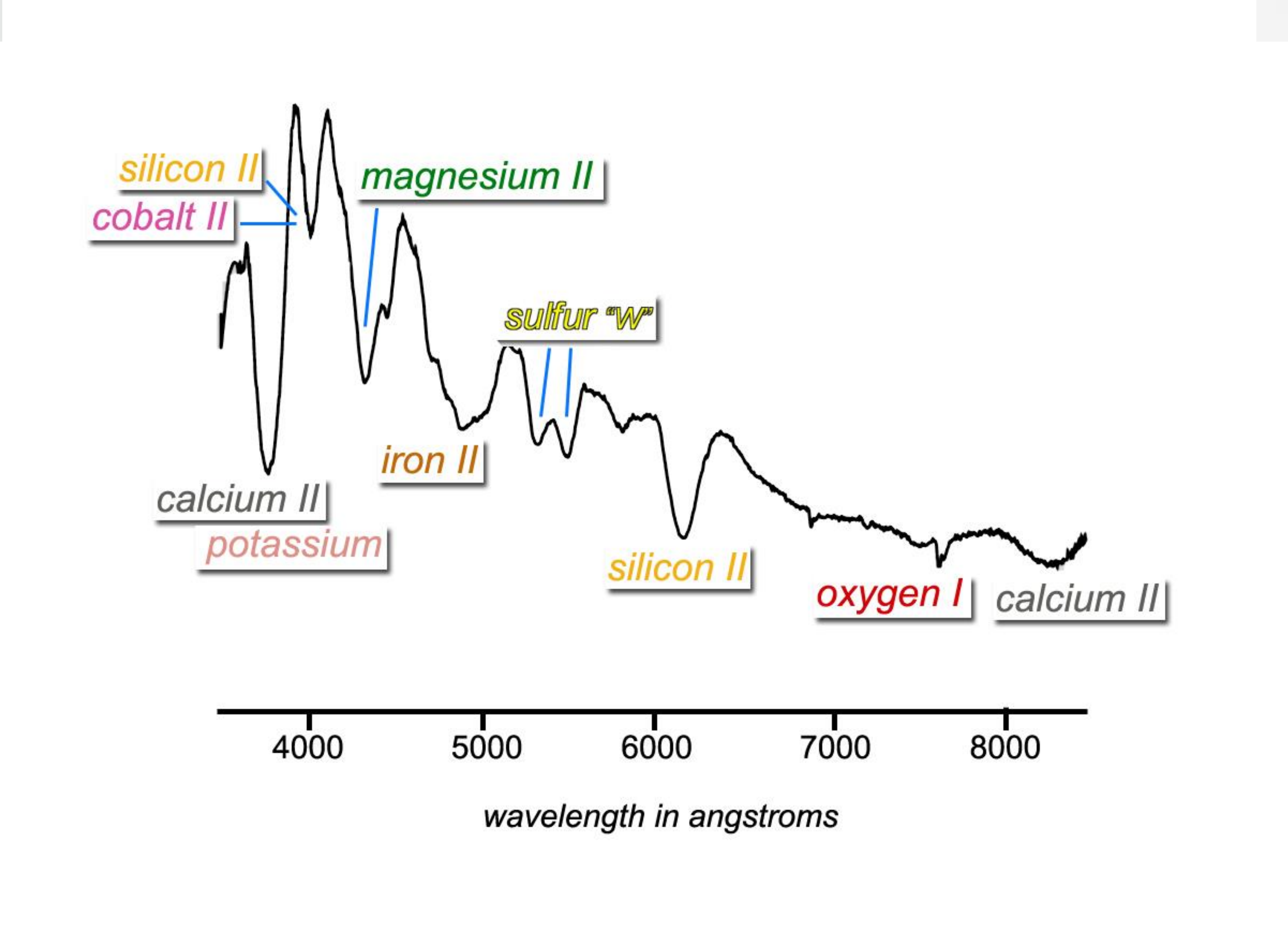
- Deep Learning for Spectral Classification
  - Overview of my software
- Model Independent Cosmology (Cosmography)
  - Why not Cosmology?
  - Transition redshift
  - Main results from paper

Deep Learning Spectral Classification

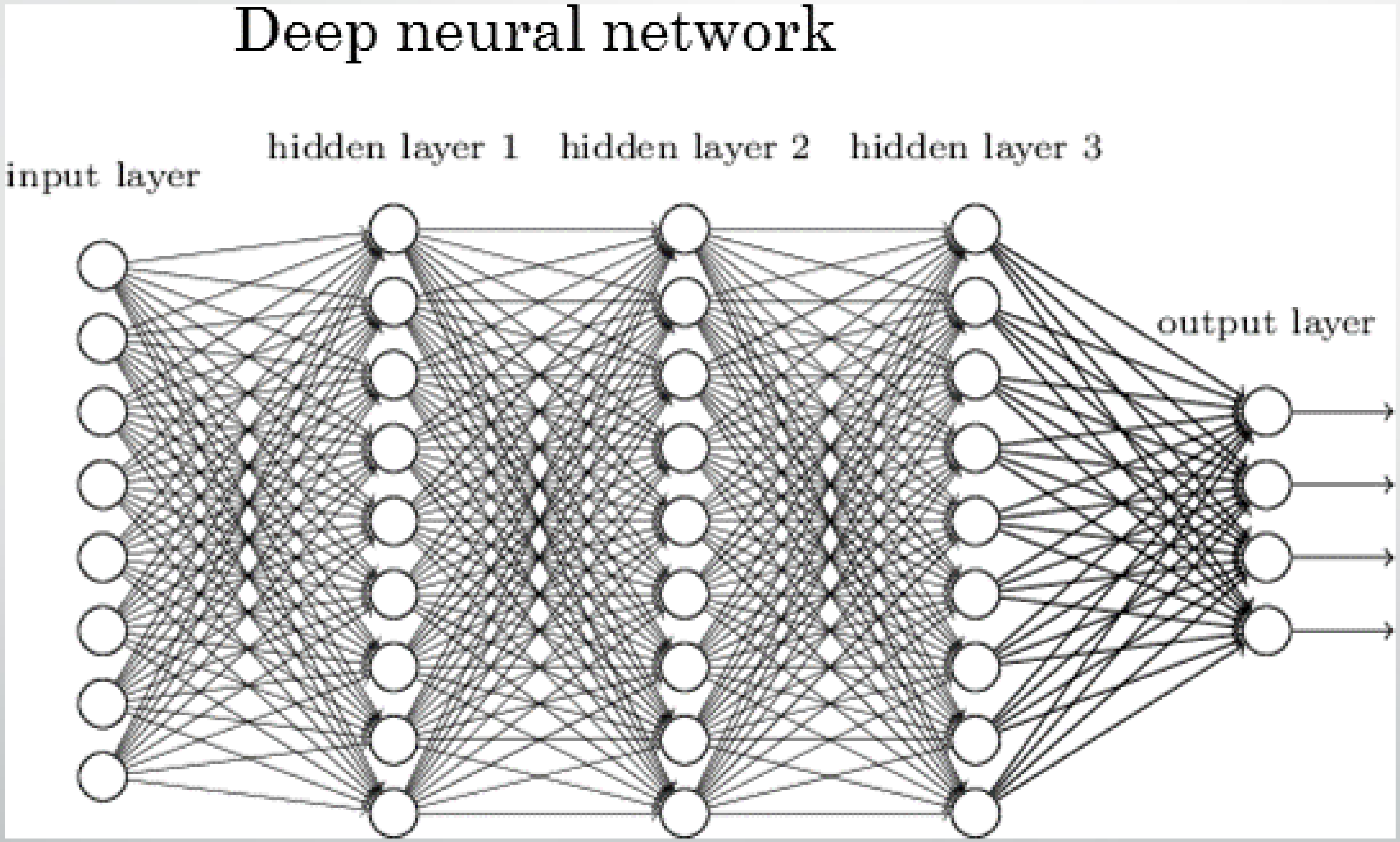
- Deep Learning is changing the world…
- Motivation
- Why is it a difficult problem?
- Google's Tensorflow Library
  - Python/C++
  - How it works… briefly
  - Layers of feature Abstraction
- Software available on GitHub



