



# LSDB-Macauff: The Trials and Tribulations of

## Catalogue Cross-Matching in the Era of LSST

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Kostya Malanchev, Sam Wyatt, Jeremy Kubica



LINCC TECH TALK - 14/MAR/24

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github.io www



University  
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LSST:UK Consortium

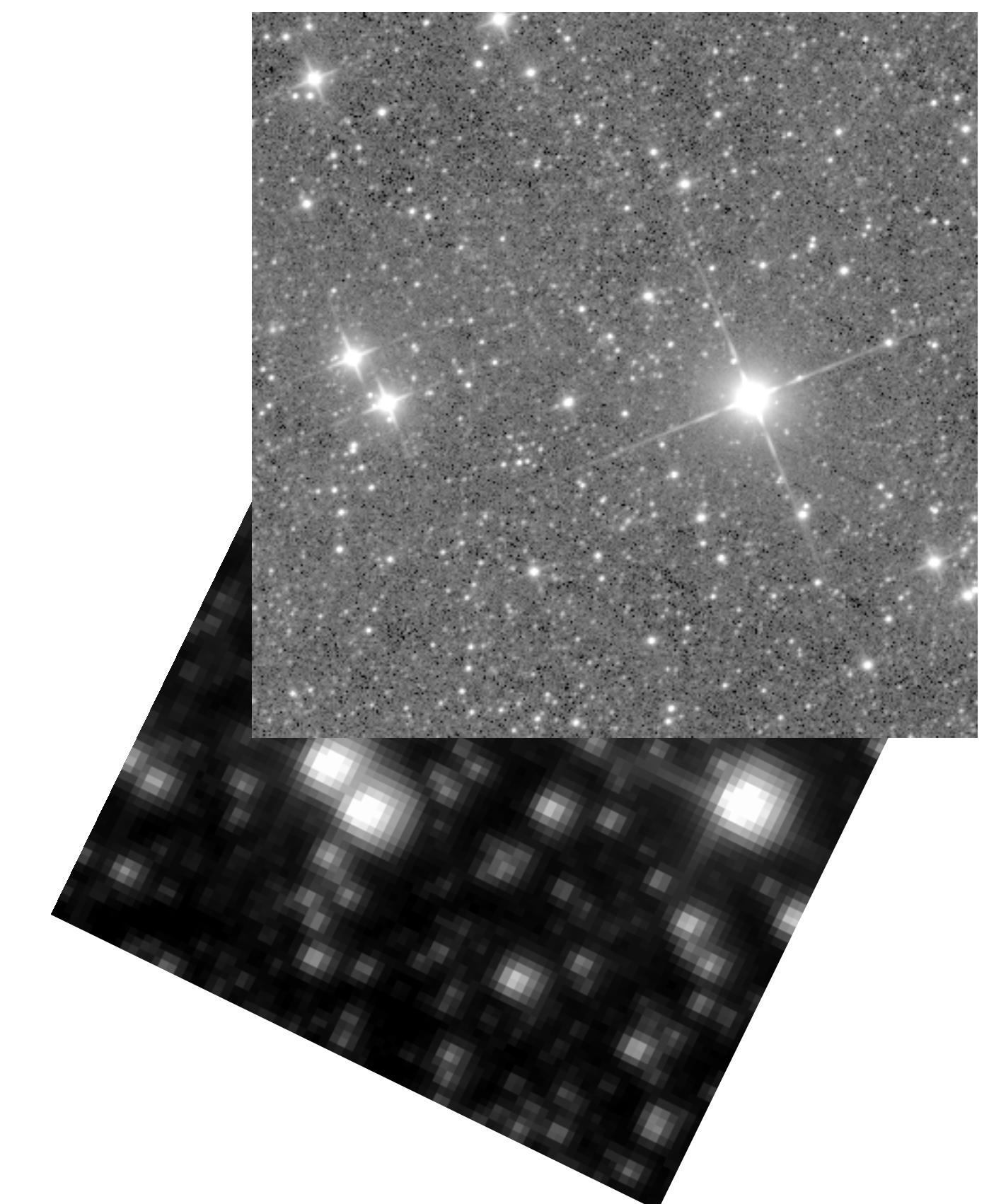
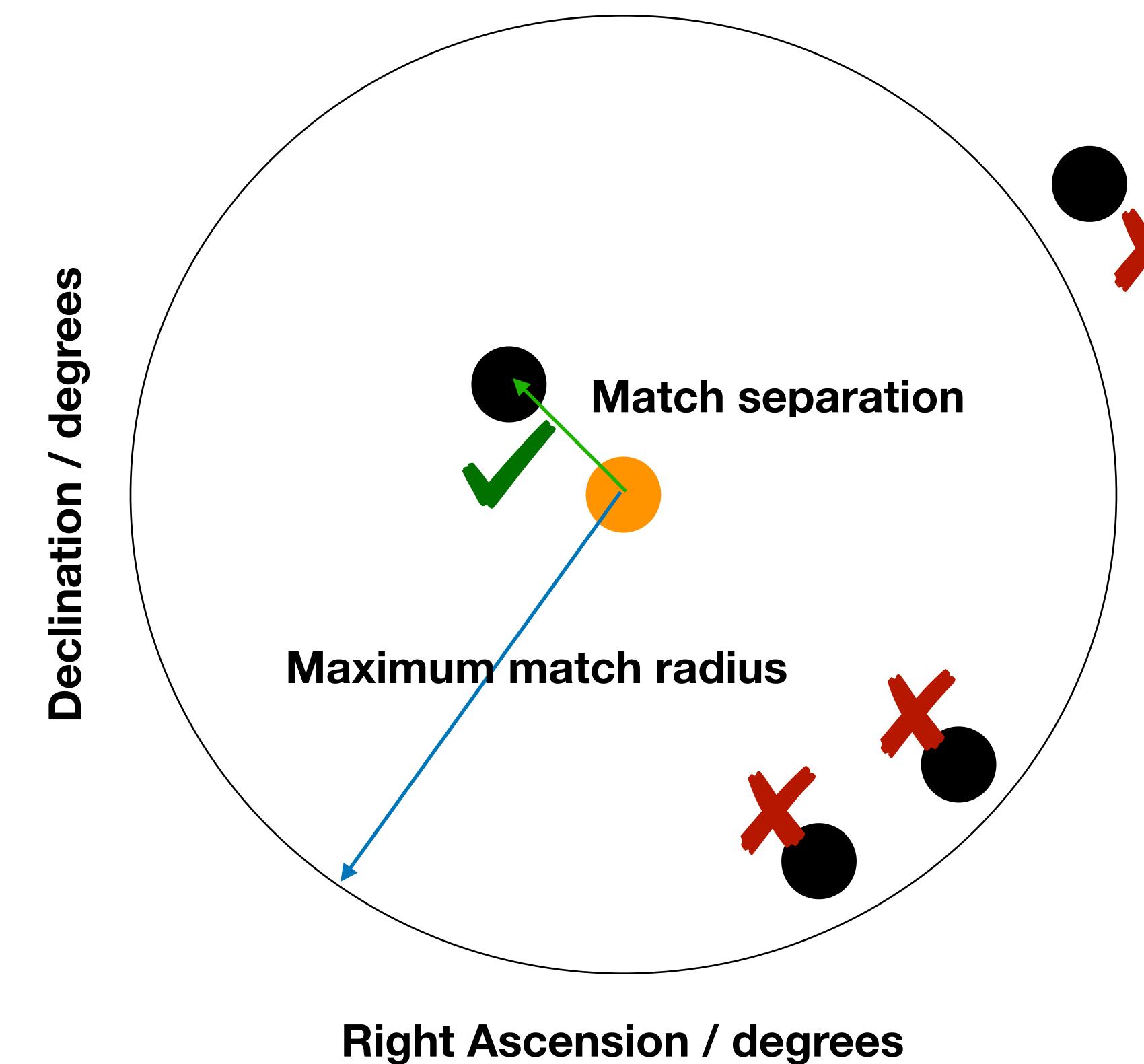
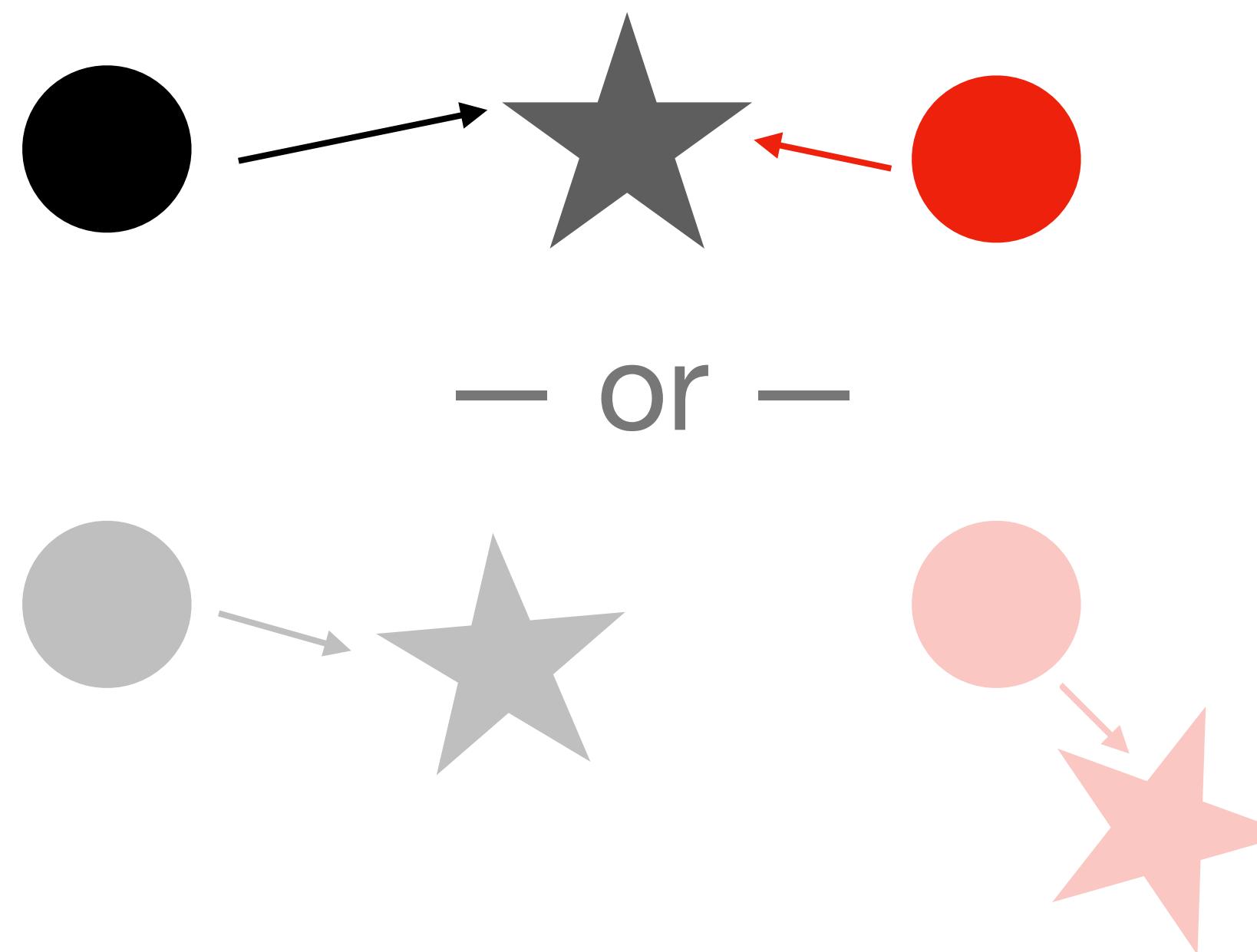


