

Are classification metrics good proxies for science output?

Colloque national Dark Energy - 5ème édition

Paris - 13 October 2021

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1. Context:

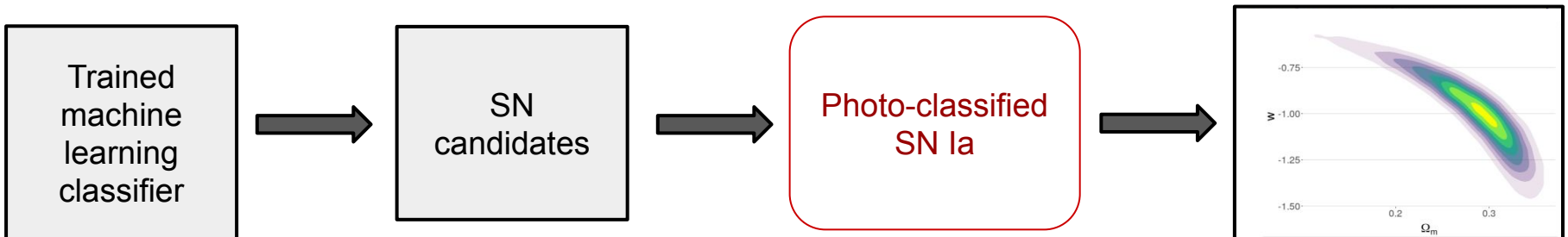
What is the goal of classification tasks?

- Organize knowledge
- Understand patterns of behavior
- Predict possible outcomes
- Separate objects for further scientific analysis

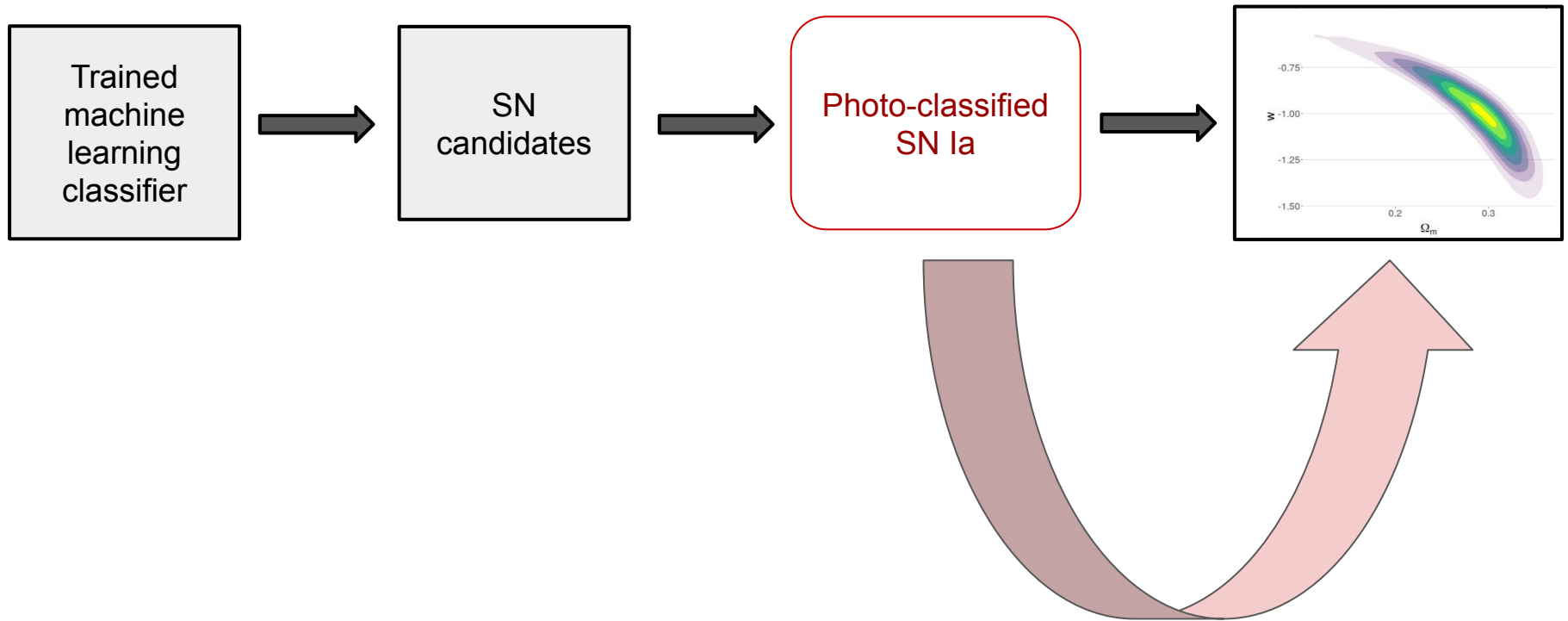
1. Context:

What is the goal of classification tasks?

- Organize knowledge
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2. Evaluating classification results



Hypothesis:

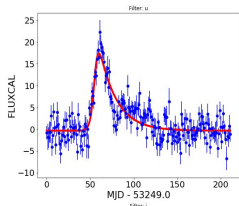
Good classification results will result in better science results

2. Experiment set-up

Goal: to understand the impact of different contaminants in a cosmology results

PS:1 There is no real classifier

1 - LCs



2 - SALT2 fit

x1, c, mB

3 - SALT2mu

mu, muerr

4.a - wfit

w-best-fit

4.b - Stan

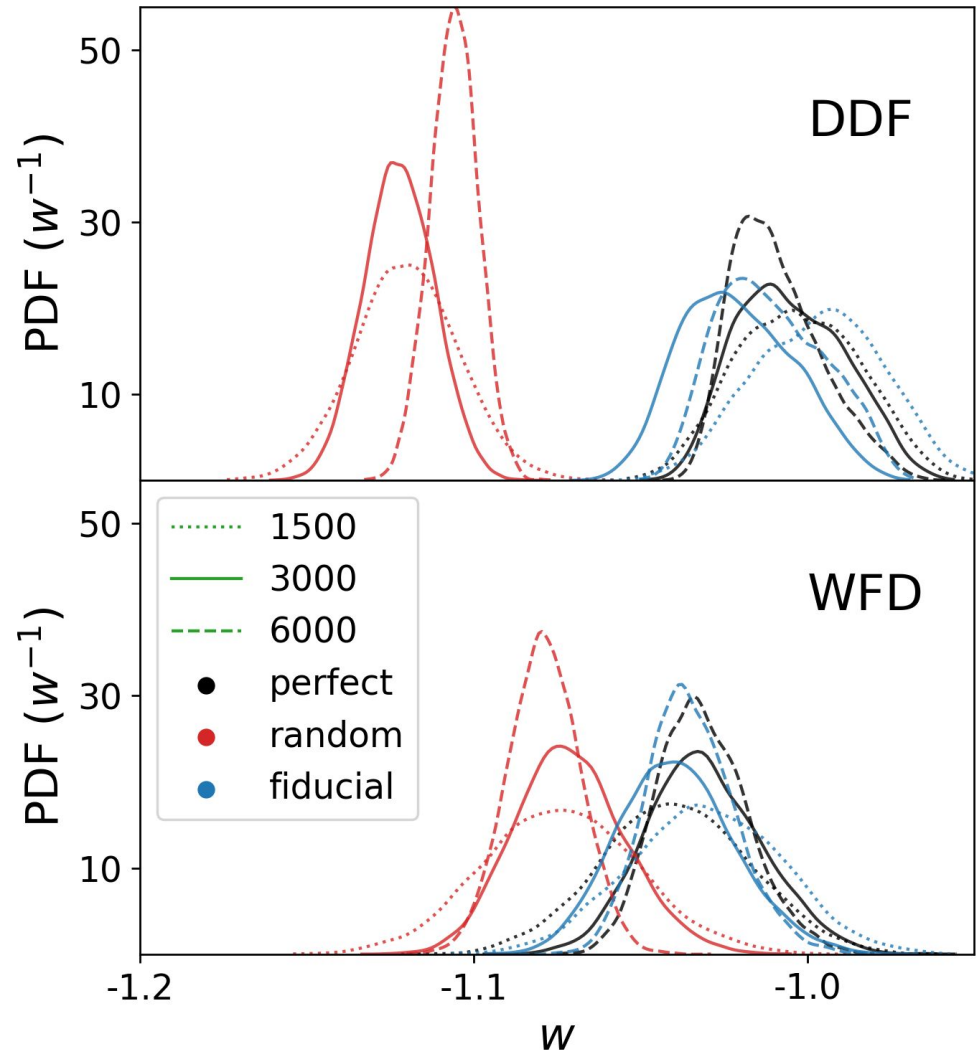
w-posterior

PS2: Very simplified cosmological analysis

- PLAsTiCC data
- Study each different contaminant at a time
- Separate analysis for DDF and WFD
- Compare traditional classification metrics with properties from posteriors