What type of supernova is this?



Layers of Feature Abstraction



Deep Learning Spectral Classification

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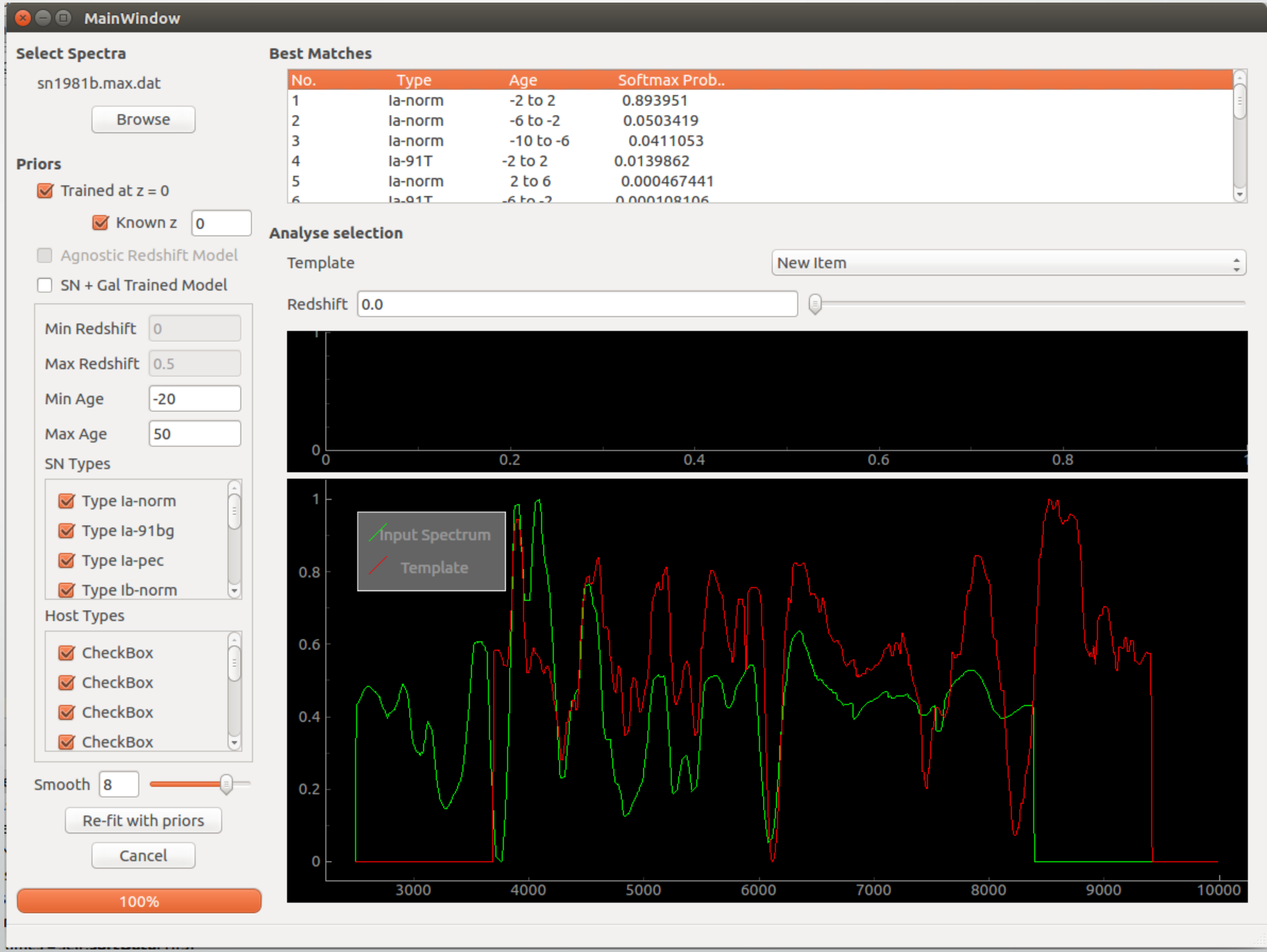