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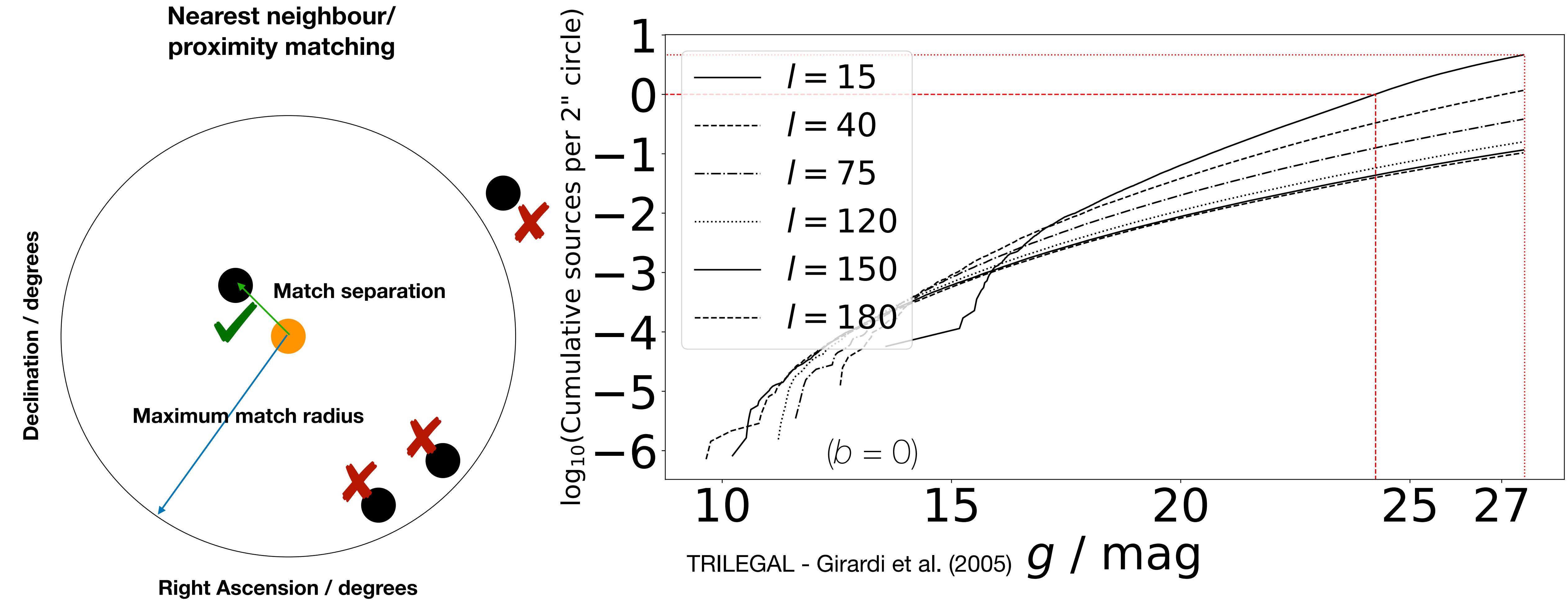


