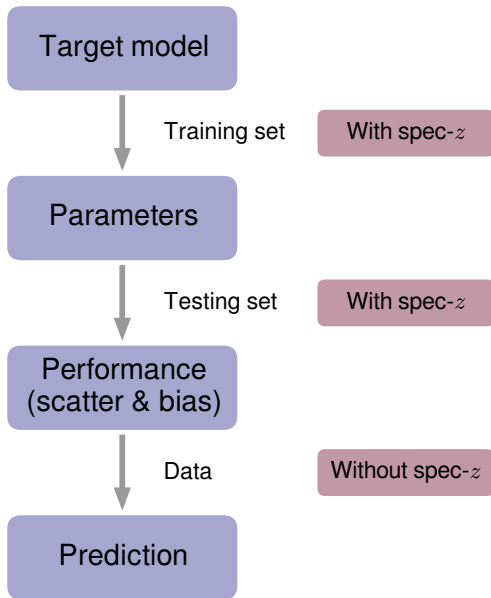


# Photometric redshifts by machine learning: Don't underestimate your scatter & bias

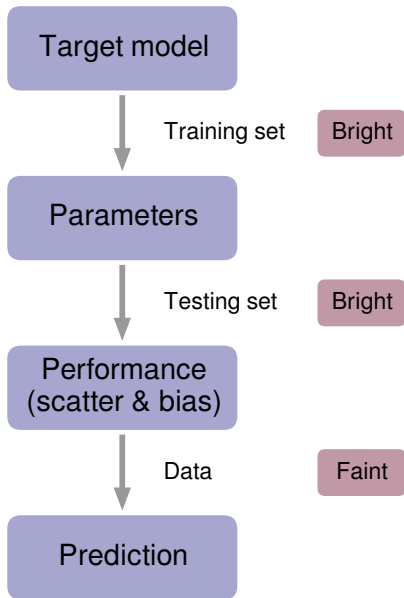
Chieh-An Lin (Linc)

April 19<sup>th</sup>, 2018  
University Oxford, UK

On behalf of  
the COIN collaboration



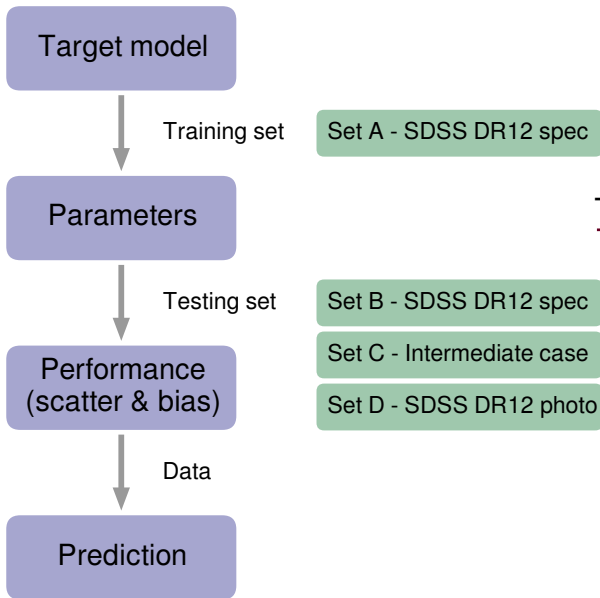
Photometric redshifts  
by machine learning



