How robust are SN Ia data?

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arXiv:1310.8435

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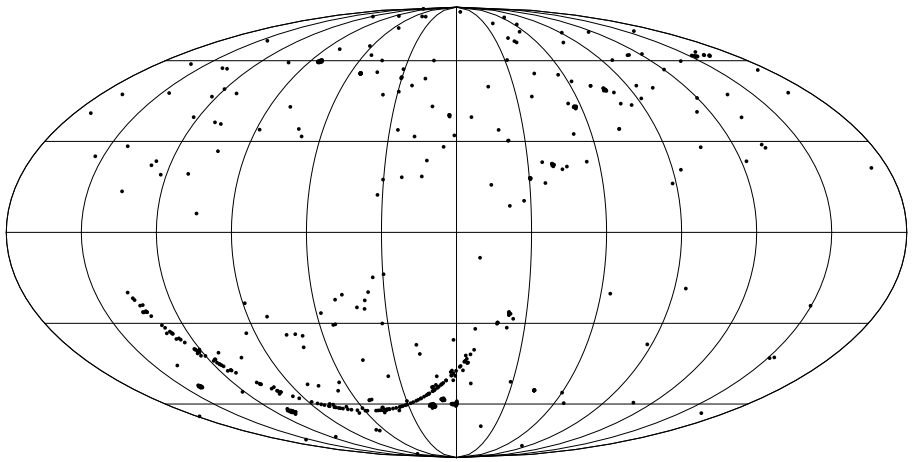


SN Ia as cosmological probes - where to improve?

increasing number of SNe & large number of effects:

→ systematic errors start dominating the overall error
→ in need of **purely statistical analysis methods**

which are able to

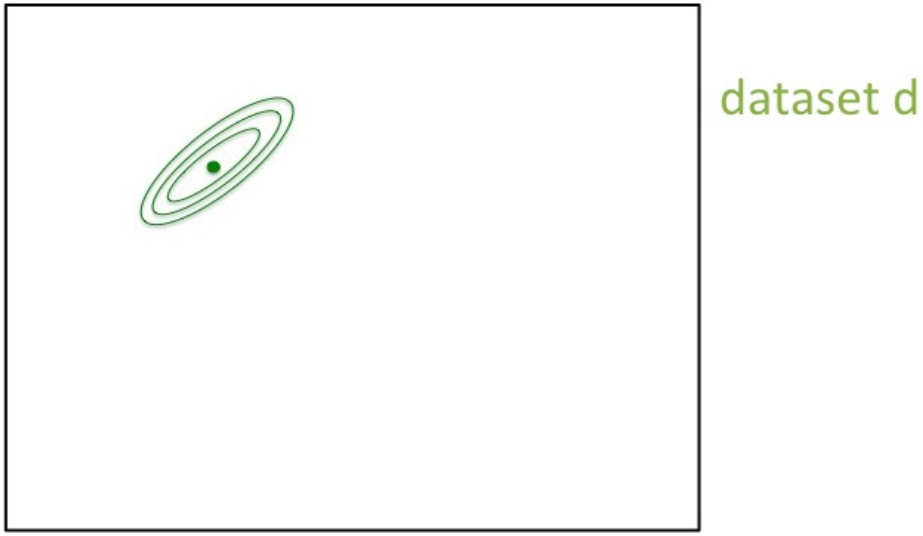
- investigate systematic effects
- detect correlations

with the aim to

- pin-point **subsets** of contaminated data
- search for astrophysical/cosmological information

What is robustness?