Machine Learning

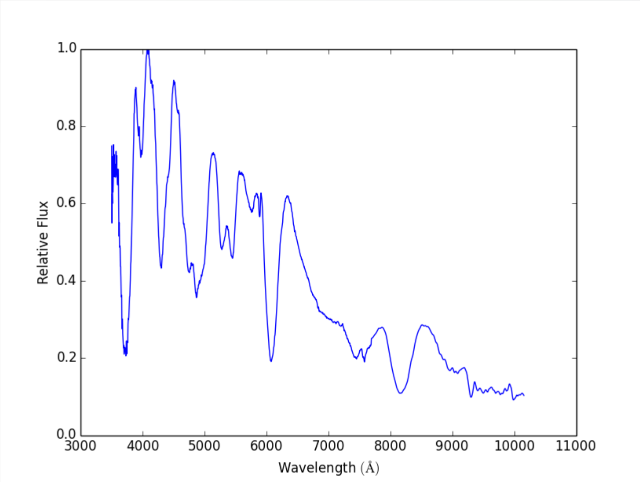
- Most of the classification software to date use a template matching techniques
  - Similar pre-processing, cross-correlation
- None of these programs have tried machine learning
  - Is a relatively new technique (always improving)
- What's wrong with machine learning?
  - Require on the order of thousands of learning samples to be effective
    - We don't have that many supernovae samples…

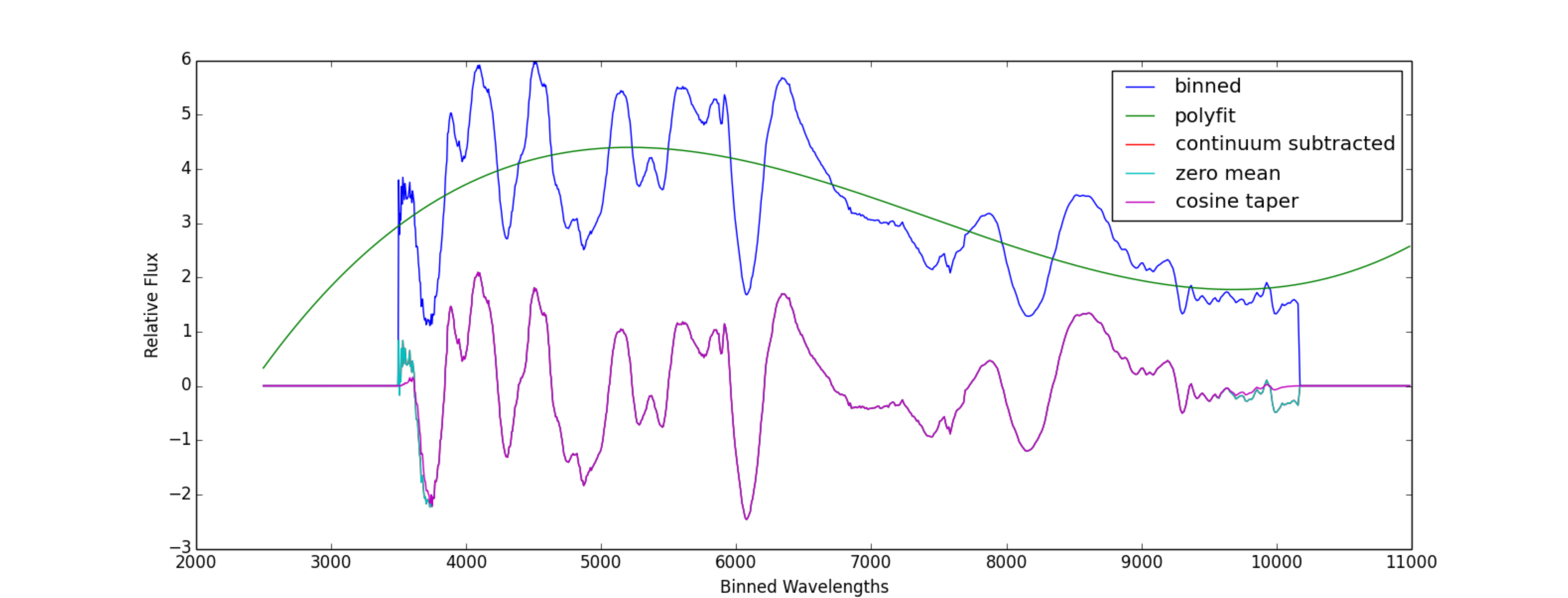
Machine Learning

- Add varying levels of Gaussian noise and create our own set of samples?
- It learns to find traits unique to each type of SN that maybe we haven't even noticed
- Implicitly cares about the emission/absorption lines
- Is faster because the learning stage is separate to the spectra being input
- Several powerful libraries already exist - Tensorflow
    - Has had an enormous amount of success in other fields

Pre-processing

- Step 1: Bin onto a log wavelength scale with 1024 bins
- Step 2: Continuum Subtraction
- Step 3: Apodizing the edges with a cosine
- Step 4: Band pass filtering the input spectra





Model-independent Cosmology – Why?

- 2011 Nobel prize awarded for the discovery of cosmic acceleration
- Challenges our understanding of the universe leaving a few possibilities:
  - Is Einstein's gravity wrong on cosmological scales?
  - What is Dark Energy?
    - Makes up about 70% of the composition of the universe
- What if General Relativity is wrong?
  - An accelerating universe is an extraordinary claim
    - We need a range of models and datasets to check it
- Multiprobe: SNIa and BAO data

What is Cosmography

- Taylor series expansion of the scale factor
- Purely kinematic analysis (independent of any cosmological model)
- Assume FLRW metric
- Cosmographic parameters:

$$
\begin{aligned}
H(t) &= +\frac{1}{a}\frac{\mathrm{d}a}{\mathrm{d}t}; \\
q(t) &= -\frac{1}{a}\frac{\mathrm{d}^2a}{\mathrm{d}t^2}\left[\frac{1}{a}\frac{\mathrm{d}a}{\mathrm{d}t}\right]^{-2}; \\
j(t) &= +\frac{1}{a}\frac{\mathrm{d}^3a}{\mathrm{d}t^3}\left[\frac{1}{a}\frac{\mathrm{d}a}{\mathrm{d}t}\right]^{-3}; \\
s(t) &= +\frac{1}{a}\frac{\mathrm{d}^4a}{\mathrm{d}t^4}\left[\frac{1}{a}\frac{\mathrm{d}a}{\mathrm{d}t}\right]^{-4}; \\
l(t) &= +\frac{1}{a}\frac{\mathrm{d}^5a}{\mathrm{d}t^5}\left[\frac{1}{a}\frac{\mathrm{d}a}{\mathrm{d}t}\right]^{-5}.
\end{aligned}
$$

Taylor Expansion

- Scale factor:

$$\frac{a(t)}{a(t_0)} = 1 + H_0(t - t_0) - \frac{q_0}{2}H_0^2(t - t_0)^2 + \frac{j_0}{3!}H_0^3(t - t_0)^3$$

