Deconvolution in Cherenkov Astronomy

Towards a Unifying View

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SFB 876 Providing Information by Resource-Constrained Data Analysis

Deconvolution

Problem: Can't measure the relevant quantity Y directly

$$g(x) = \int_y R(x \,|\, y) \cdot \underline{f(y)} \,\mathrm{d}y$$

pdf of measured quantity $X \neq Y$

pdf of target variable Y
– wanted –

Deconvolution

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$$g(x) = \int_{\mathcal{Y}} R(x \mid y) \cdot \underline{f(y)}\, \mathrm{d}y$$

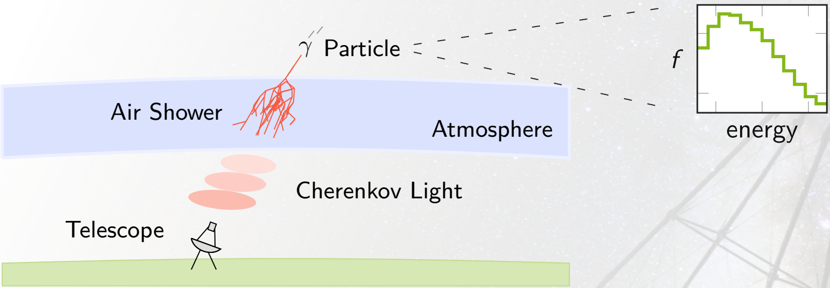
pdf of measured quantity $X \neq Y$ (→ $g(x)$)

conditional pdf of measuring $x \in \mathcal{X}$ from $y \in \mathcal{Y}$ (→ $R(x \mid y)$)

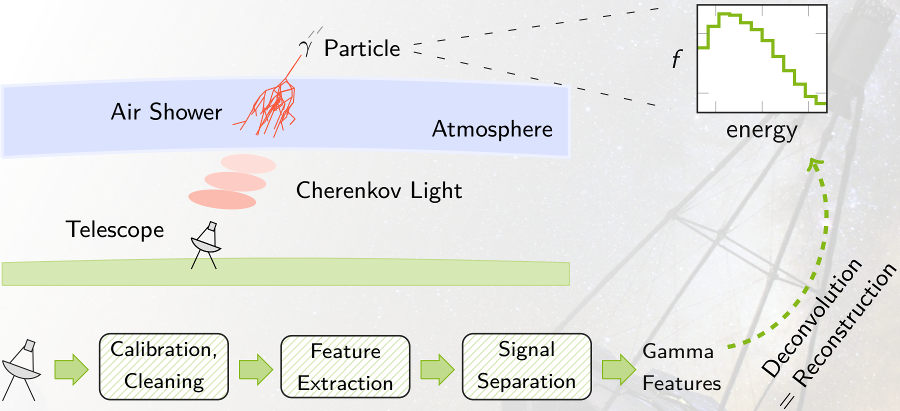
pdf of target variable Y **– wanted –** (→ $f(y)$)

Deconvolution: Obtaining f from g and R

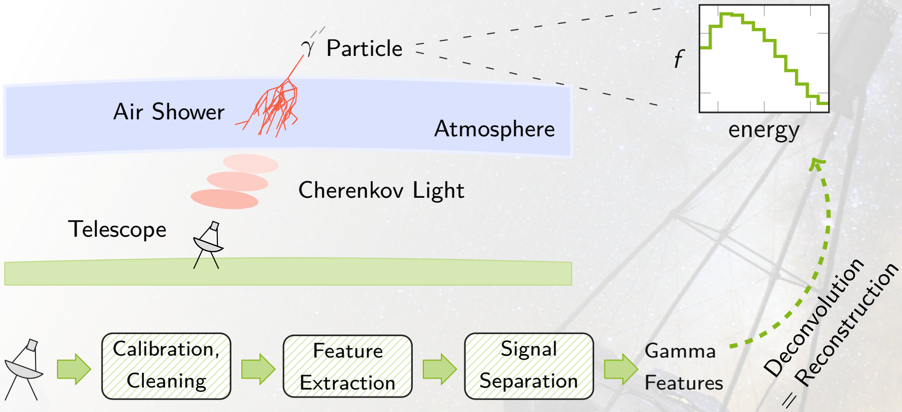
Cherenkov Astronomy



Cherenkov Astronomy



CHERENKOV ASTRONOMY



Deconvolution:

$$g(x) = \int_y R(x \mid y) \cdot f(y) \, \mathrm{d}y$$

feature density — energy density

$$g(x) = \int_y R(x \mid y) \cdot \underbrace{f(y)}_{\text{wanted}} \, \mathrm{d}y$$