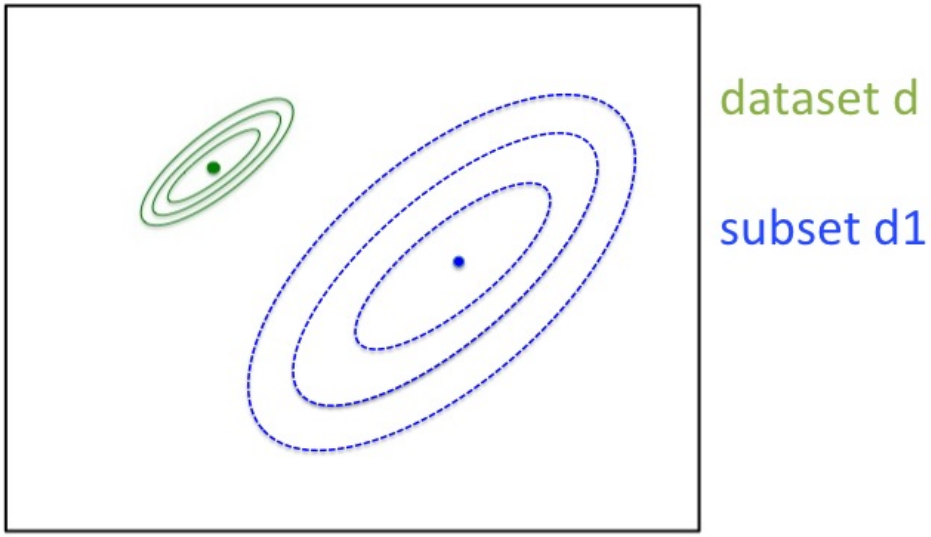
robustness = **consistency** among subsets



Is there any subset statistically incompatible with others?
→ likelihood contours **shift** and **change size**

Bayesian view of robustness

robustness = **consistency** among subsets



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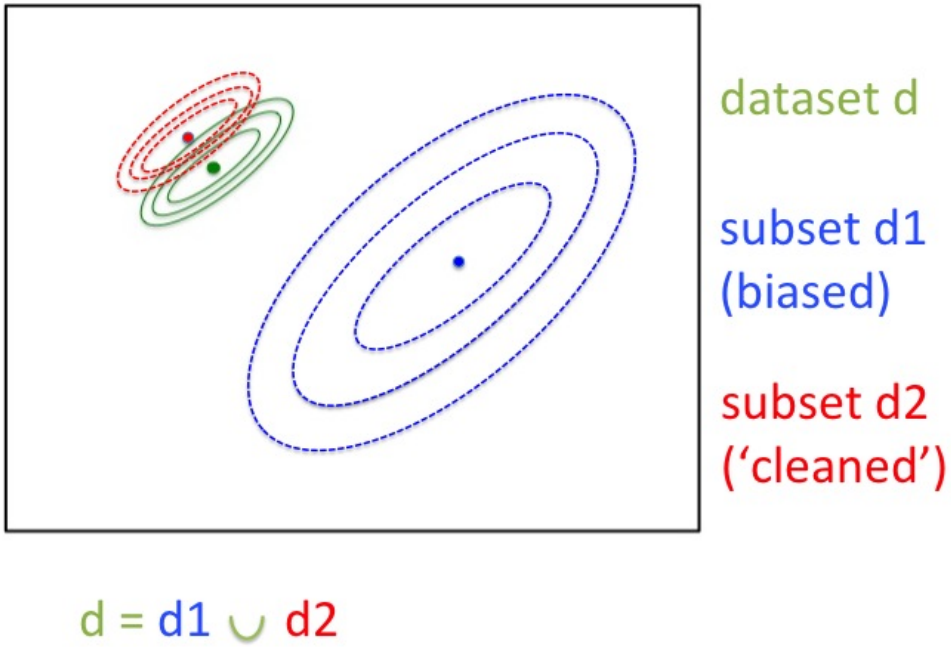

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Internal Robustness

Bayesian comparison of 2 hypothesis:

one set of parameters ⇔ two independent distributions

Bayes' ratio:

$$\mathcal{B}_{tot,ind} = \frac{\mathcal{E}(d; M_C)}{\mathcal{E}(d_1; M_C)\,\mathcal{E}(d_2; M_S)}$$

$d =$ full set, subsets d_1 and d_2, with $d_1 + d_2 = d$
independent models M_C and M_S

Internal Robustness:

$$R \equiv \log \mathcal{B}_{tot,ind}$$

Amendola, Quartin, Marra (arXiv:1209.1897)