- Physical Distance:

$$D = c\int dt = c(t_0 - t)$$

- Scale factor as function of distance

$$\frac{a(t_0 - D/c)}{a(t_0)} = 1 - \left(\frac{H_0 D}{c}\right) - \frac{q_0}{2}\left(\frac{H_0 D}{c}\right)^2 - \frac{j_0}{3!}\left(\frac{H_0 D}{c}\right)^3$$

Two issues with series expansions

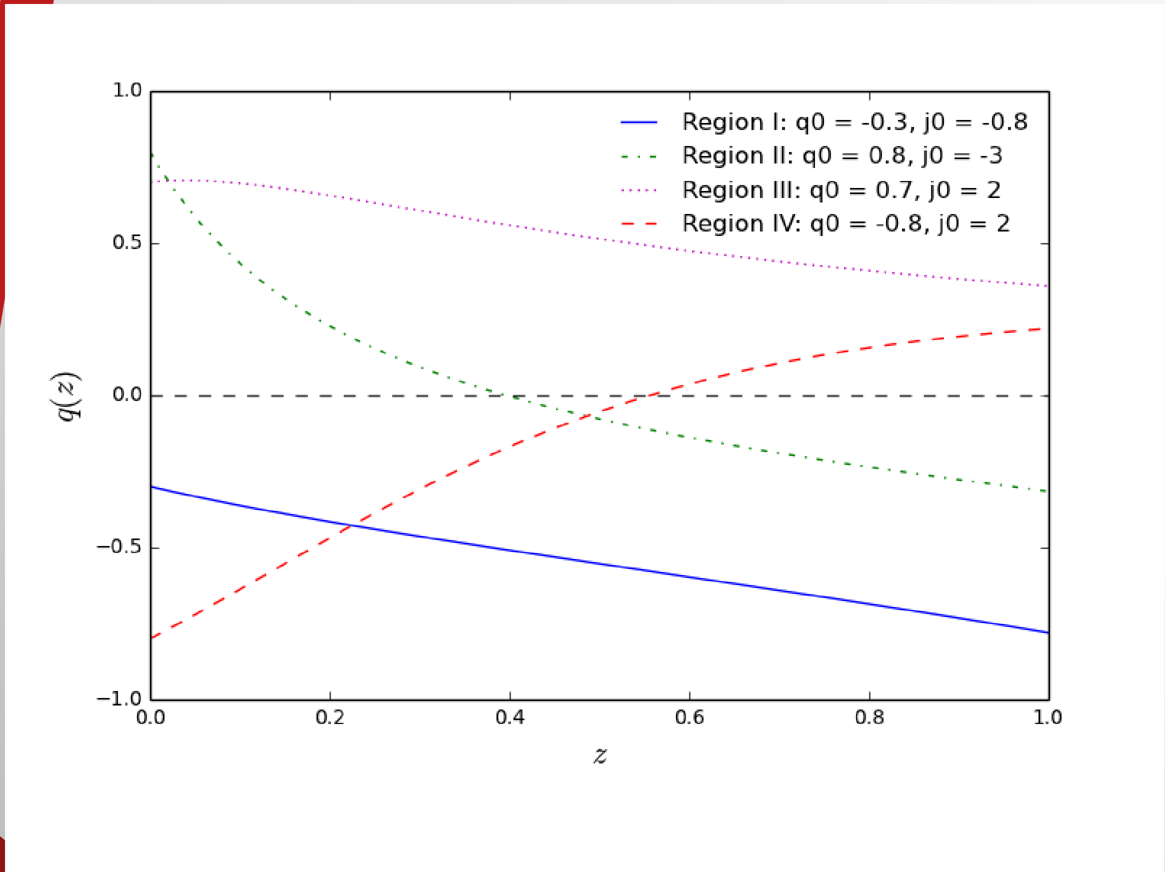
- Truncation problem
  - Can be limited by going to more terms in the expansion
  - But every additional term brings a new parameter that must be solved (q, j, s, l)
- Convergence problem
  - Redshift larger than zero has an inherent error in a series expansion
  - Introduce new parameter, zeta