Or, Catalogue Cross-Matching in the Crowded LSST Sky

# “Simple” Cross-Matching



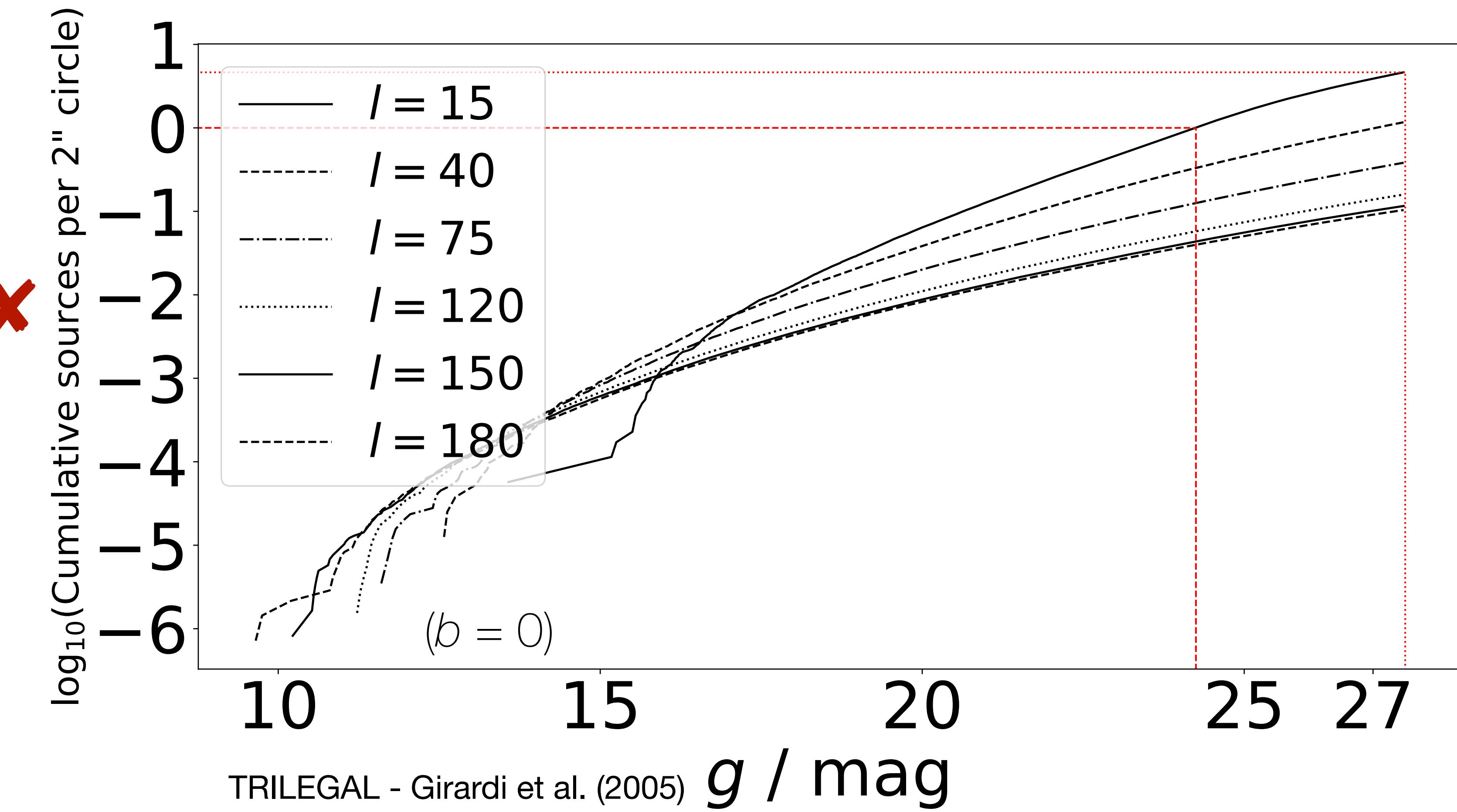
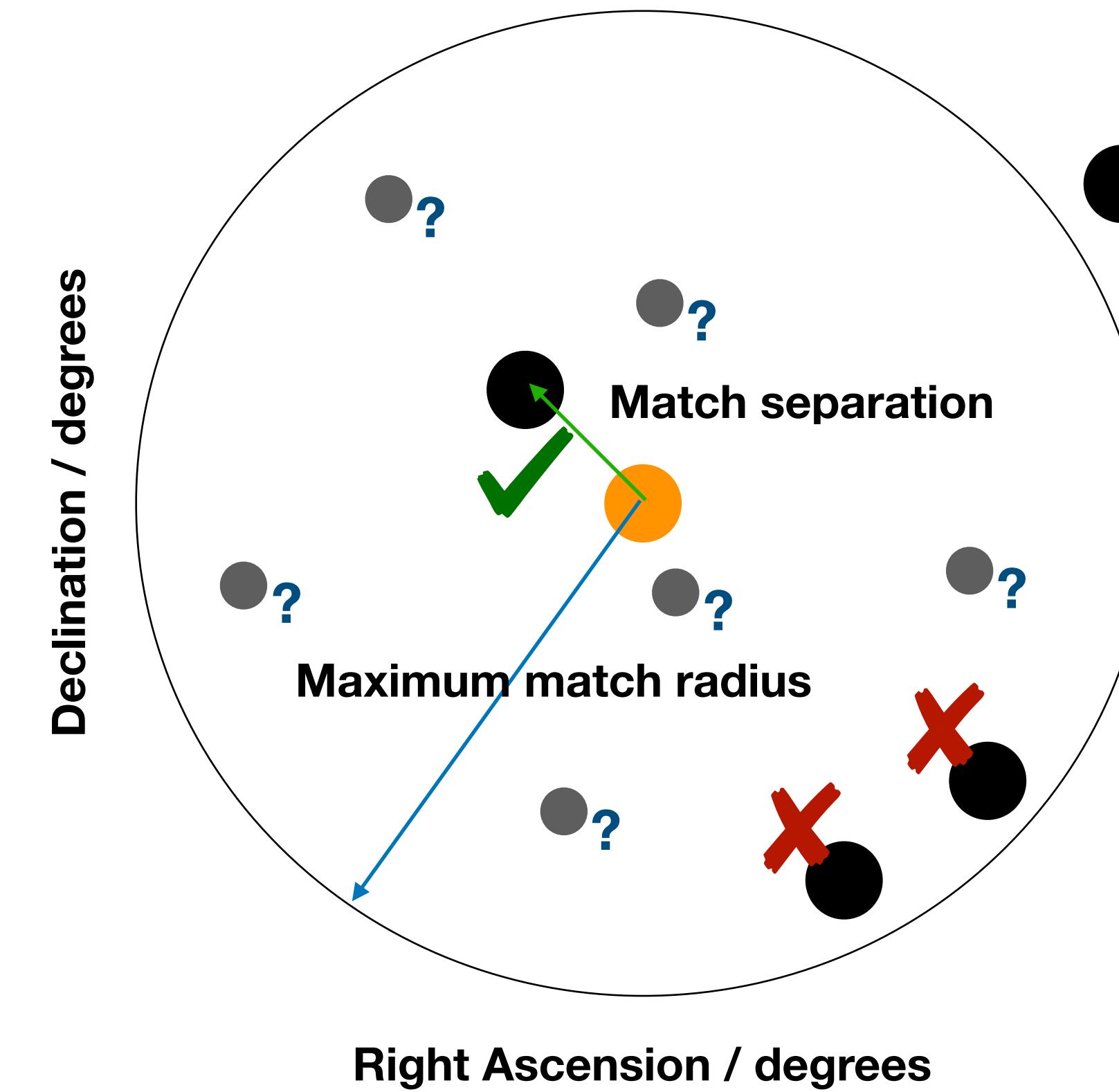
# The Problem With LSST