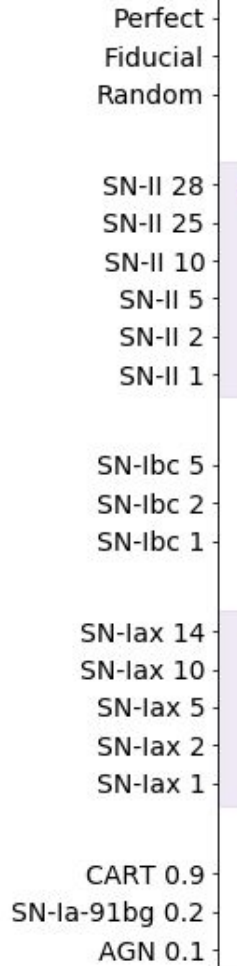
3. Total number of objects

- **Perfect:** all real SN Ia
- **Random:** sampling from the set of objects surviving SALT2 fit (14% cont - DDF, 10% cont WFD)
- **Fiducial:** objects classified as SNIa by Avocado (Boone, 2019) which survived SALT2 fit -- (lbc, ll, lax ~ 5%, 3% cont - WFD)



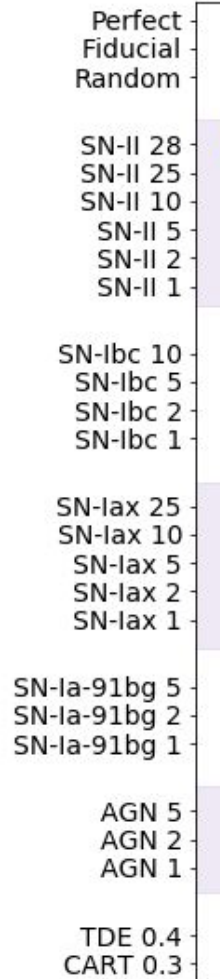
4. Samples surviving SALT2 fit

DDF

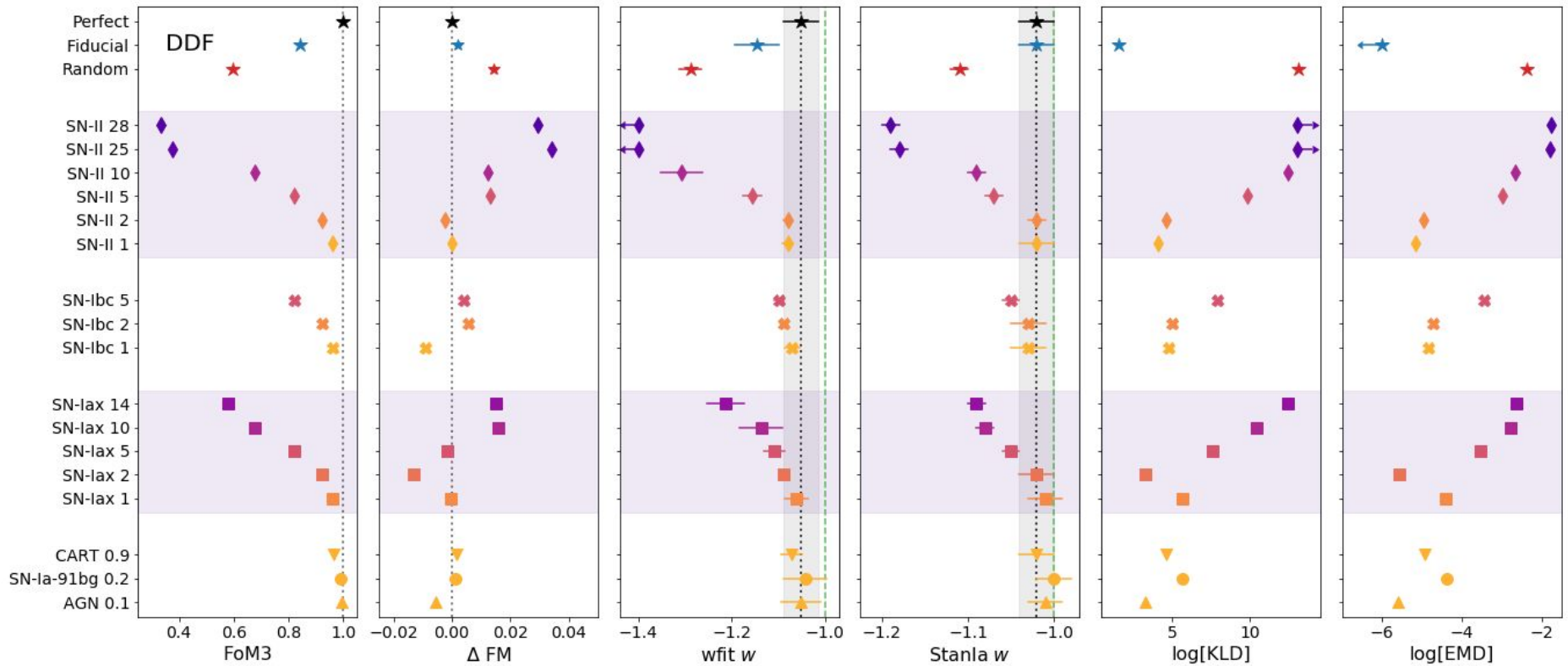


PS:1 There is no real classifier
(apart from Avocado)