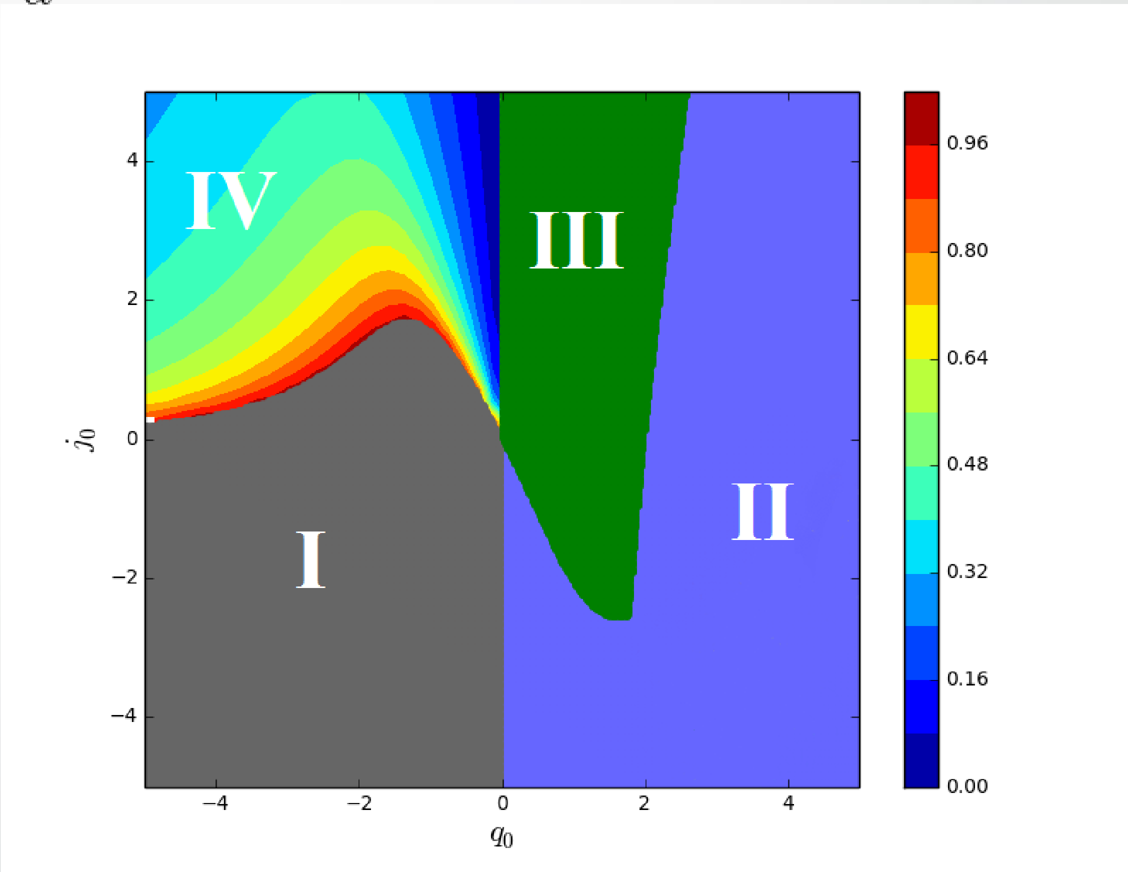
$$\zeta = \frac{z}{z+1}$$

$$D(\zeta) = \frac{c}{H_0}\{\zeta - \frac{1}{2}q_0\zeta^2 + \frac{1}{6}(-j_0 + 3q_0^2)\zeta^3\}$$

Redshift of transition

$$q(\zeta) = -\frac{a\ddot{a}}{\dot{a}^2}$$





- If we add prior assumption of early deceleration (from CMB data), Region I and Region II are eliminated.
- Region III represents a currently decelerating universe

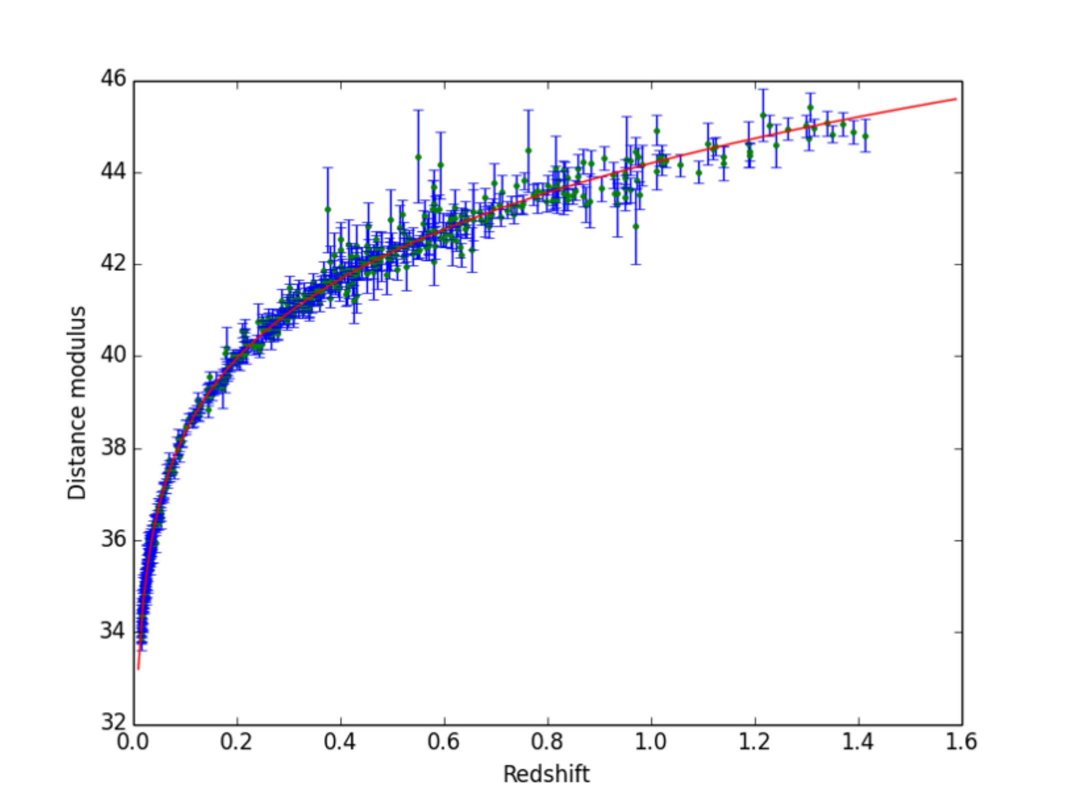
BAO Data

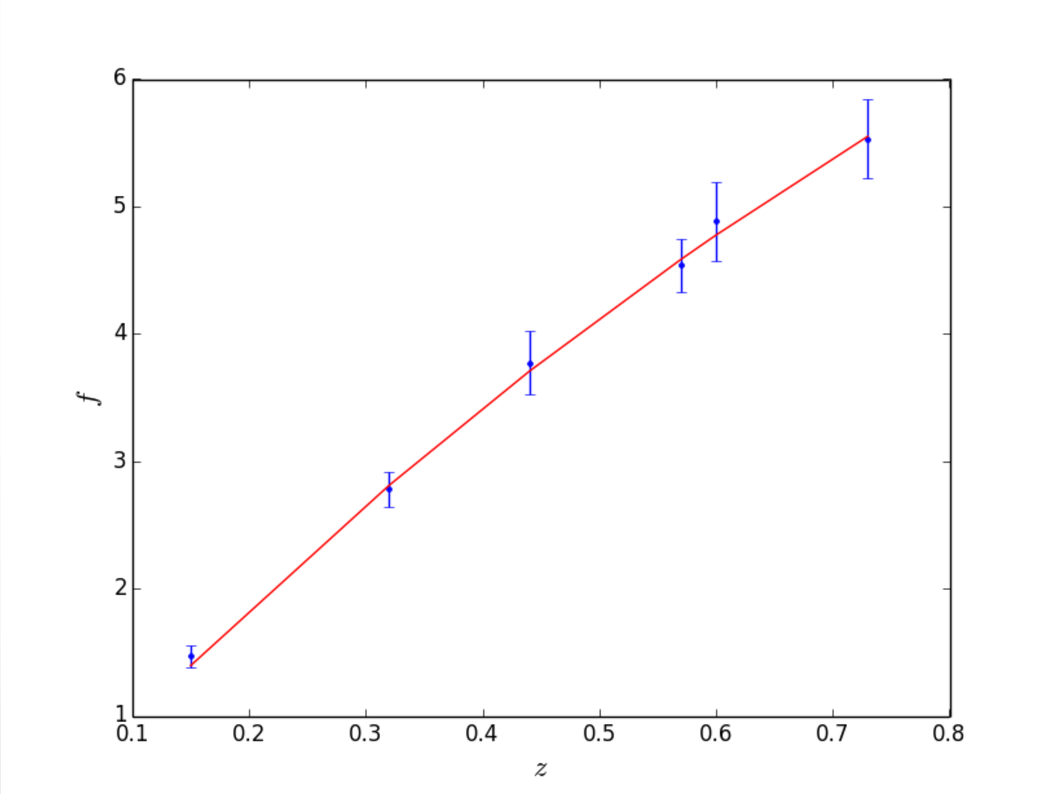
Sample	z	D_V/r_d	$f(z)$
6dFGS	0.106	3.05 ± 0.137	
SDSS-MGS	0.15	4.48 ± 0.17	1.47 ± 0.08
BOSS-LOWZ	0.32	8.47 ± 0.17	2.78 ± 0.13
BOSS-CMASS	0.57	13.77 ± 0.14	4.52 ± 0.21
WiggleZ w/recon	0.44	11.50 ± 0.55	3.77 ± 0.25
WiggleZ w/recon	0.6	14.88 ± 0.67	4.88 ± 0.31
WiggleZ w/recon	0.73	16.86 ± 0.57	5.53 ± 0.31