# The Problem With LSST

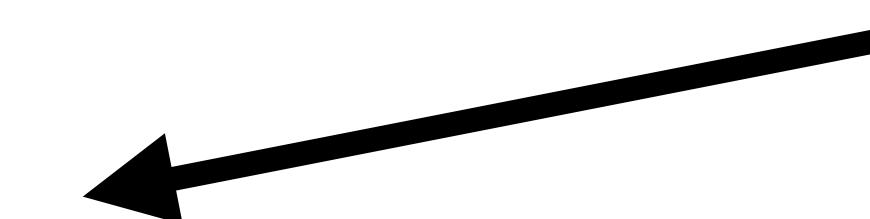
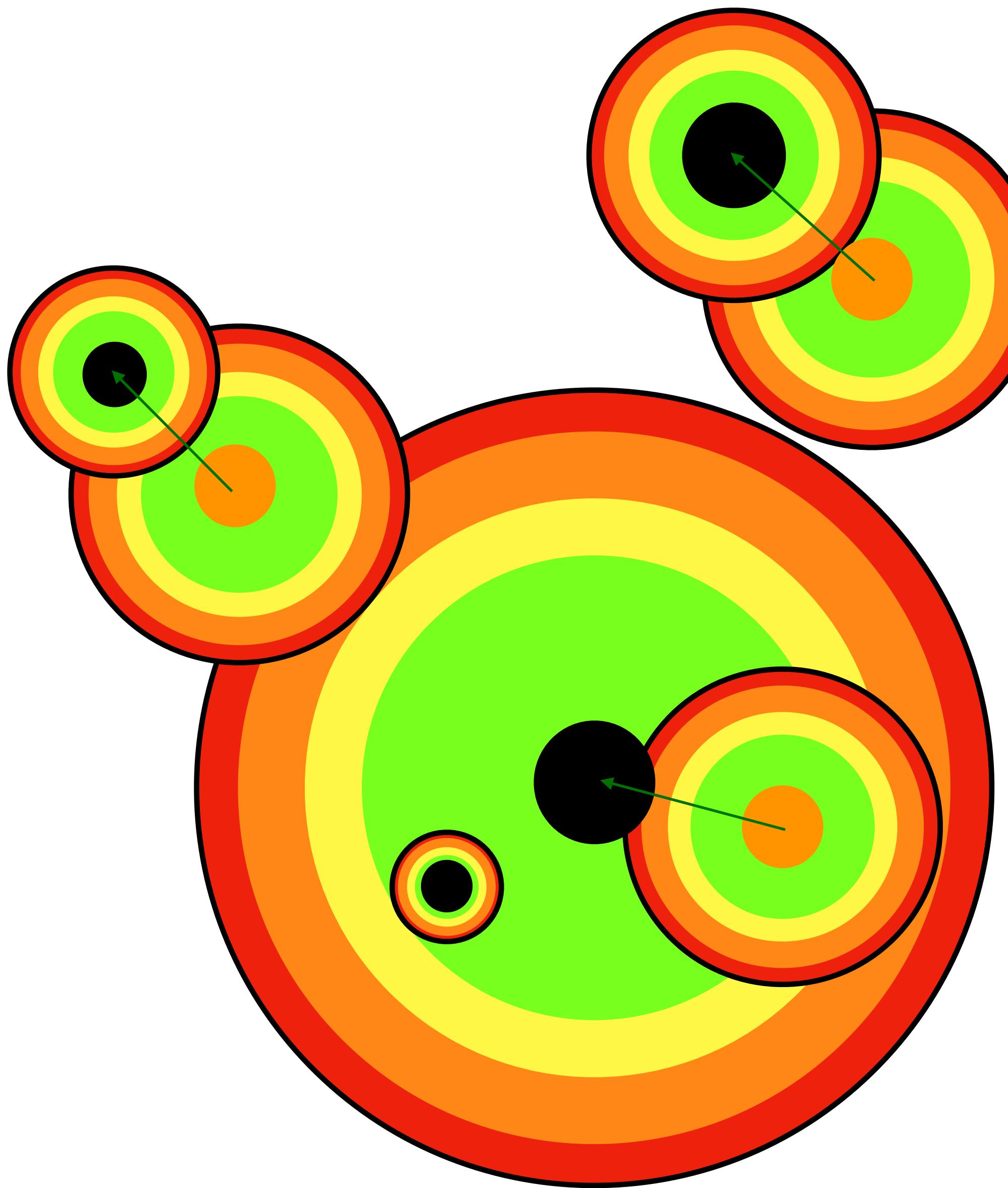
(It's still a few randomly placed objects in every match radius at high Galactic latitudes)

Nearest neighbour/  
proximity matching



**Nearest-neighbour matching *will not* work in the era of Rubin!**

# Probabilistic Cross-Matching



Probability of two sources having their on-sky separation given the hypothesis they are counterparts