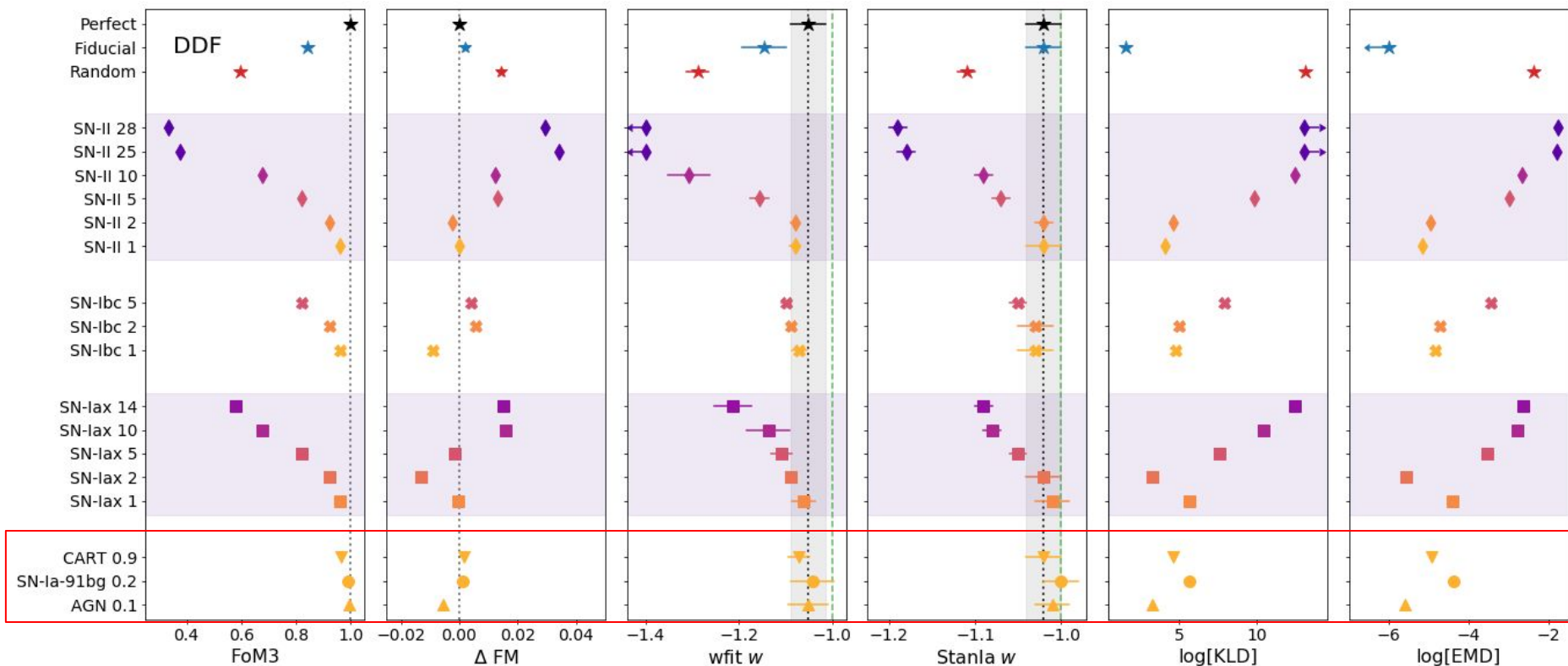
WFD



5. Results: DDF

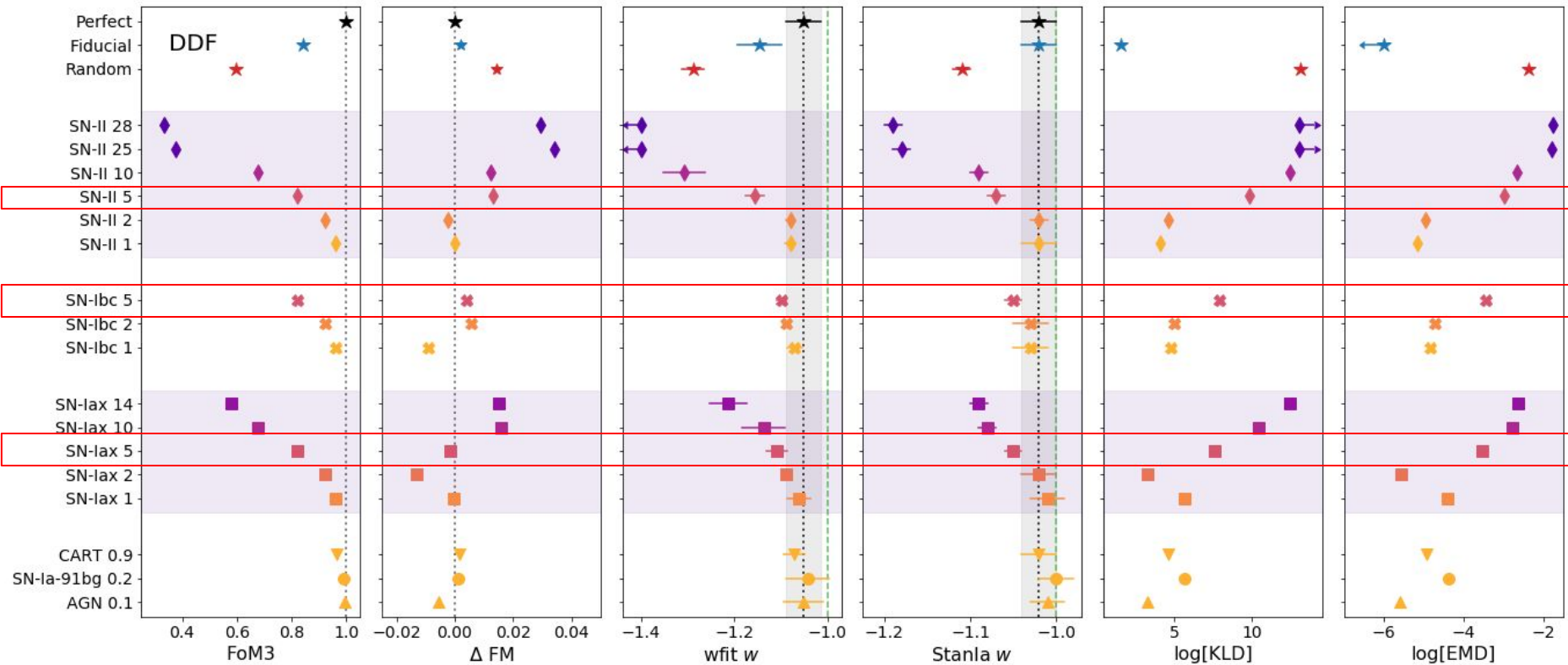


5. Results: DDF



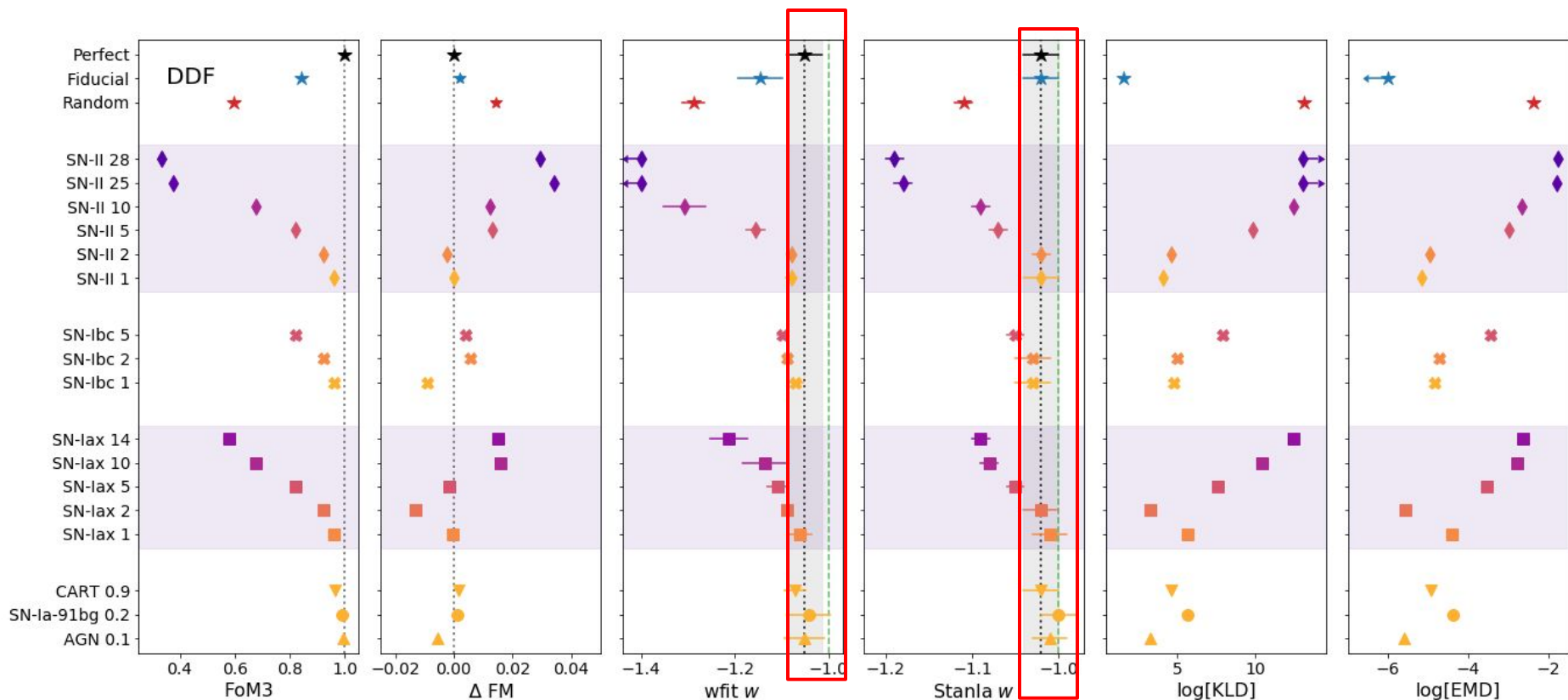
1. Metrics based on posteriors are sensitive to small contaminations