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Internal Robustness - Fisher:

$$R = R_0 + \frac{1}{2}\log\frac{|\boldsymbol{F}_1||\boldsymbol{F}_2|}{|\boldsymbol{F}_{tot}|} - \frac{1}{2}\left(\widetilde{\chi}^2_{tot} - \widetilde{\chi}^2_1 - \widetilde{\chi}^2_S\right)$$

Amendola, Quartin, Marra (arXiv:1209.1897)

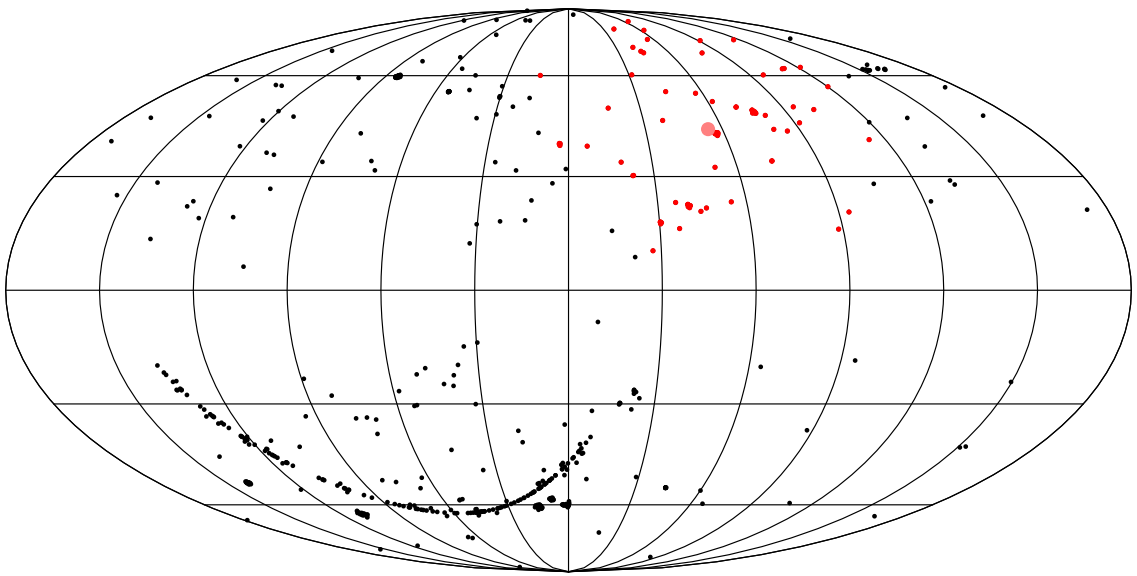
Internal Robustness probability distribution function (IR-PDF)

parametrization choice of observable & **partitioning** of data
$\downarrow$
evaluate **R** – **value** for each chosen partition
$\downarrow$
IR – **PDF**

complete scan of all subsets impossible
$\rightarrow$ IR-PDF will depend on chosen partitions!
$\rightarrow$ IR-PDF for mock catalogues to test significance

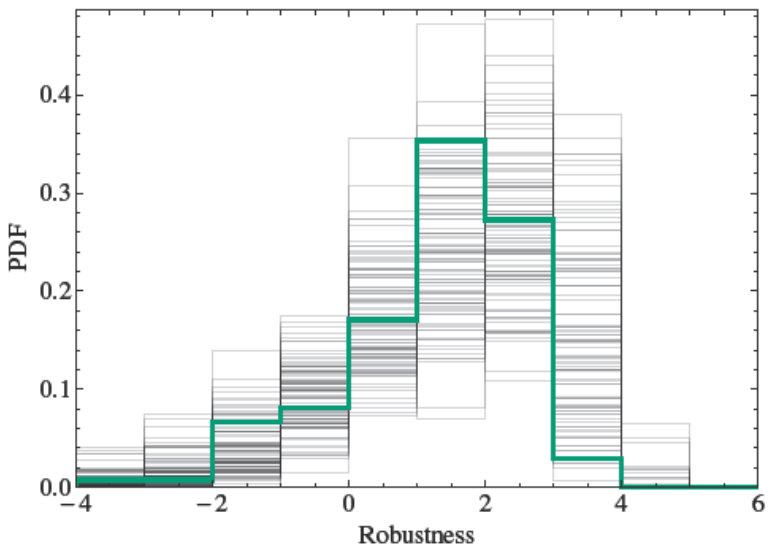
Our partitioning (arXiv:1310.8435) of Union2.0/2.1