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$

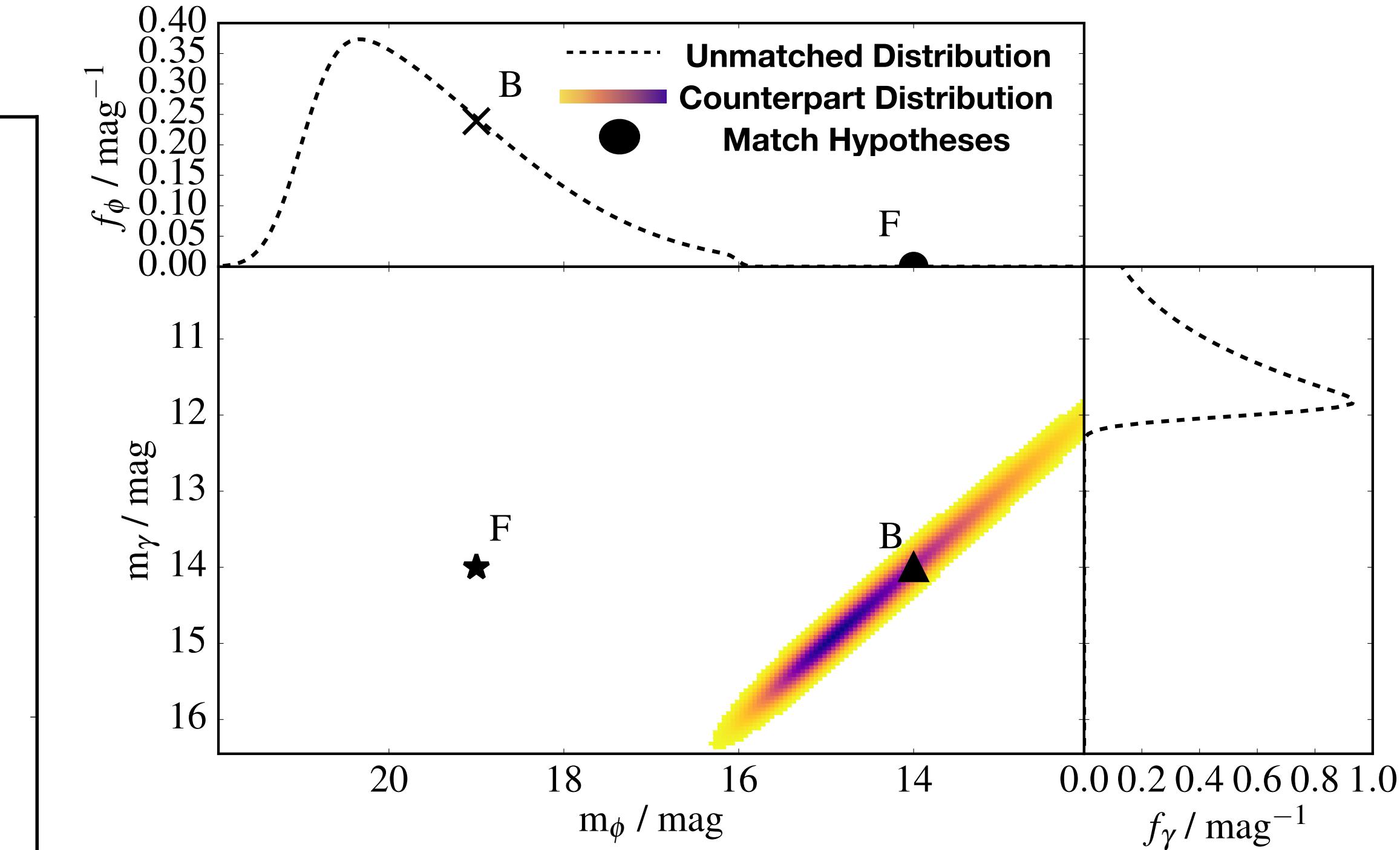
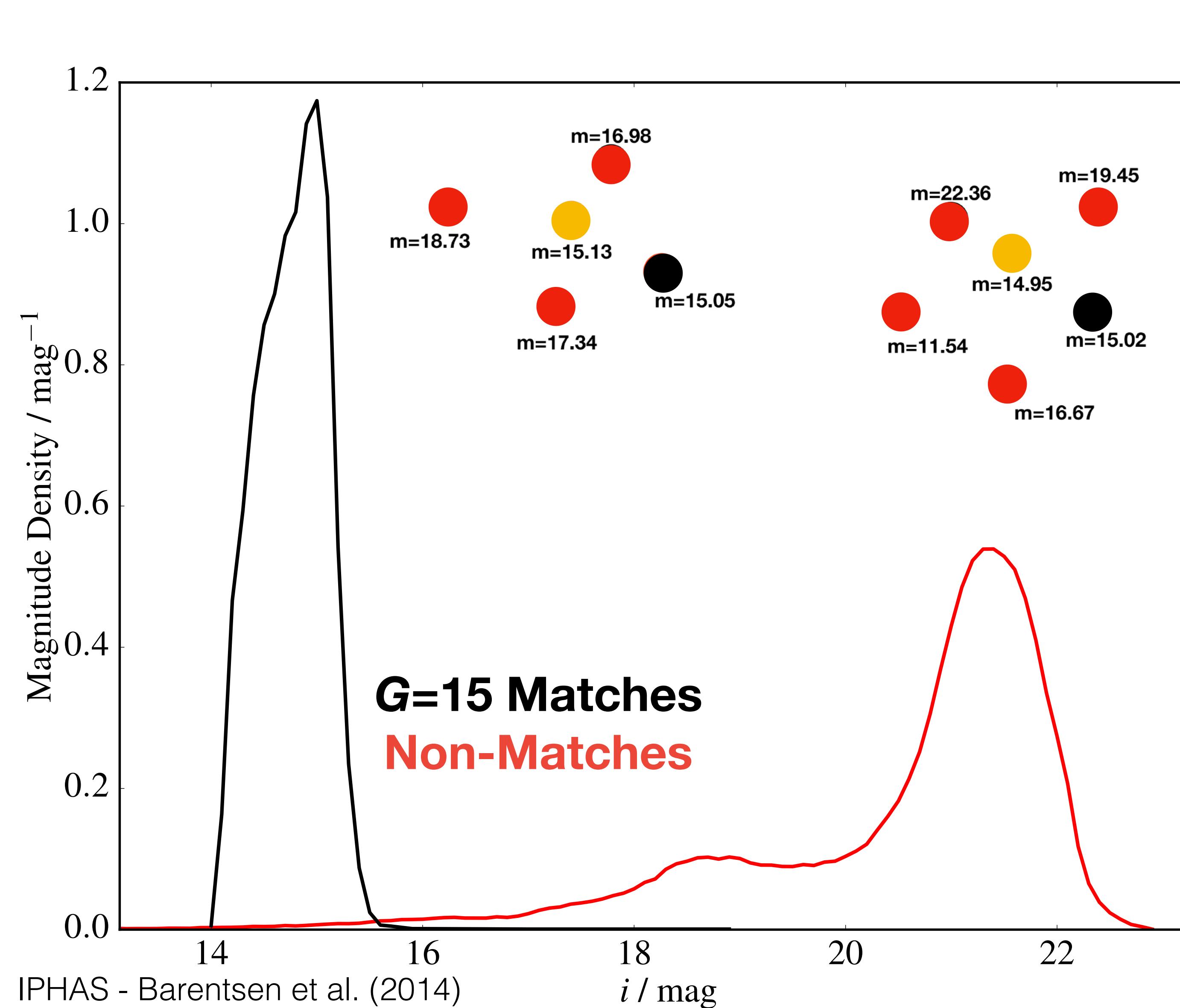
Wilson & Naylor (2018a)