5. Results: DDF



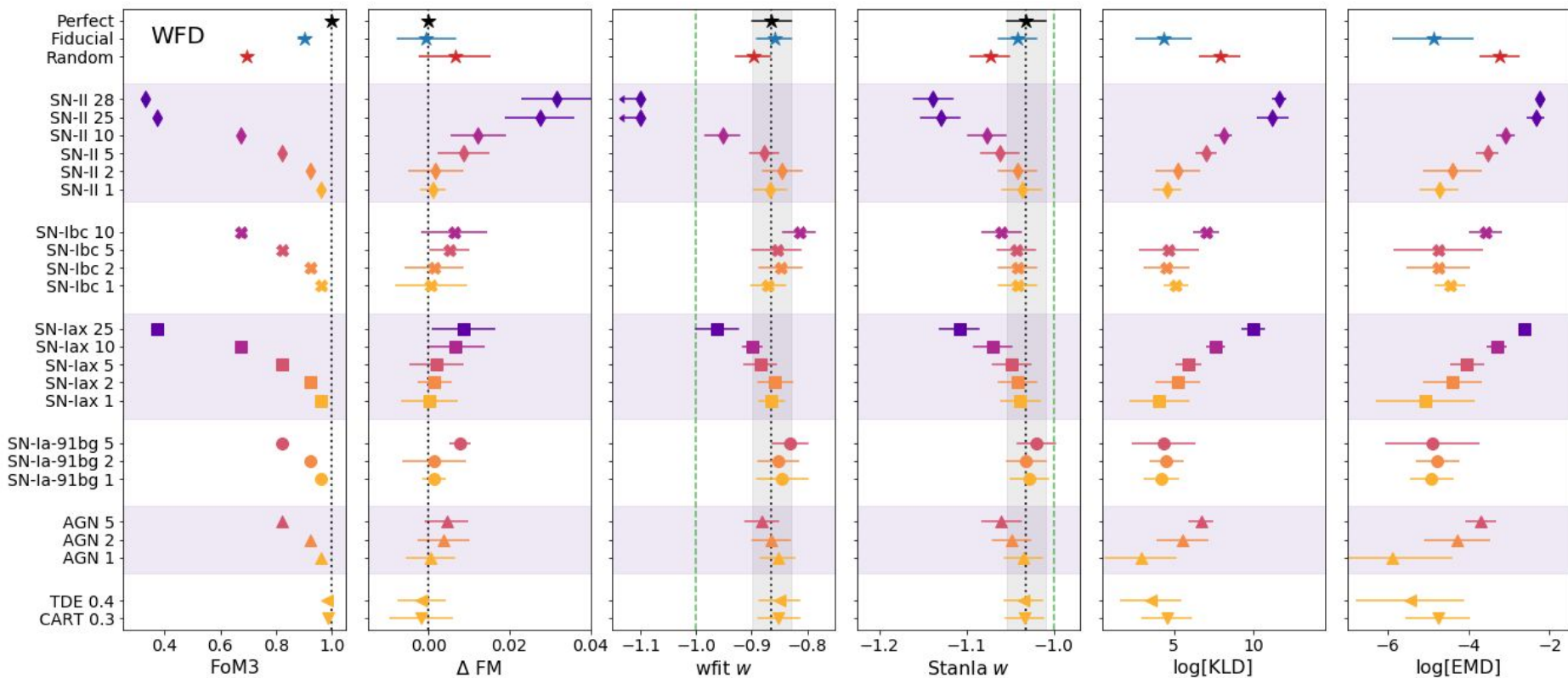
1. Metrics based on posteriors are sensitive to small contaminations
2. 5% contamination is already too much

5. Results: DDF

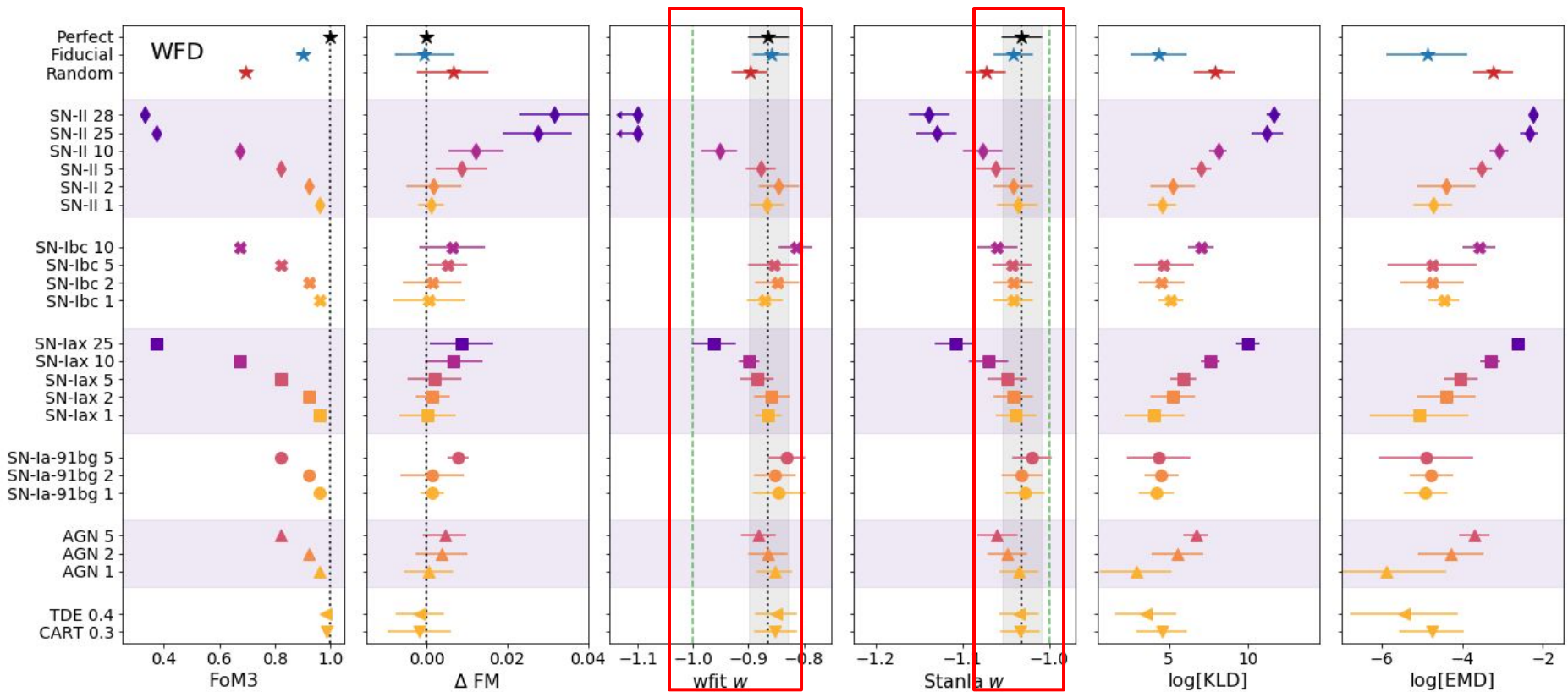


1. Metrics based on posteriors are sensitive to small contaminations
2. 5% contamination is already too much
3. Perfect borders the simulated model