$$f = \frac{D_V}{D_V^{\mathrm{6dFGS}}}$$

Fit SNIa and BAO Data

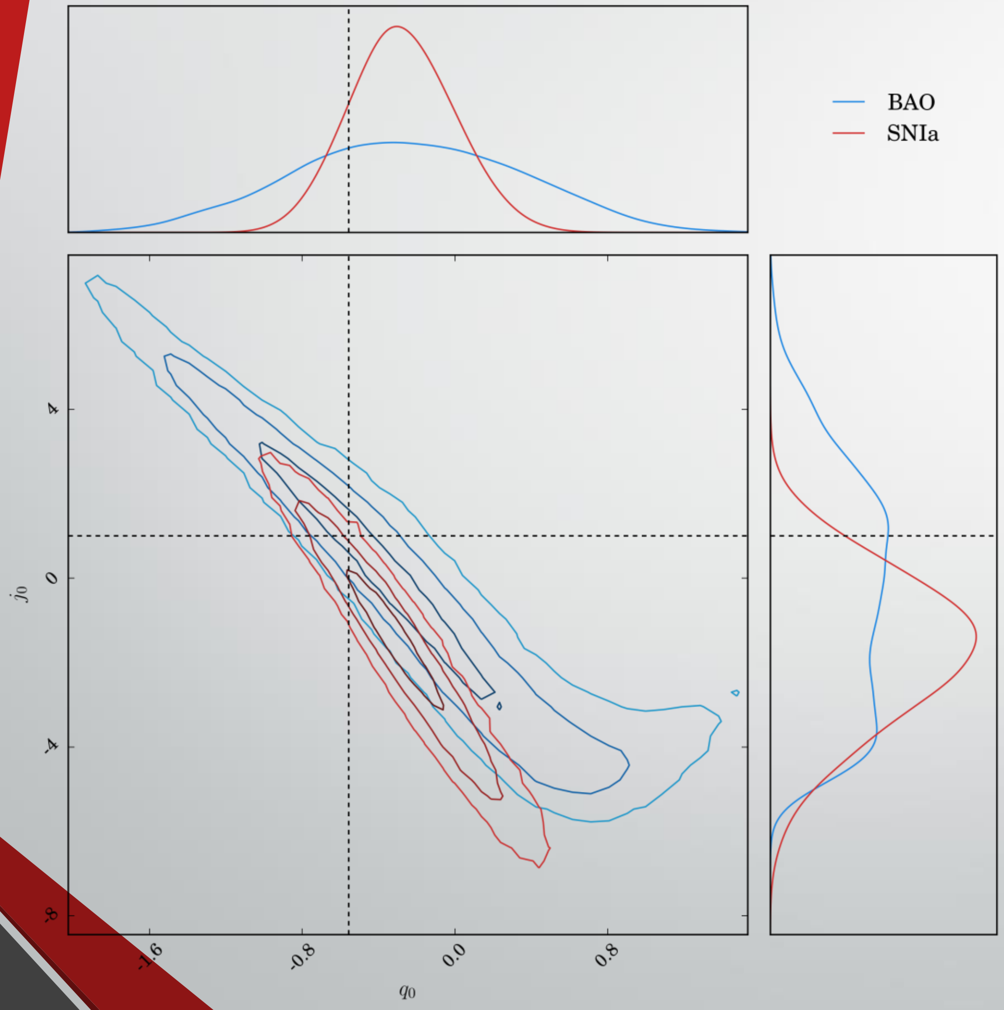
Minimise Chi-squared with MCMC

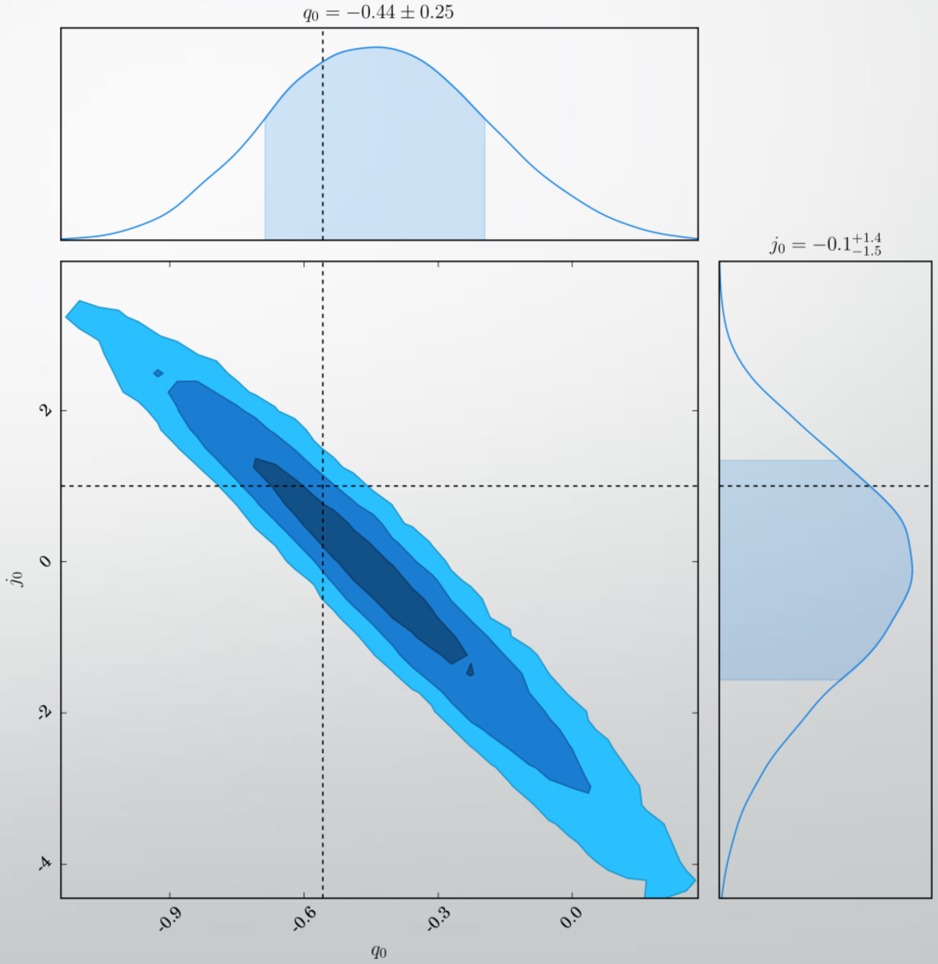


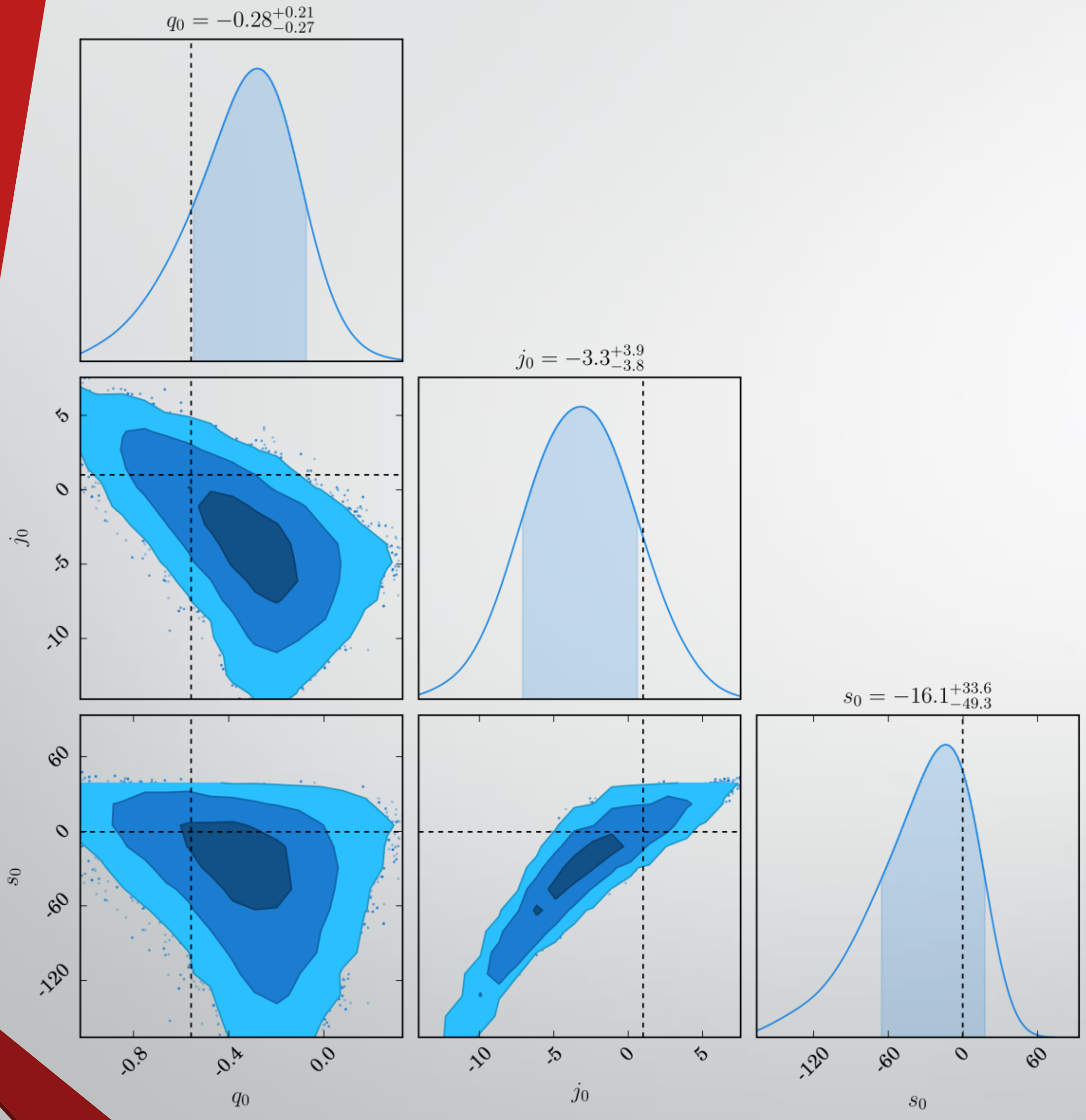


$$D_V = \left[\frac{d_L^2}{(1+z)^2}\frac{cz}{H(z)}\right]^{1/3}$$

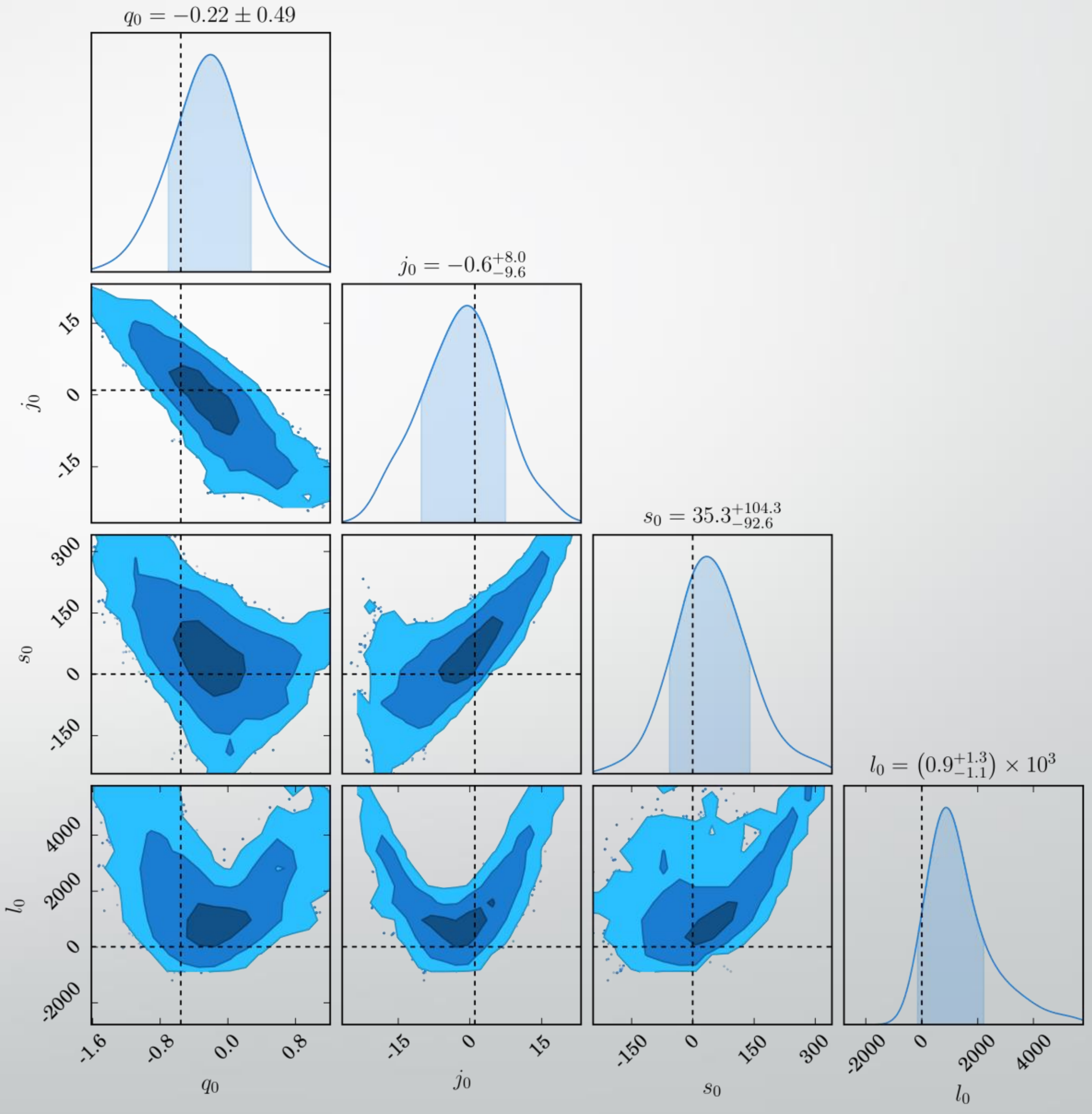