Photometric redshifts  
by machine learning

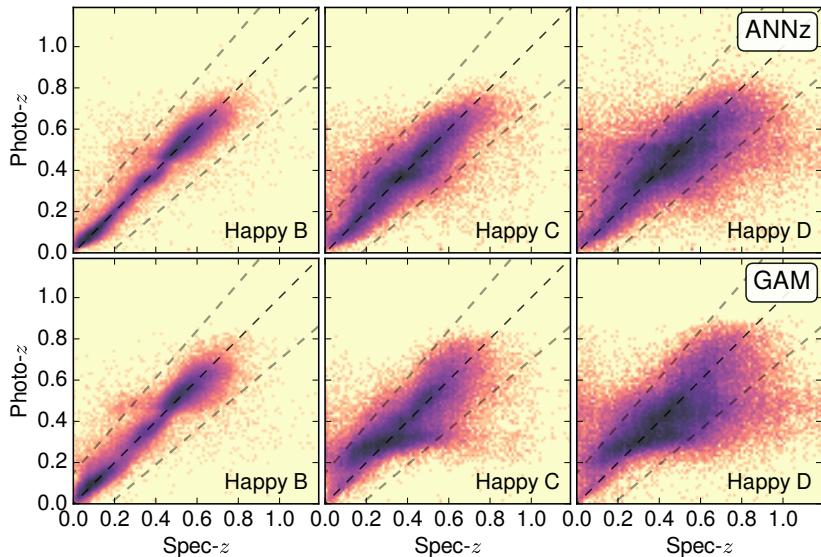
## Question

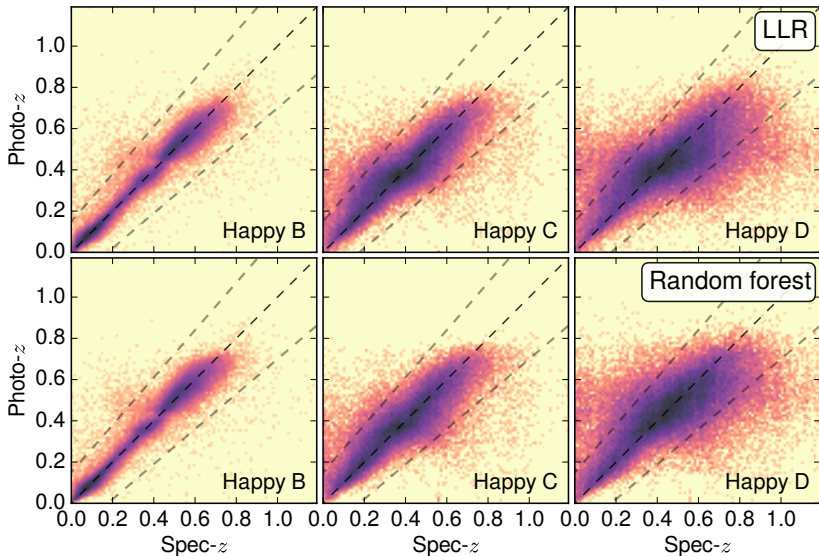
Will different error properties between the bright & faint samples bias the estimates?

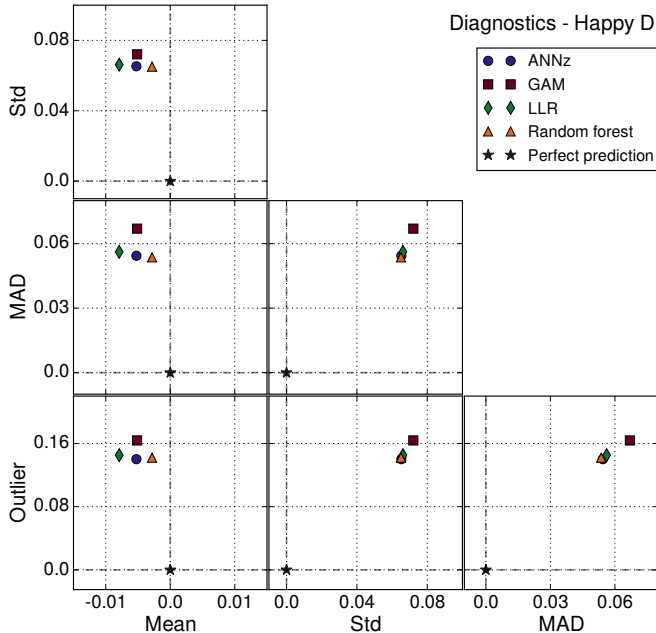


Let's design  
some tests:

The Happy catalogue







## Diagnostics

$$b \equiv \frac{z_{\text{photo}} - z_{\text{spec}}}{1 + z_{\text{spec}}}$$

MAD = median(|b|)  
 Outliers: |b| > 0.15

Beck, Lin, et al. (2017)