Probability of sources having their brightnesses given they are unrelated to one another (“field stars”)

Probability of sources having their brightnesses given they are counterparts

# Photometry: Rejecting False Positives

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$

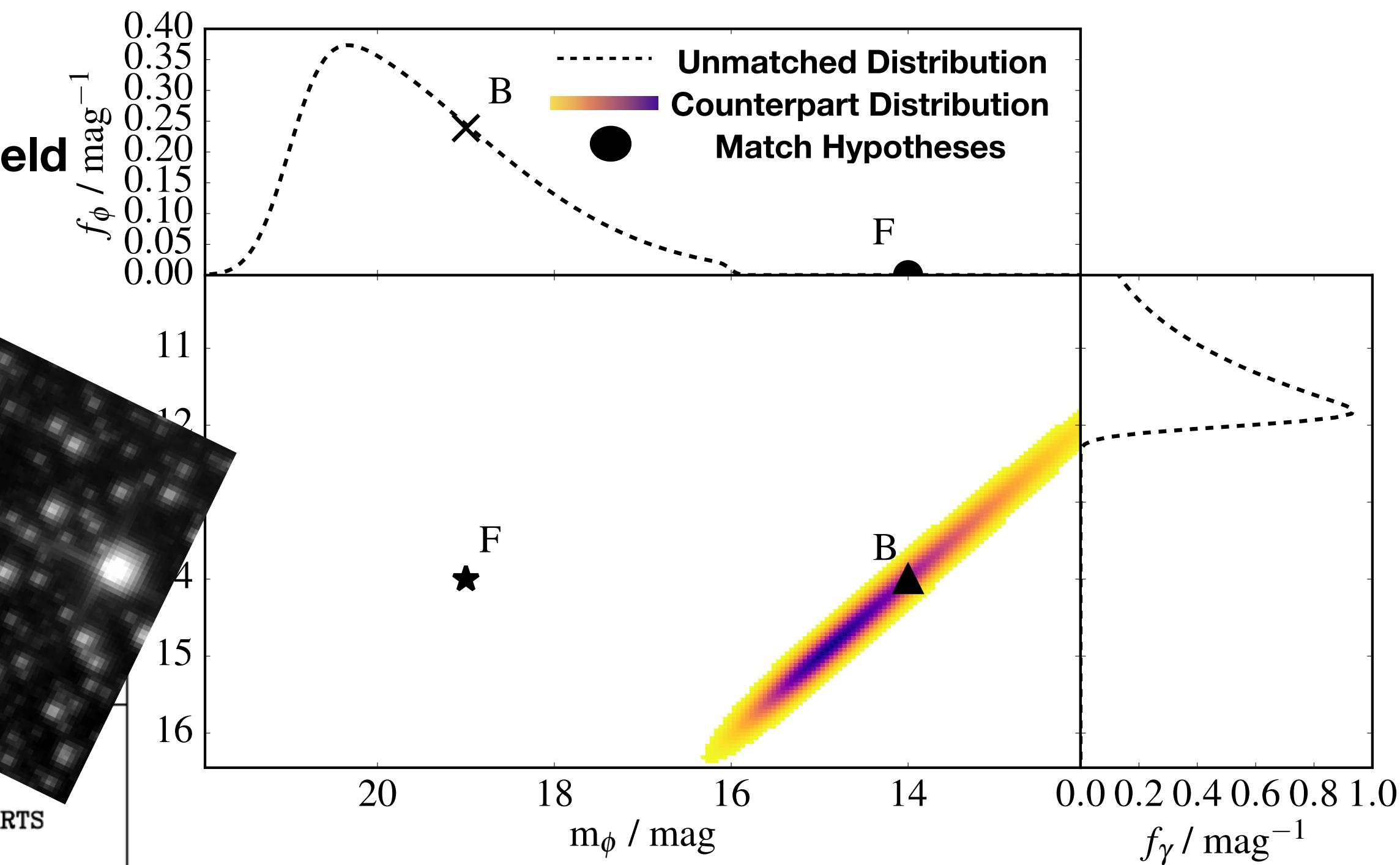
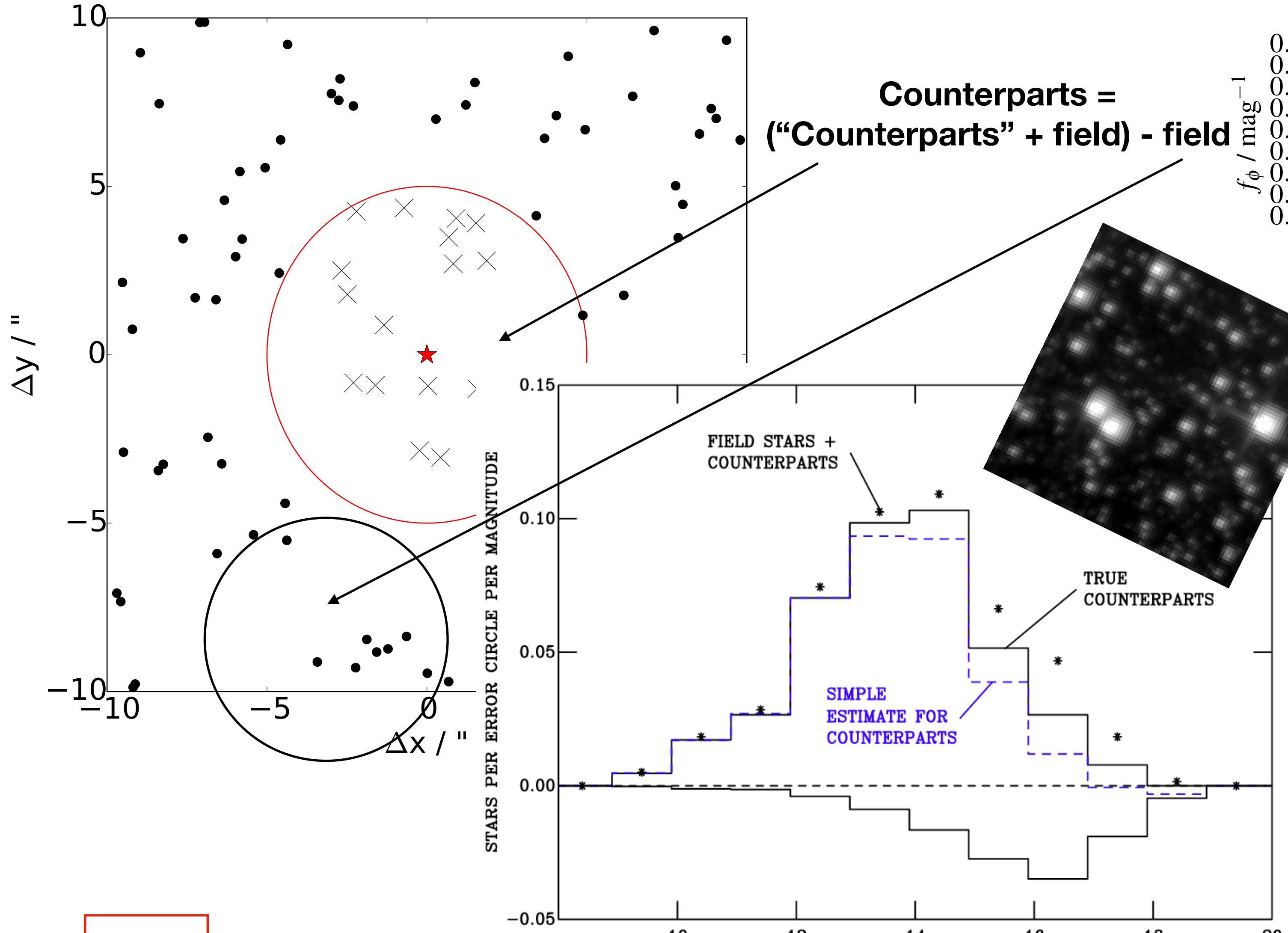