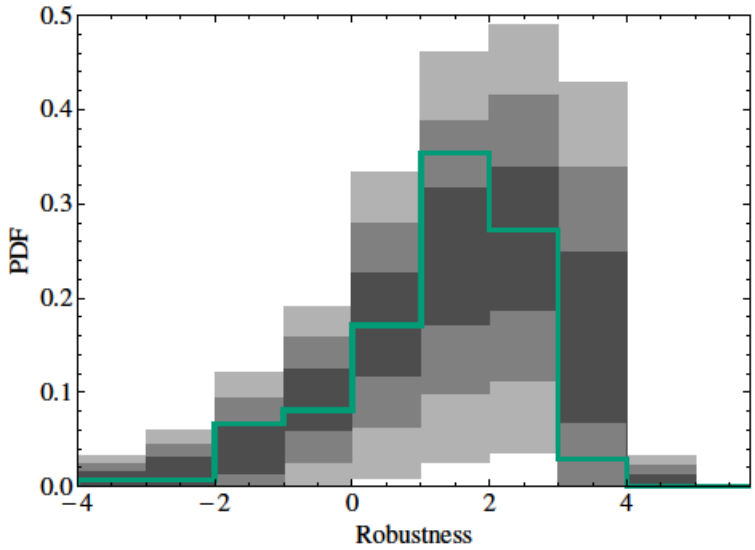
- angular separation
- z-binning
- survey-wise
- hemispheres



arXiv:1310.8435: Heneka, Marra, Amendola

Internal Robustness probability distribution function: separation sorted





→ agreement within 2σ!
→ no significant effects depending on angular separation
→ similar for z-binning and survey-wise analysis