# Don't underestimate your scatter & bias

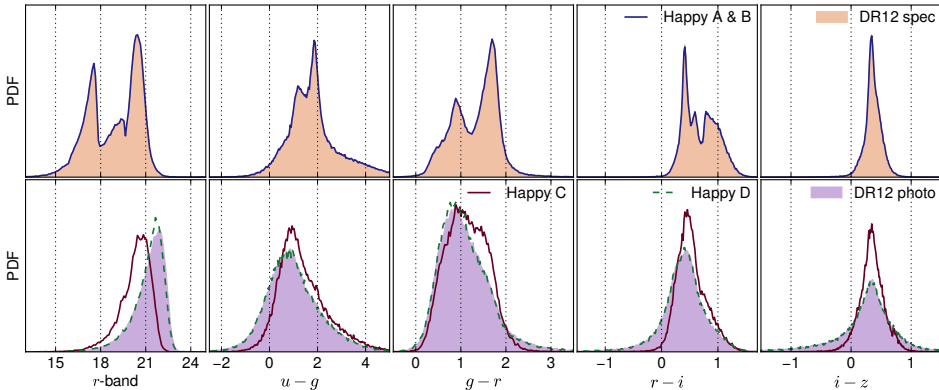


Catalogues available on GitHub

[https://github.com/COINtoolbox/photoz\\_catalogues](https://github.com/COINtoolbox/photoz_catalogues)

**Backup slides**

Beck, Lin, et al. (2017)

Color distributions

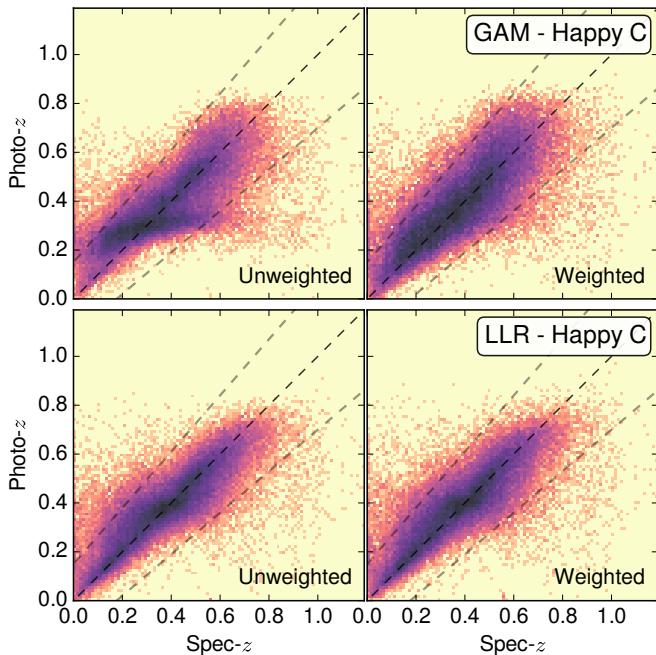
Method	Set	Mean	Std	MAD	Outliers
ANNz	B	0.04	2.87	1.49	0.99
	C	0.16	5.41	3.60	5.59
	D	-0.52	6.53	5.44	14.01
GAM	B	0.09	3.50	1.95	1.36
	C	0.86	6.34	4.84	7.37
	D	-0.51	7.21	6.70	16.38
LLR	B	0.13	2.81	1.39	1.11
	C	0.52	5.45	3.59	6.07
	D	-0.79	6.62	5.62	14.52
Random forest	B	0.05	2.82	1.41	1.02
	C	0.34	5.39	3.51	5.58
	D	-0.28	6.51	5.36	14.2

## Diagnostics

Units:  $10^{-2}$

## Extended spectroscopic samples

Survey	References	Number of matches
2dF	Colless et al. (2001, 2003)	770
6dF	Jones et al. (2004, 2009)	765
DEEP2	Davis et al. (2003); Newman et al. (2013)	7456
GAMA	Driver et al. (2011); Baldry et al. (2014)	53373
PRIMUS	Coil et al. (2011); Cool et al. (2013)	32459
VIPERS	Garilli et al. (2014); Guzzo et al. (2014)	18967
VVDS	Le Fèvre et al. (2004); Garilli et al. (2008)	8381
WiggleZ	Drinkwater et al. (2010); Parkinson et al. (2012)	43874
zCOSMOS	Lilly et al. (2007, 2009)	2789
Total		168834



Reweighting  
does not  
cure