How robust are SN Ia data?

Caroline Heneka

Valerio Marra, Luca Amendola (ITP Heidelberg)
arXiv:1310.8435

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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**

How robust are SN Ia data?
Bayesian view of robustness

robustness = **consistency** among subsets

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

\[ \text{robustness} = \text{consistency among subsets} \]

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

**Bayesian** comparison of 2 hypothesis:
one set of parameters $\Leftrightarrow$ two independent distributions

Bayes’ ratio:

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

$d = \text{full set, subsets } d_1 \text{ and } d_2, \text{ with } d_1 + d_2 = d$

independent models $M_C$ and $M_S$

**Internal Robustness:**

$$R \equiv \log B_{tot, ind}$$

Amendola, Quartin, Marra (arXiv:1209.1897)
Internal Robustness

**Bayesian** comparison of 2 hypothesis:
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independent models $M_C$ and $M_S$

**Internal Robustness - Fisher:**

$$R = R_0 + \frac{1}{2} \log \left| \frac{F_1 \| F_2}{|F_{tot}|} \right| - \frac{1}{2} \left( \hat{\chi}^2_{tot} - \hat{\chi}^2_1 - \hat{\chi}^2_S \right)$$

Amendola, Quartin, Marra (arXiv:1209.1897)
Internal Robustness probability distribution function (IR-PDF)

- parametrization choice of observable & partitioning of data
- evaluate $R$ – value for each chosen partition
- 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
Internal Robustness probability distribution function: separation sorted

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

arXiv:1310.8435: Heneka, Marra, Amendola
## Hemispherical directions

<table>
<thead>
<tr>
<th>single partition (Planck)</th>
<th>((\alpha, \delta))</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemispherical asymmetry</td>
<td>((270°, 66.6°))</td>
<td>(1.26\sigma)</td>
</tr>
<tr>
<td>Dipole anisotropy</td>
<td>((167°, -7°))</td>
<td>(0.39\sigma)</td>
</tr>
<tr>
<td>Quadrupole-octupole alignment</td>
<td>((177.4°, 18.7°))</td>
<td>(0.35\sigma)</td>
</tr>
<tr>
<td>Grid of hemispheres</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direction of lowest robustness</td>
<td>((150°, 70°))</td>
<td>(2.20\sigma)</td>
</tr>
</tbody>
</table>

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
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: \( m(z) = \sum_i \lambda_i \cdot z^i \)
- lognormal assumption for synthetic catalogues

580 SN, \( z=0.015-1.414, \mu=0.22, \sigma=0.13 \)

52 SN, \( z=0.6-0.8, \mu=0.27, \sigma=0.15 \)
Extra slide: Distribution of most and least robust SNe