6. Results: WFD

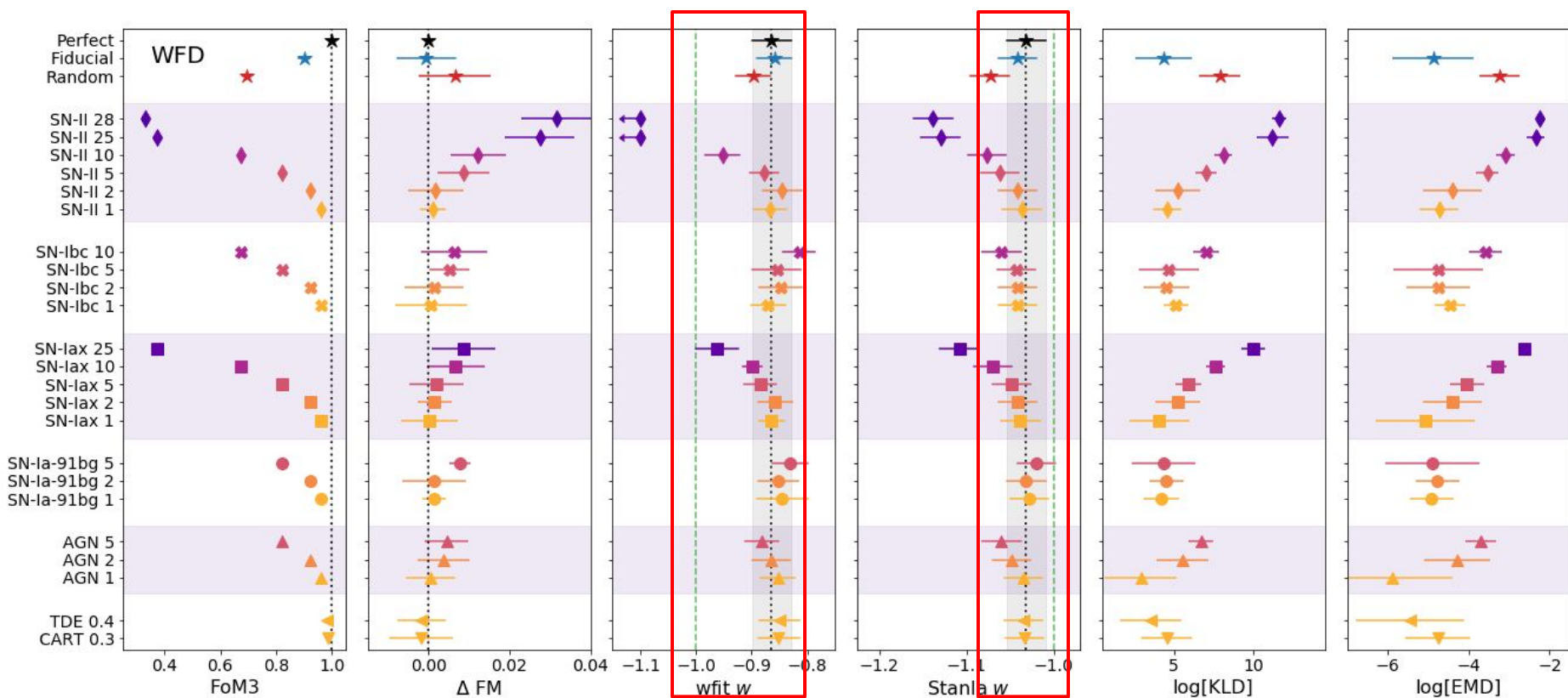


6. Results: WFD



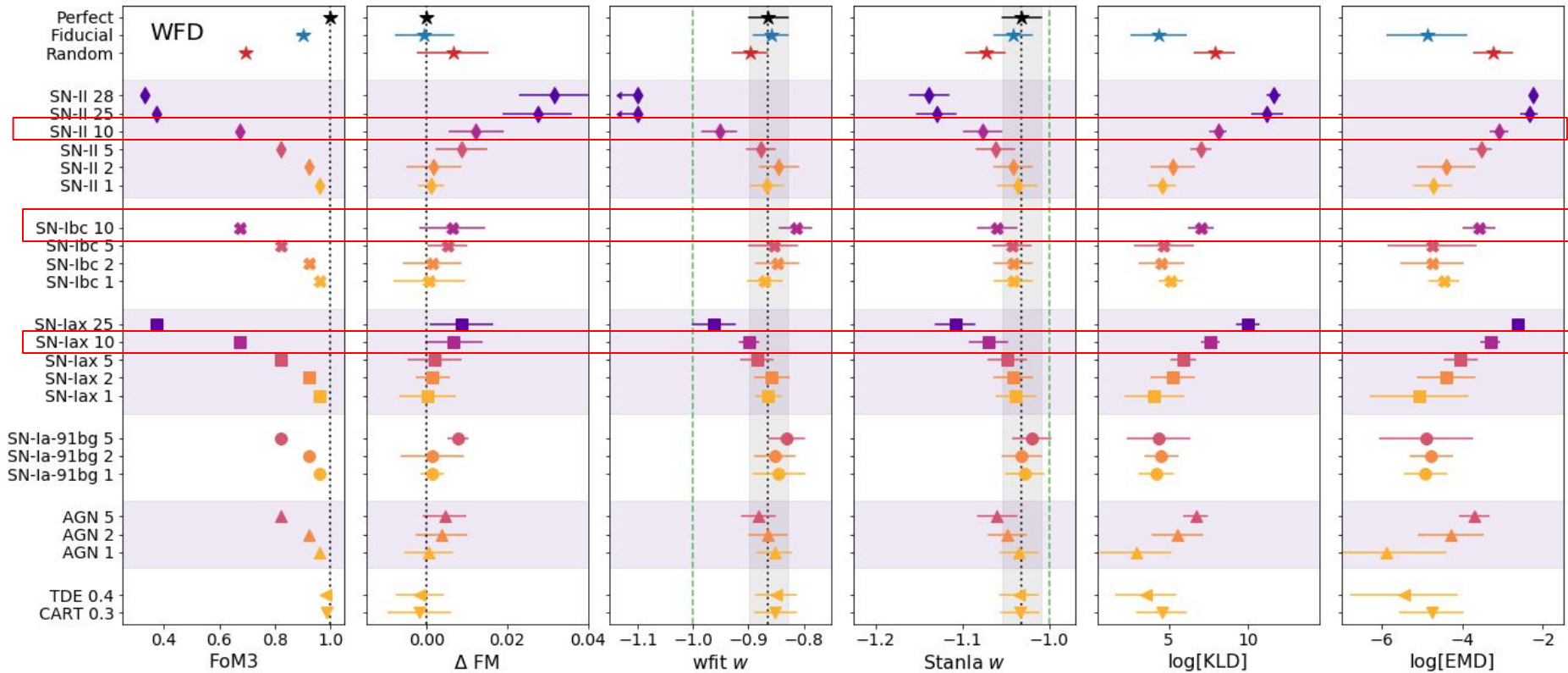
1. Perfect results are further from simulated model + larger error bars

6. Results: WFD



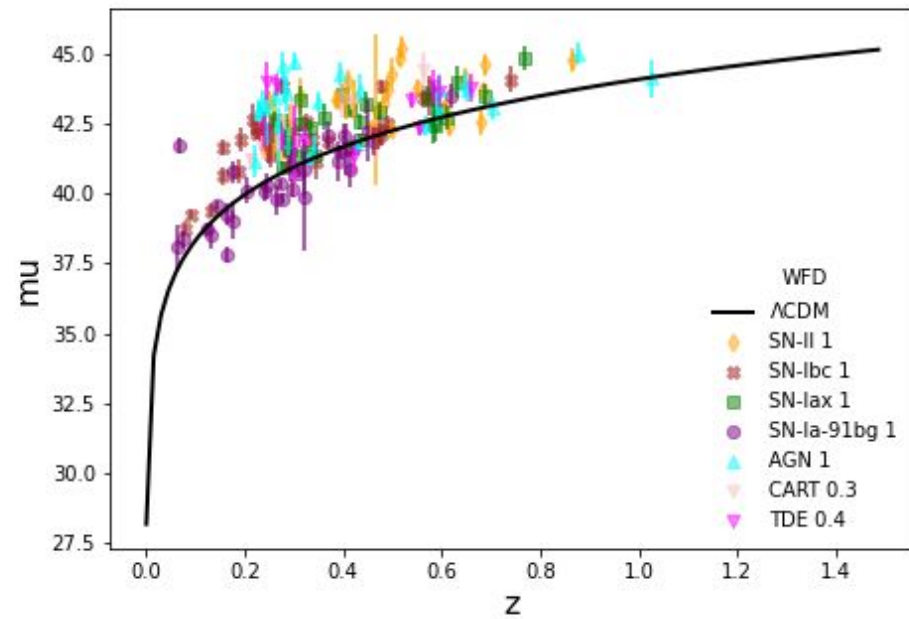
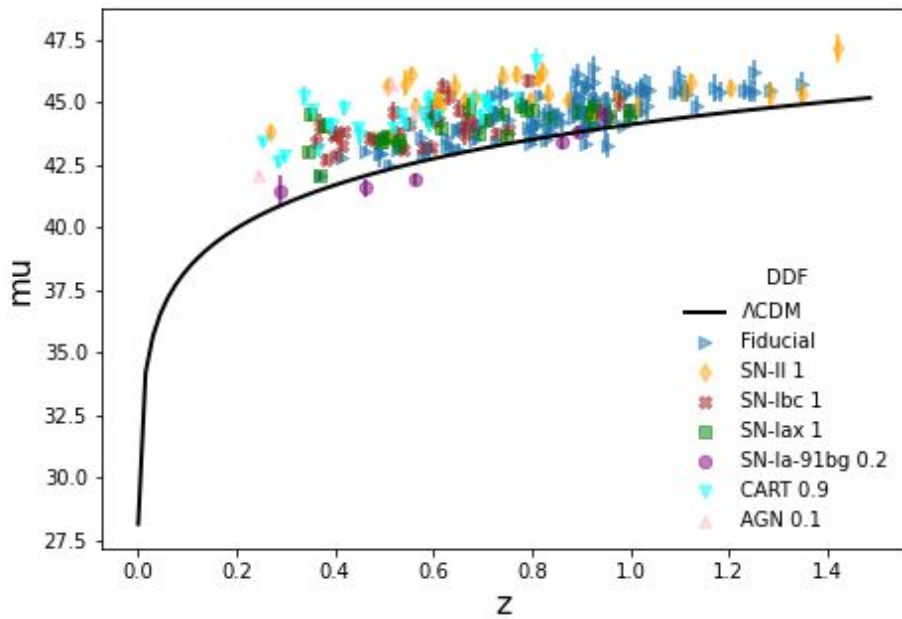
1. Perfect results are further from simulated model + larger error bars