Wilson & Naylor (2018a)

The photometry-based likelihoods  
( $c$  and  $f$ ) allow us to mitigate high  
false positive rate in crowded fields

# Photometry: Rejecting False Positives

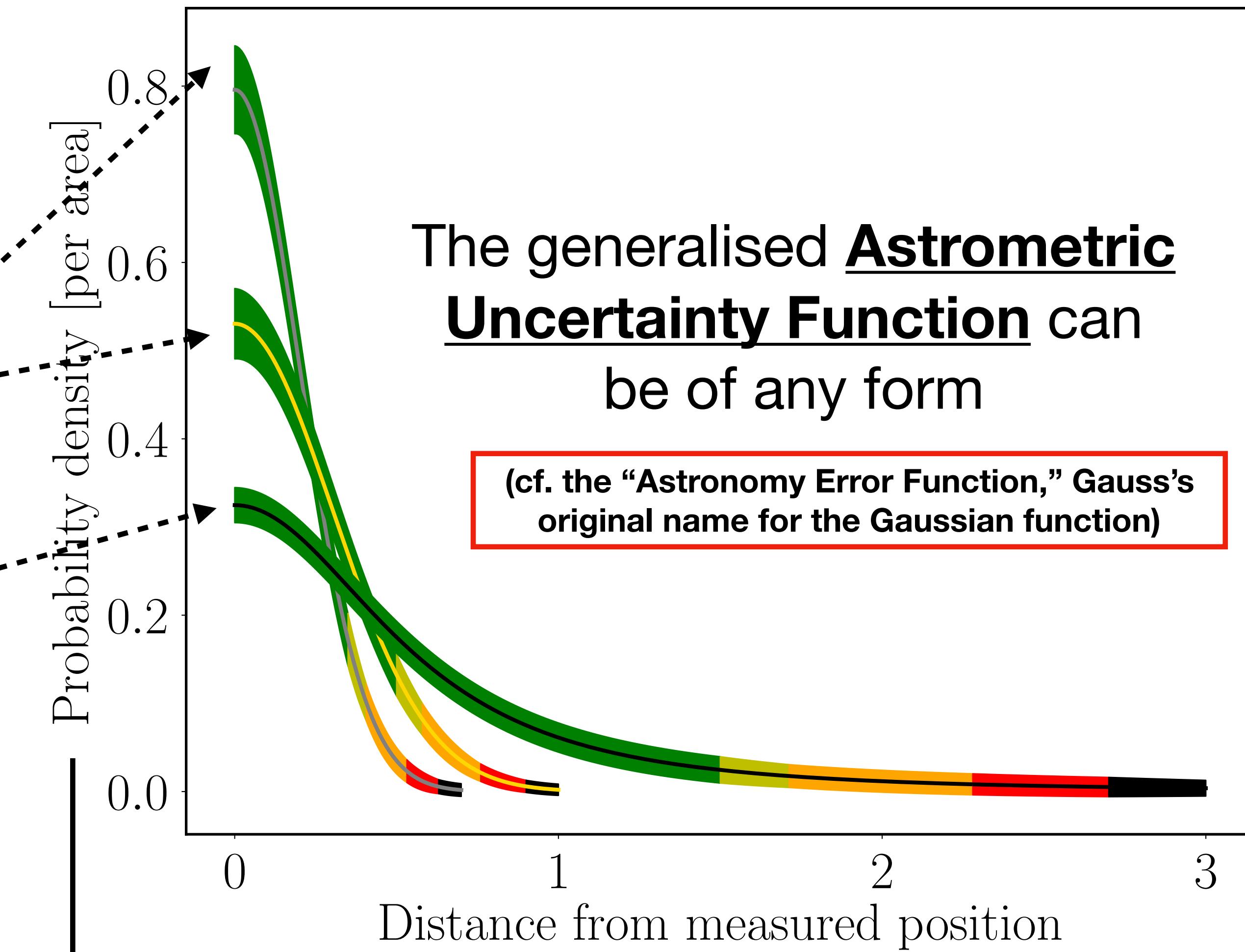
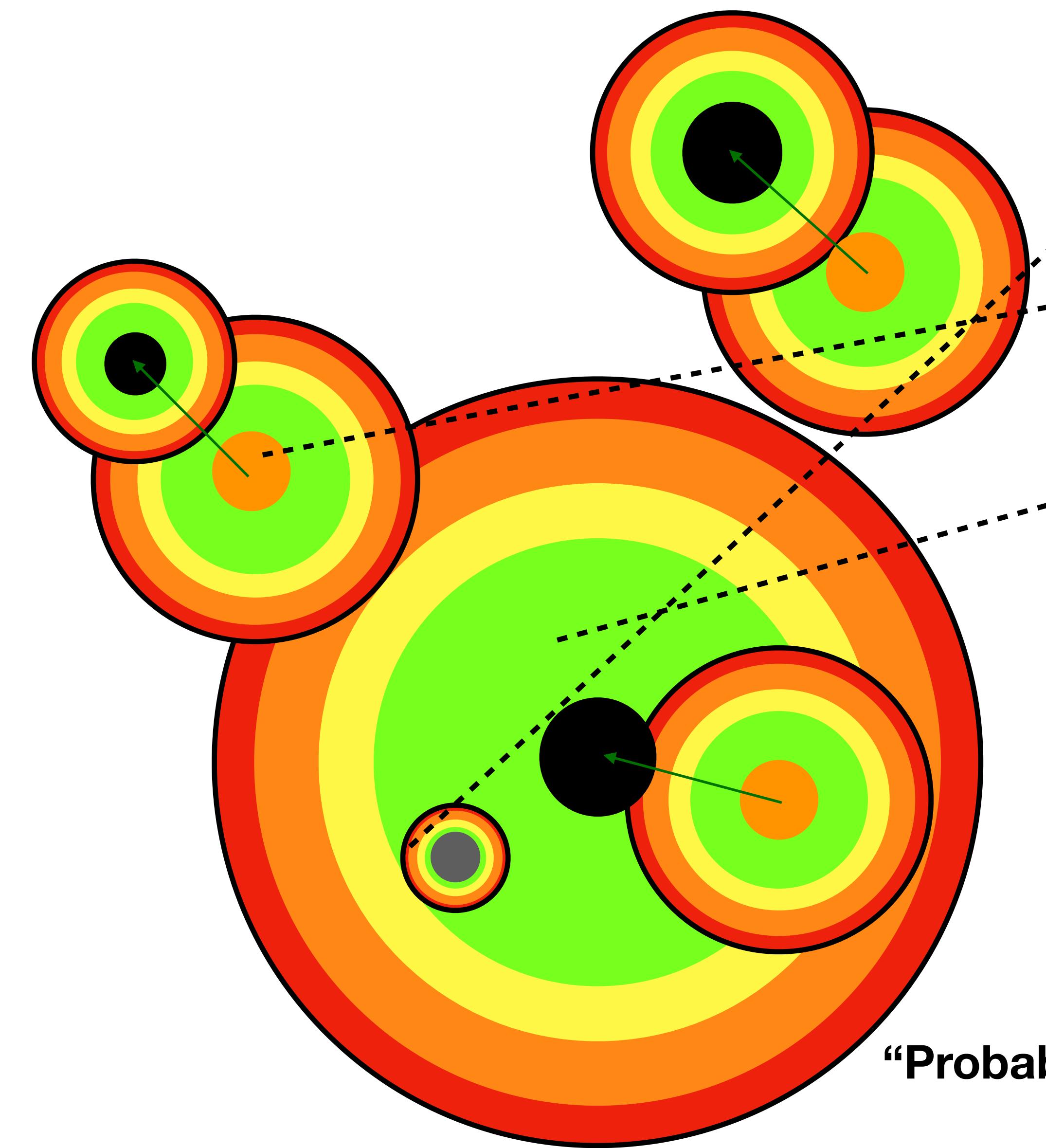
$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$