Classical Deconvolution: $\mathbf{g} = \mathbf{R}\,\mathbf{f}$

- ... with maximum likelihood $\rightarrow$ Regularized Unfolding [Blo02]
- ... or with Bayes' theorem $\rightarrow$ Iterative Bayesian Unfolding [D'A10]

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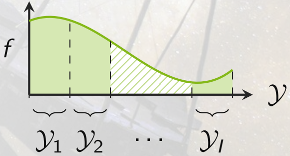
Dortmund **S**pectrum **E**stimation **A**lgorithm [R+16]:

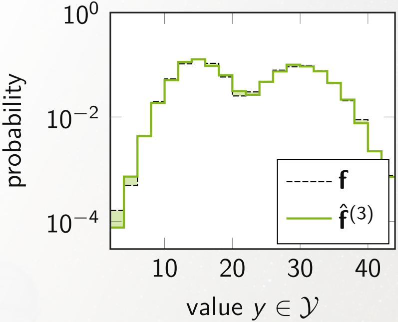
1. Train classifier $\mathcal{M}$ with $\mathcal{D}_{\text{train}}$

2. $\widehat{\mathbf{f}}_i \;=\; \frac{1}{N} \sum_{\mathbf{x} \in \mathcal{D}_{\text{obs}}} \mathit{confidence}_{\mathcal{M}}(i \,|\, \mathbf{x})$

3. Reweight $\mathcal{D}_{\text{train}}$ with $\widehat{\mathbf{f}}$ **…and repeat**

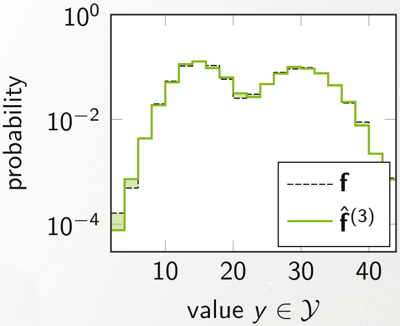


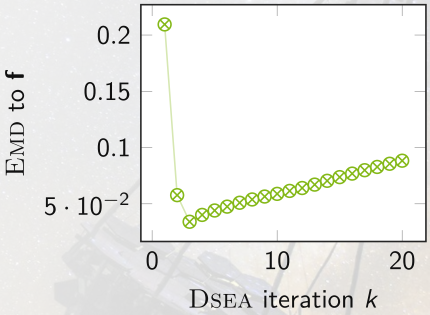
Problem: DSEA finds suitable estimate. . .



DSEA

Problem: DSEA finds suitable estimate... but then diverges





Even worse: The stopping criterion does not identify the optimum!

Scalable Steps

Solution: Approach the optimum **slowly** (and stay there!)

$$\hat{\mathbf{f}}^{(k)+} = \hat{\mathbf{f}}^{(k-1)} + \alpha^{(k)} \cdot p^{(k)}$$

$$p^{(k)} = \hat{\mathbf{f}}^{(k)} - \hat{\mathbf{f}}^{(k-1)}$$

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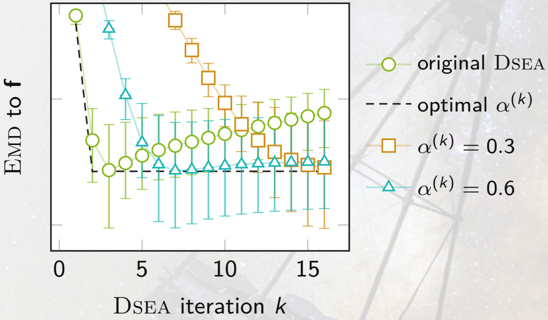

→ Stopping criterion works!

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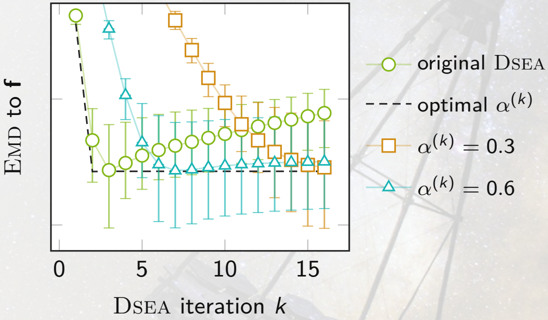

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Outlook:

- **Adaptive step size** is faster and more accurate!
- **Similar accuracy** achieved by DSEA and classical algorithms

Conclusions

- **Deconvolution estimates the pdf of the target variable**
- **DSEA is the machine learning approach**

To appear: M. Bunse, N. Piatkowski, K. Morik, T. Ruhe, and W. Rhode. *Unification of Deconvolution Algorithms for Cherenkov Astronomy*, 5th IEEE DSAA, 2018.

Proudly Open Source:

`https://sfb876.tu-dortmund.de/deconvolution`

References:

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G. D'Agostini, *Improved iterative bayesian unfolding*, 2010.

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