6. Results: WFD



1. Perfect results are further from simulated model + larger error bars
2. 10% contamination borders the simulated model

6. Results: Hubble diagram



Summary



Classification metrics not necessarily follow
impact on final scientific results

Summary



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For SN Ia cosmology: the class of the
contaminants matters

Summary



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For SN Ia cosmology: the class of the
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We should aim for classifiers specifically
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Summary



Classification metrics not necessarily follow impact on final scientific results

For SN Ia cosmology: the class of the contaminants matters

We should aim for classifiers specifically designed for the science question at hand

The full posterior analysis will be part of the cosmology metric of RESSPECT

Extra slides

Recommendation System for Spectroscopic Follow-up -- RESSPECT

Cosmology results from photometrically classified SN Ia

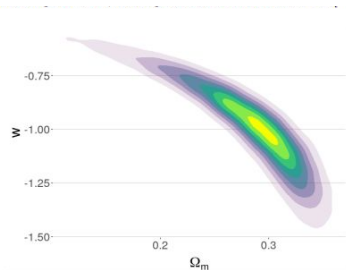
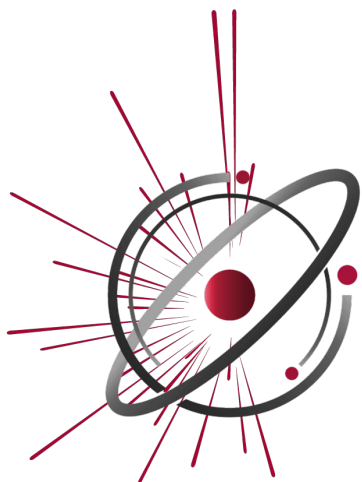


Photo-classified SN Ia

SN candidates

Trained machine learning classifier

2. To improve this!



LSST DESC & COIN
RESSPECT
Recommendation System for Spectroscopic Follow-up

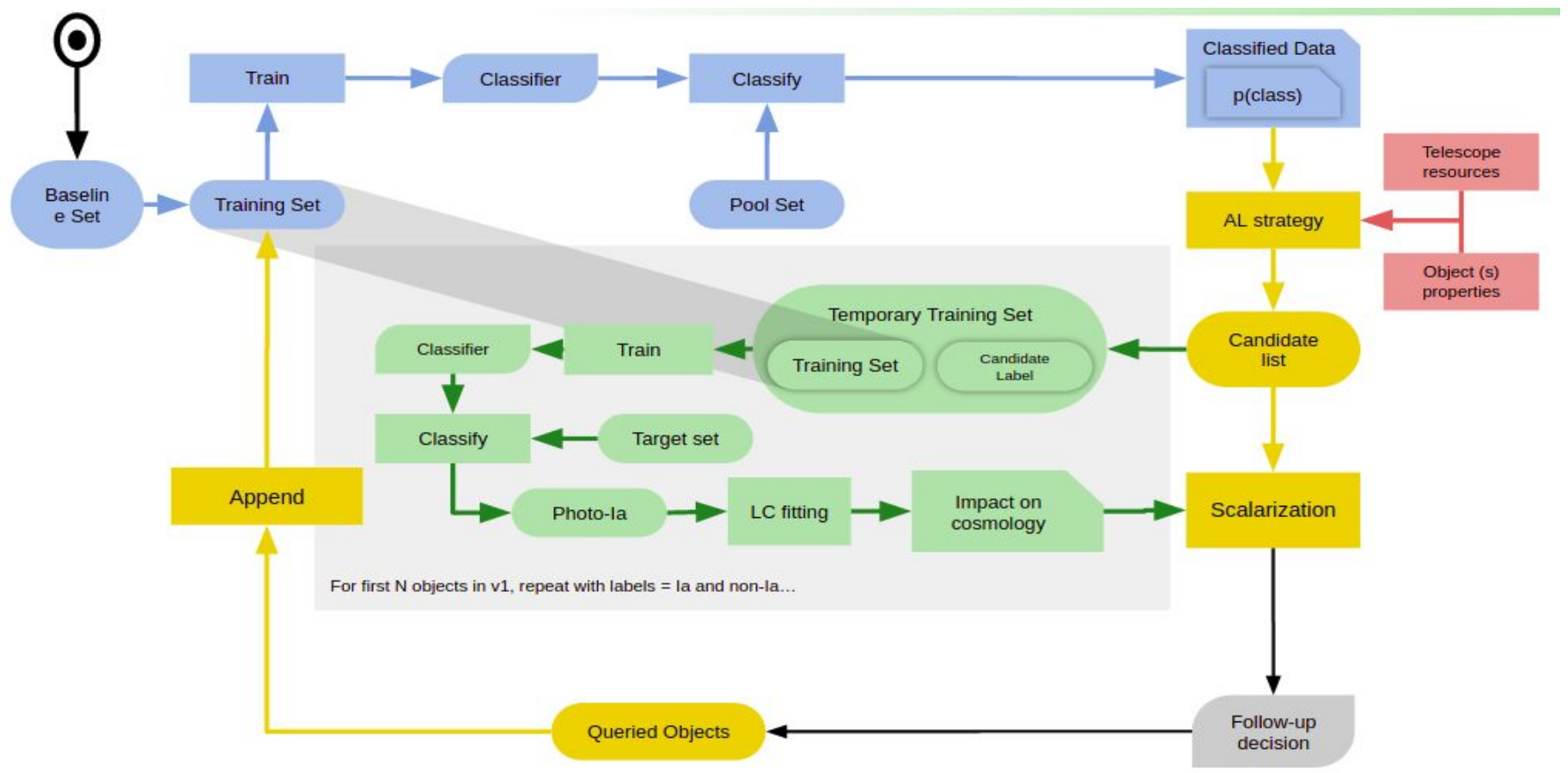
1. Optimize this!

learning algorithm

+

Training sample

The RESSPECT pipeline



Legend

- Machine Learning (Blue circle)
- Active Learning (Yellow circle)
- External factor (Red circle)
- Cosmological Feedback (Green circle)

Datasets (Black rounded rectangle)