arXiv:1310.8435: Heneka, Marra, Amendola

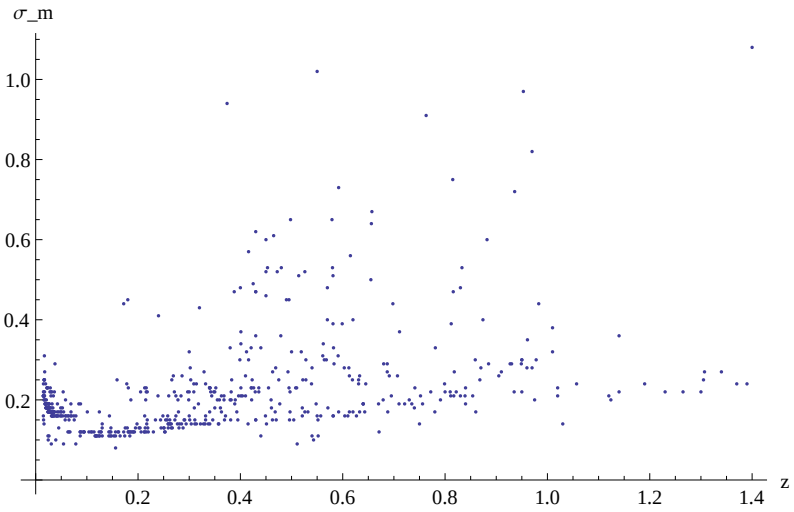
Hemispherical directions

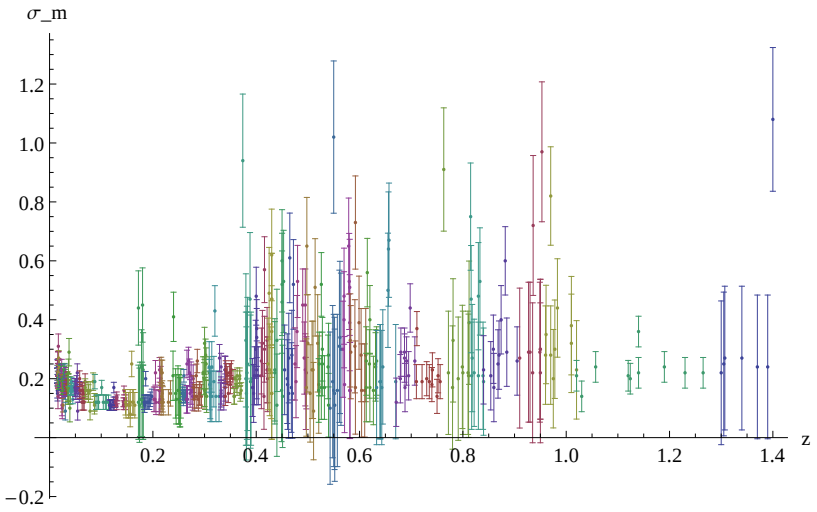
single partition (Planck)	(α, δ)	Significance
Hemispherical asymmetry	$(270°, 66.6°)$	1.26σ
Dipole anisotropy	$(167°, -7°)$	0.39σ
Quadrupole-octupole alignment	$(177.4°, 18.7°)$	0.35σ
Grid of hemispheres		
Direction of lowest robustness	$(150°, 70°)$	2.20σ

arXiv:1310.8435: Heneka, Marra, Amendola

Preliminary: analysis of distance modulus errors

analysis applicable to **any observable**!