MCMC results
SNIa and BAO data





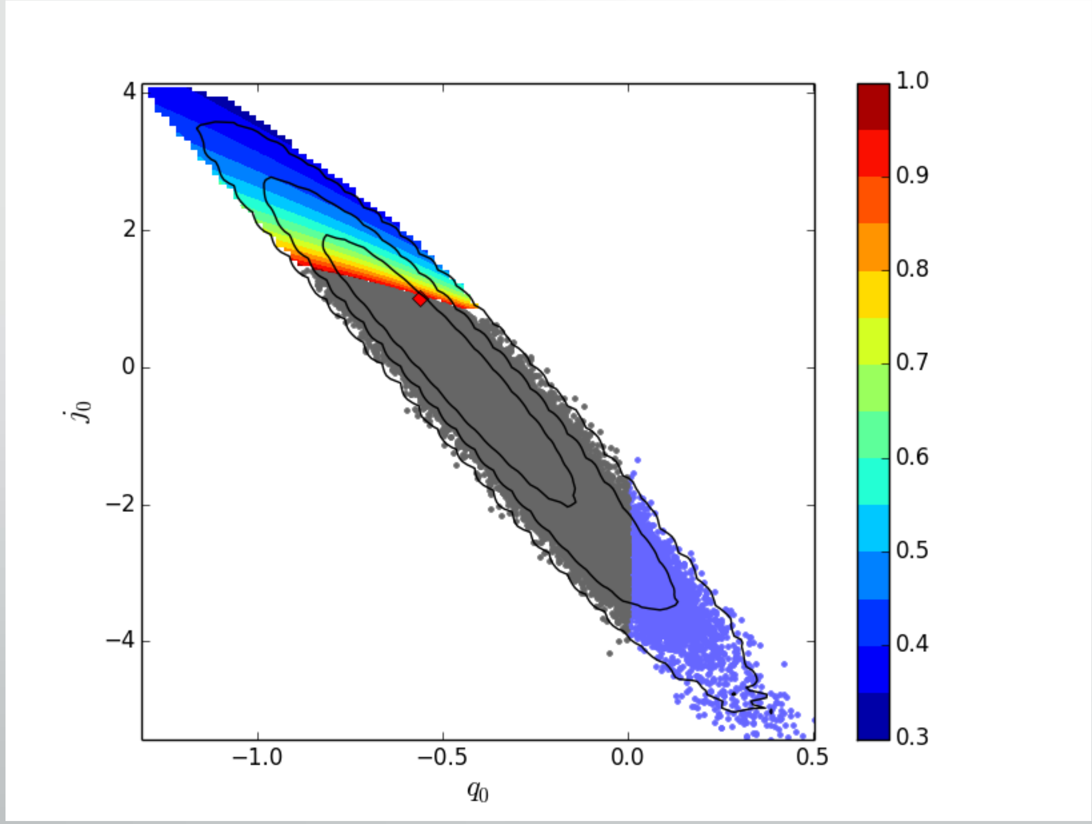


$q_0 = -0.28^{+0.21}_{-0.27}$
$j_0 = -3.3^{+3.9}_{-3.8}$
$s_0 = -16.1^{+33.6}_{-49.3}$
q_0
j_0
s_0



$q_0 = -0.22 \pm 0.49$
$j_0 = -0.6^{+8.0}_{-9.6}$
$s_0 = 35.3^{+104.3}_{-92.6}$
$l_0 = (0.9^{+1.3}_{-1.1}) \times 10^3$
q_0
j_0
s_0
l_0

Transition Limits



Lower limits on redshift of acceleration at 95% confidence

Model	Transition limit
q_0, j_0	$z_{\rm acc} > 0.44$
q_0, j_0, s_0	$z_{\rm acc} > 0.21$
q_0, j_0, s_0, l_0	$z_{\rm acc} > 0.14$

Spectral Classification using Deep Learning and Model-independent Cosmology

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