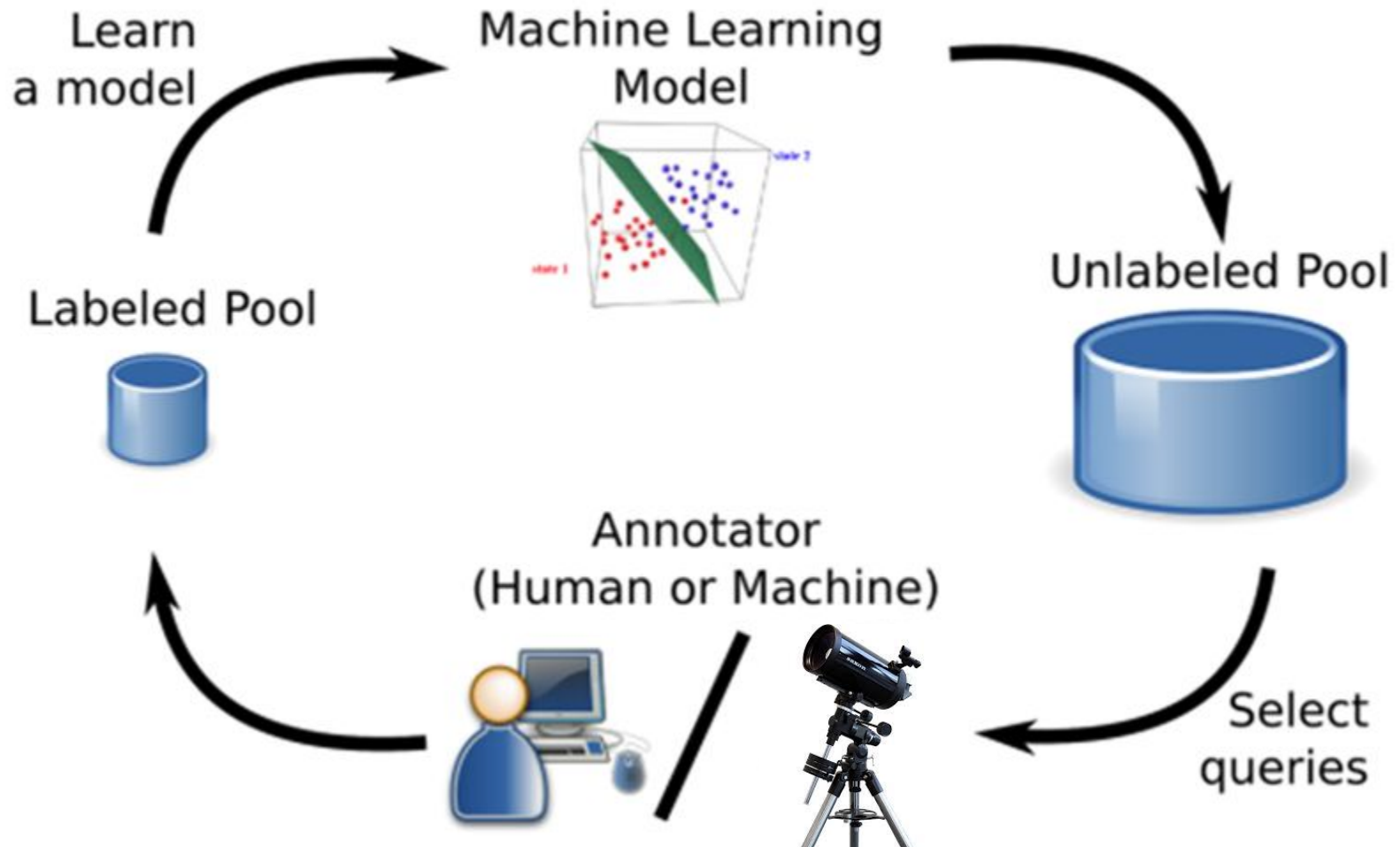
Process (Black rounded rectangle)

Models (Black rounded rectangle)

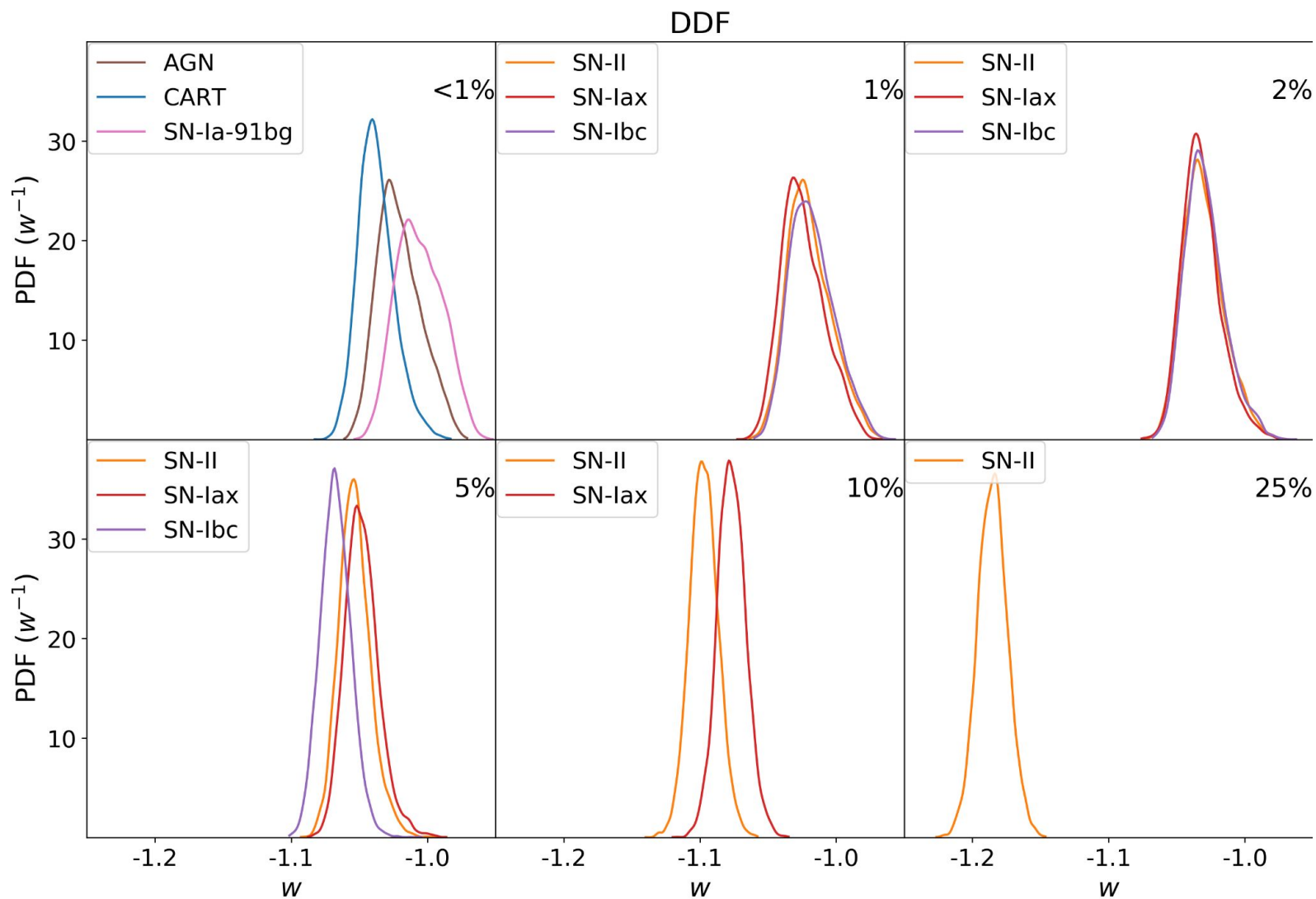
Products (Black trapezoidal shape)