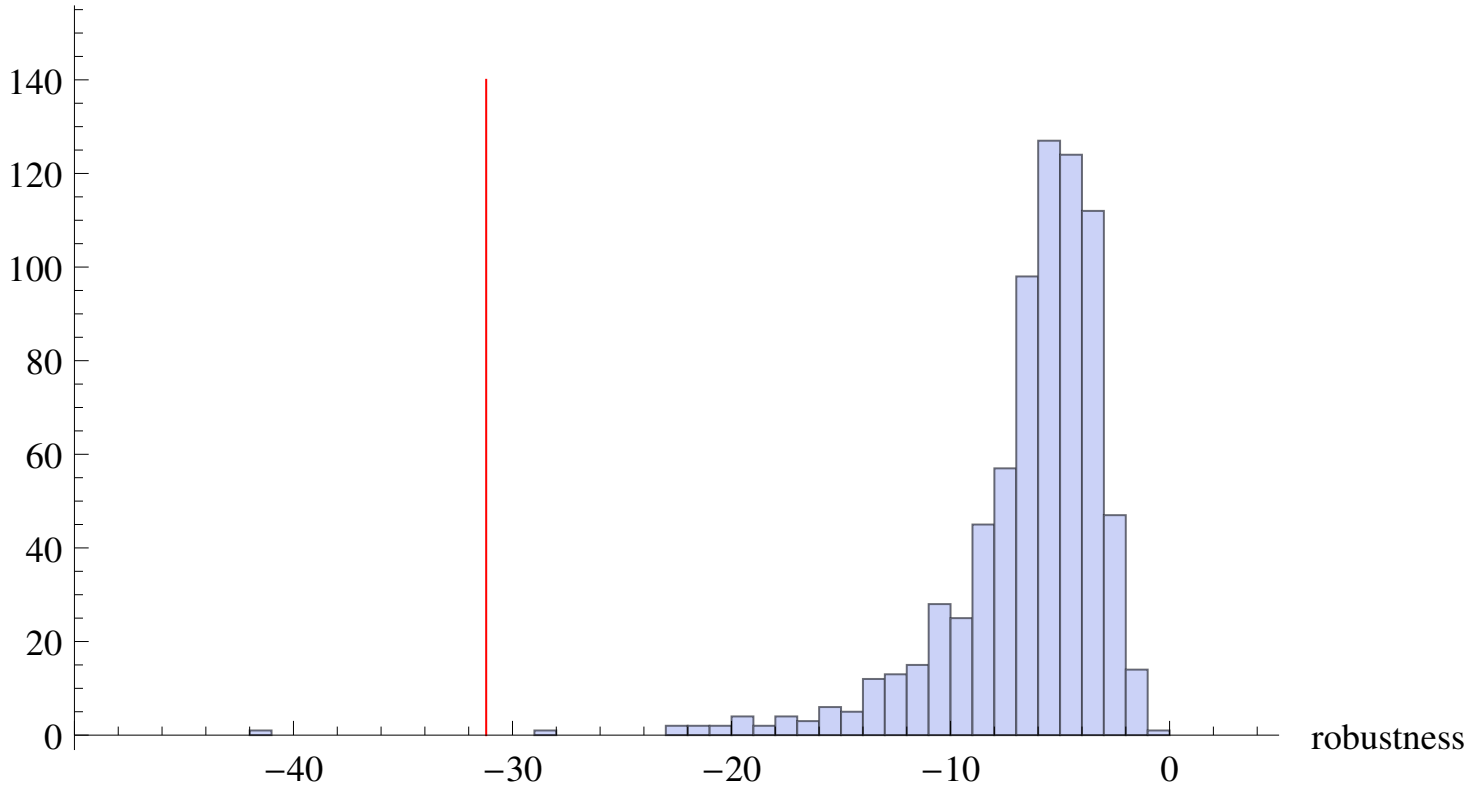




polynomial model for errors, lognormal distribution for mocks

Preliminary: distribution of minimal robustness values

analysis of errors for 10^5 random partitions



preliminary

Take-away

advantages

- no specific effect assumed
- fully Bayesian approach

application

- improve understanding of systematics and correlations
- find most probable systematics-contaminated data