Active Learning

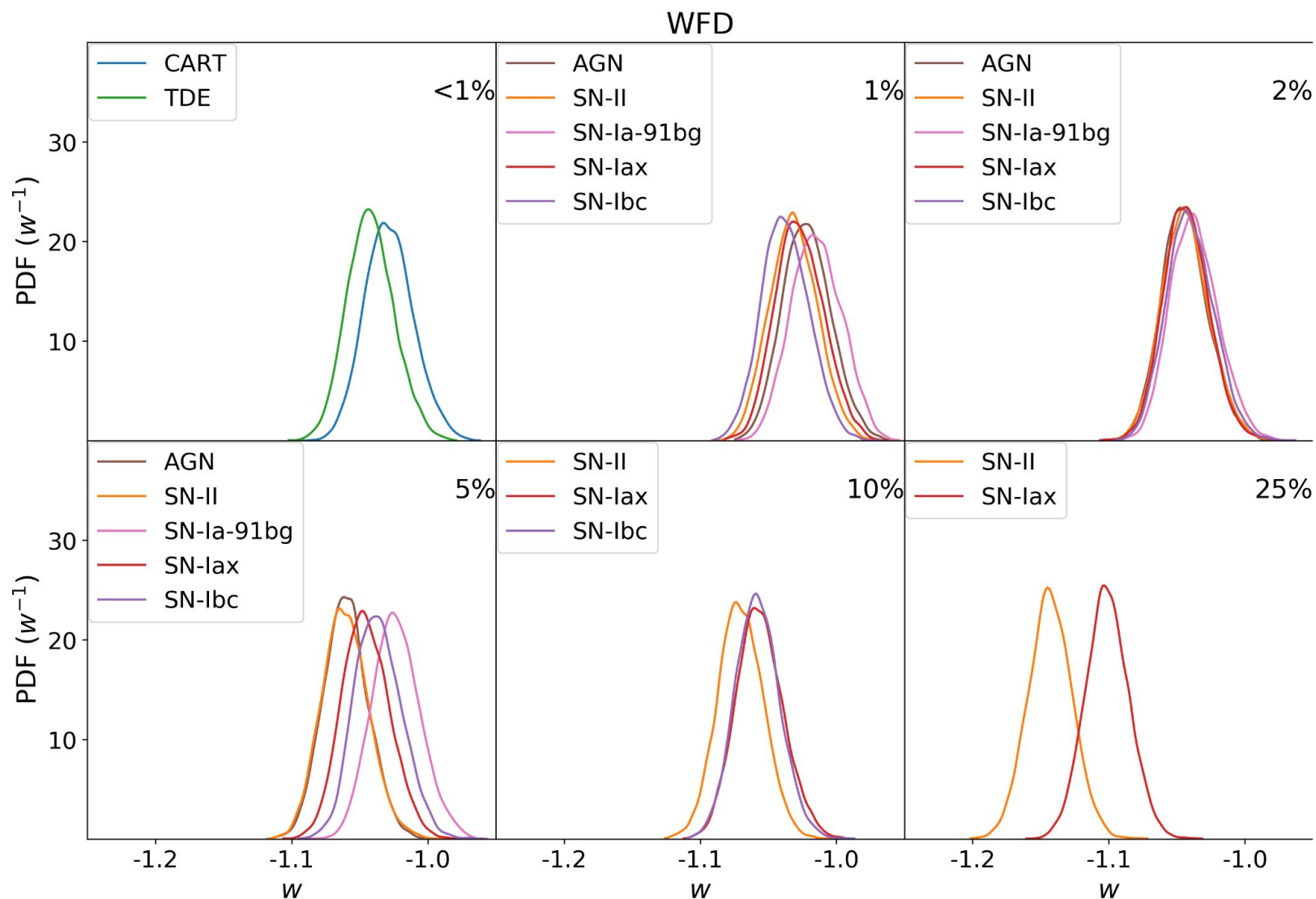
Optimal classification, minimum training



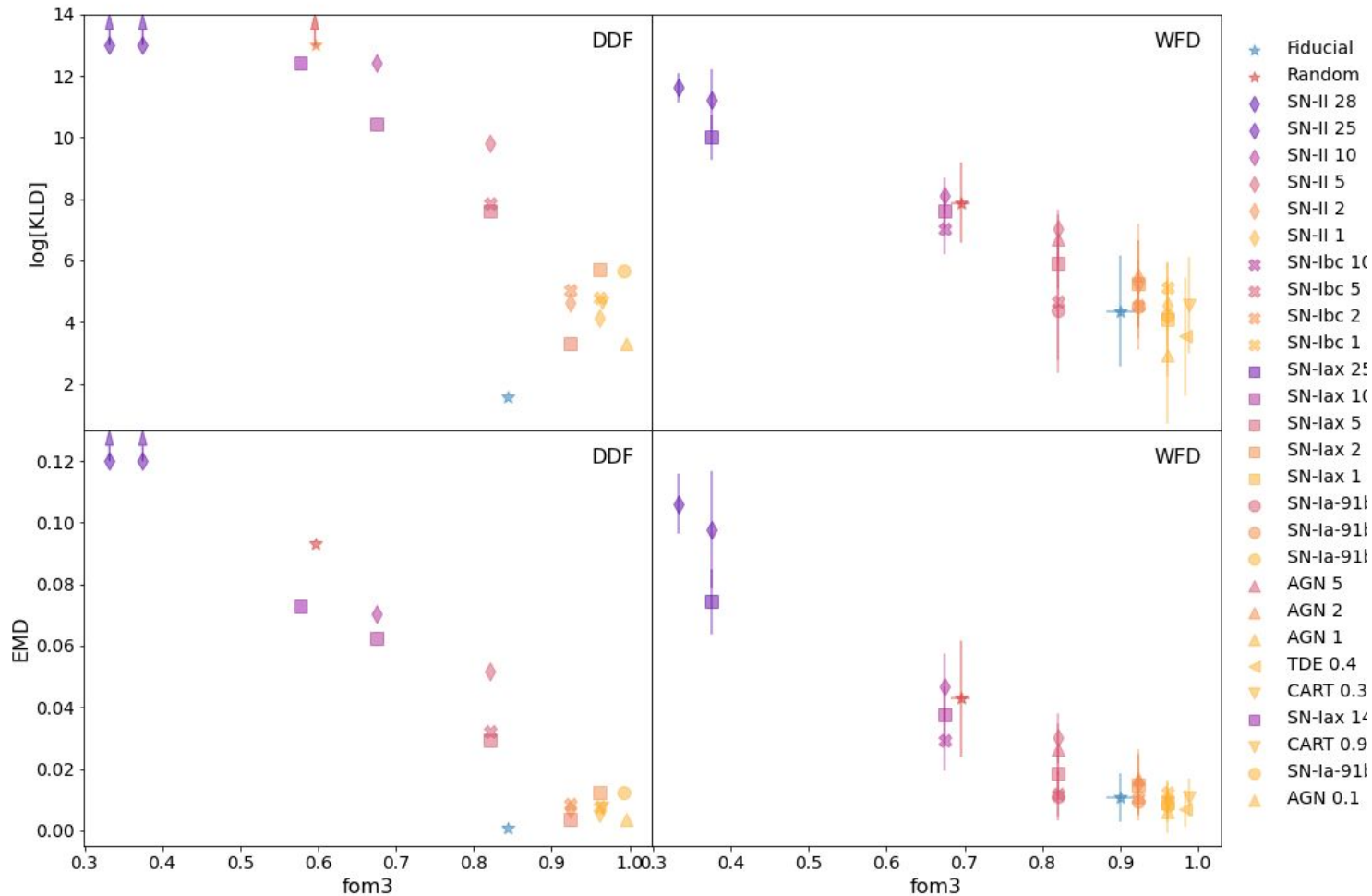
7. Posteriors: DDF



7. Posteriors: WFD



6. Metrics comparison



Stan model

Physical Constants:

$$H_0 = 70 \text{ km/s/Mpc}$$

$$c = 3 \times 10^5 \text{ km/s}$$

Model relationships:

$$E(z) = \int_0^z \frac{1}{\sqrt{\Omega_m(1+z)^3 + (1-\Omega_m)(1+z)^{3(w+1)}}}$$

$$\mu_{\text{th}}(z) = 25 + 5 \log_{10} \left[\frac{c}{H_0} (1+z) E(z) \right]$$

Priors:

$$\Omega_m \sim \mathcal{U}(0.299, 0.301)$$

$$w \sim \mathcal{N}(-1, 0.2)$$

Likelihood:

$$\mu \sim \mathcal{N}(\mu_{\text{th}}, \mu_{\text{err}}^2)$$