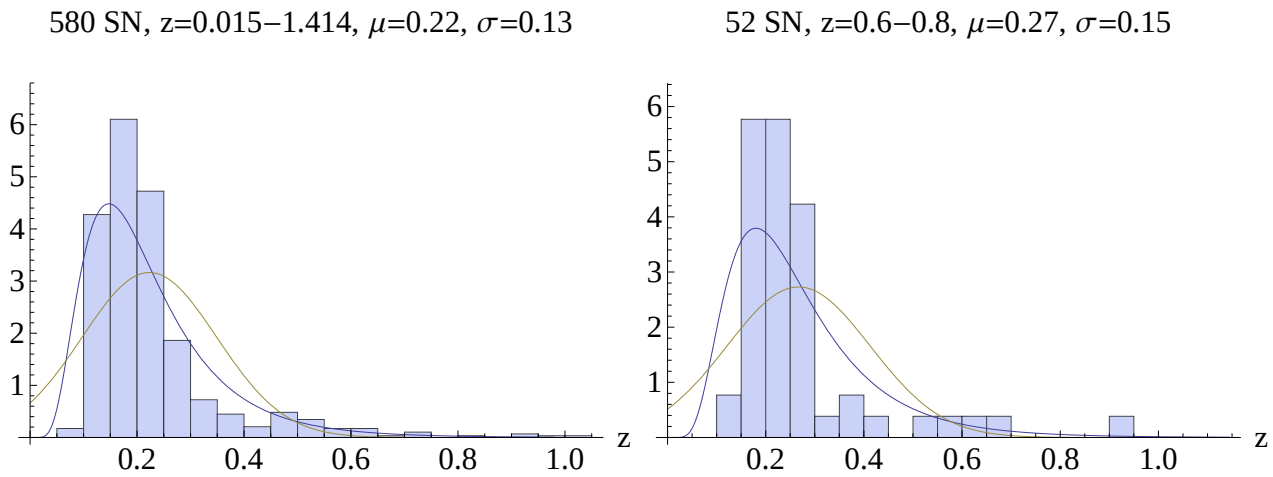
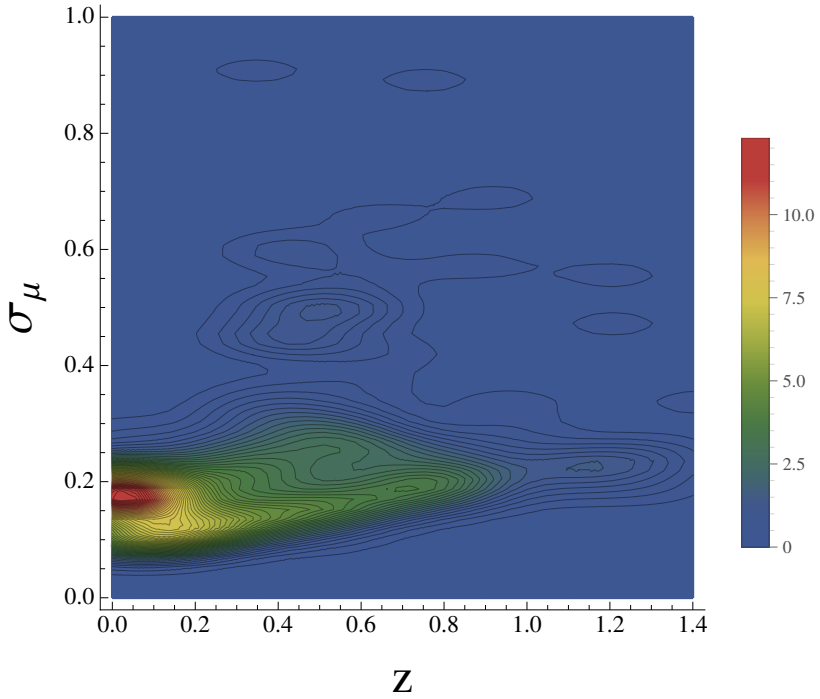
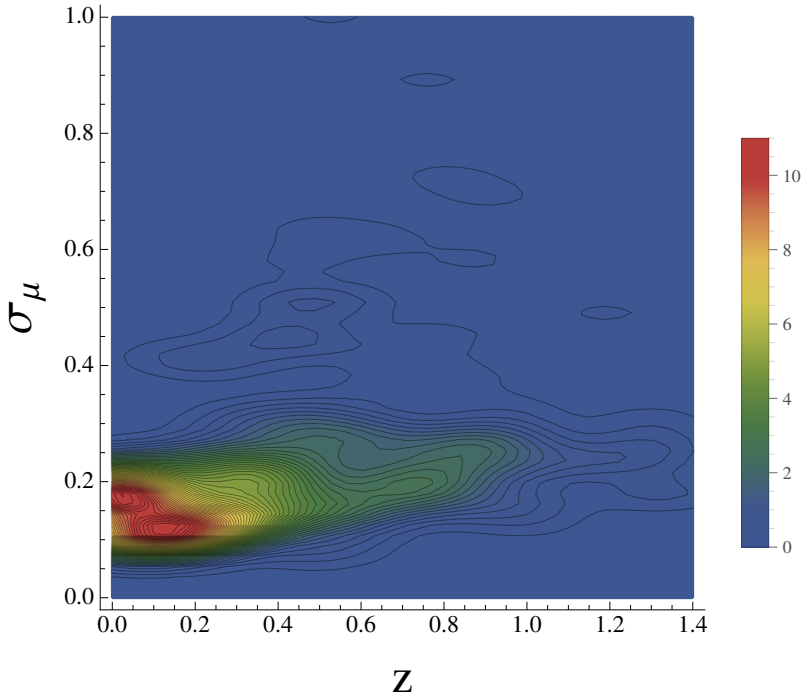
future

- test dependencies on SN and host galaxy properties
- applicable to other data than SNe

quite robust, but still room for improvement!

Extra slide: Distance modulus errors

- systematic parametrization: $m(z) = \sum_i \lambda_i * z^i$
- lognormal assumption for synthetic catalogues



Extra slide: Distribution of most and least robust SNe