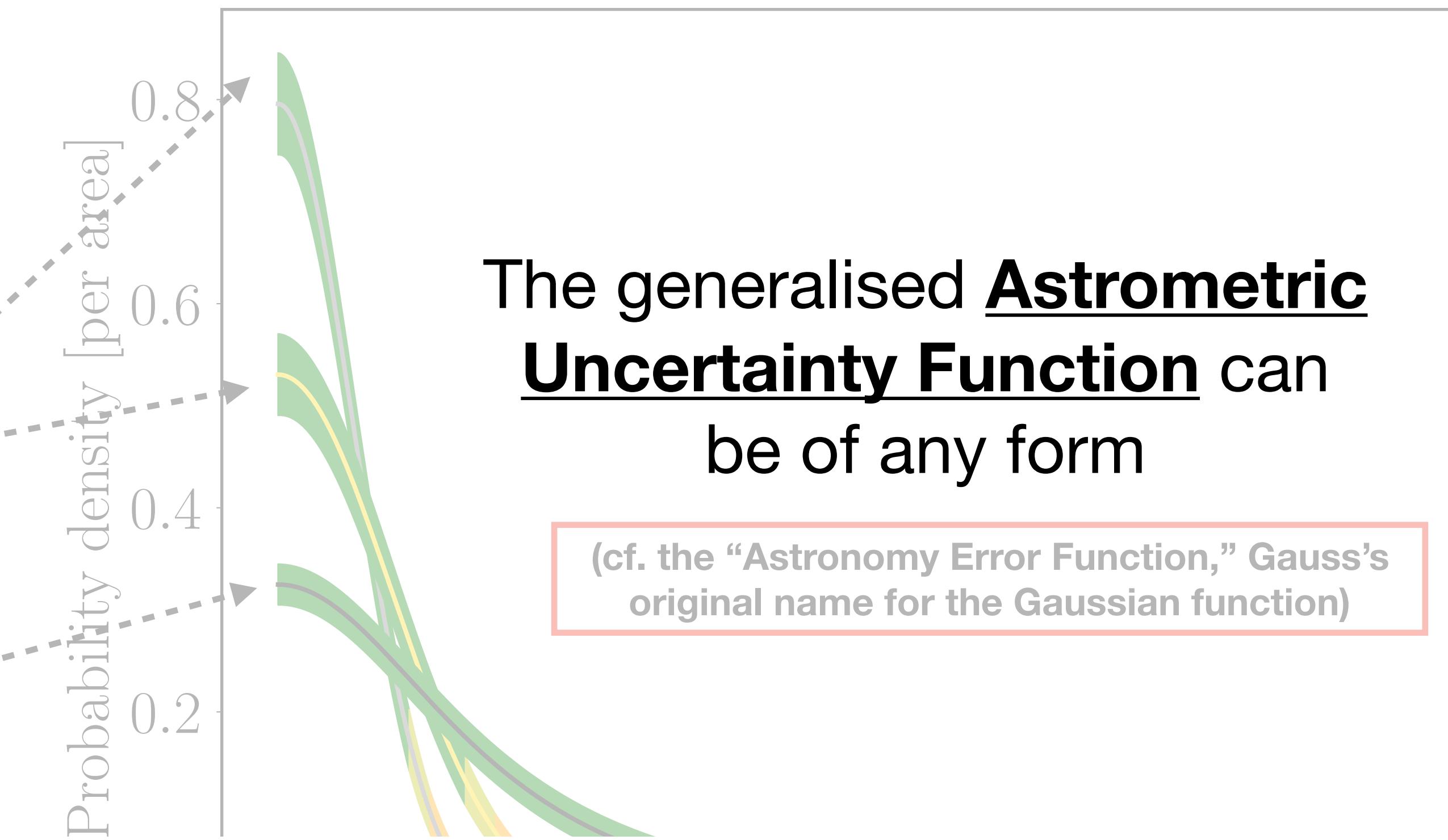
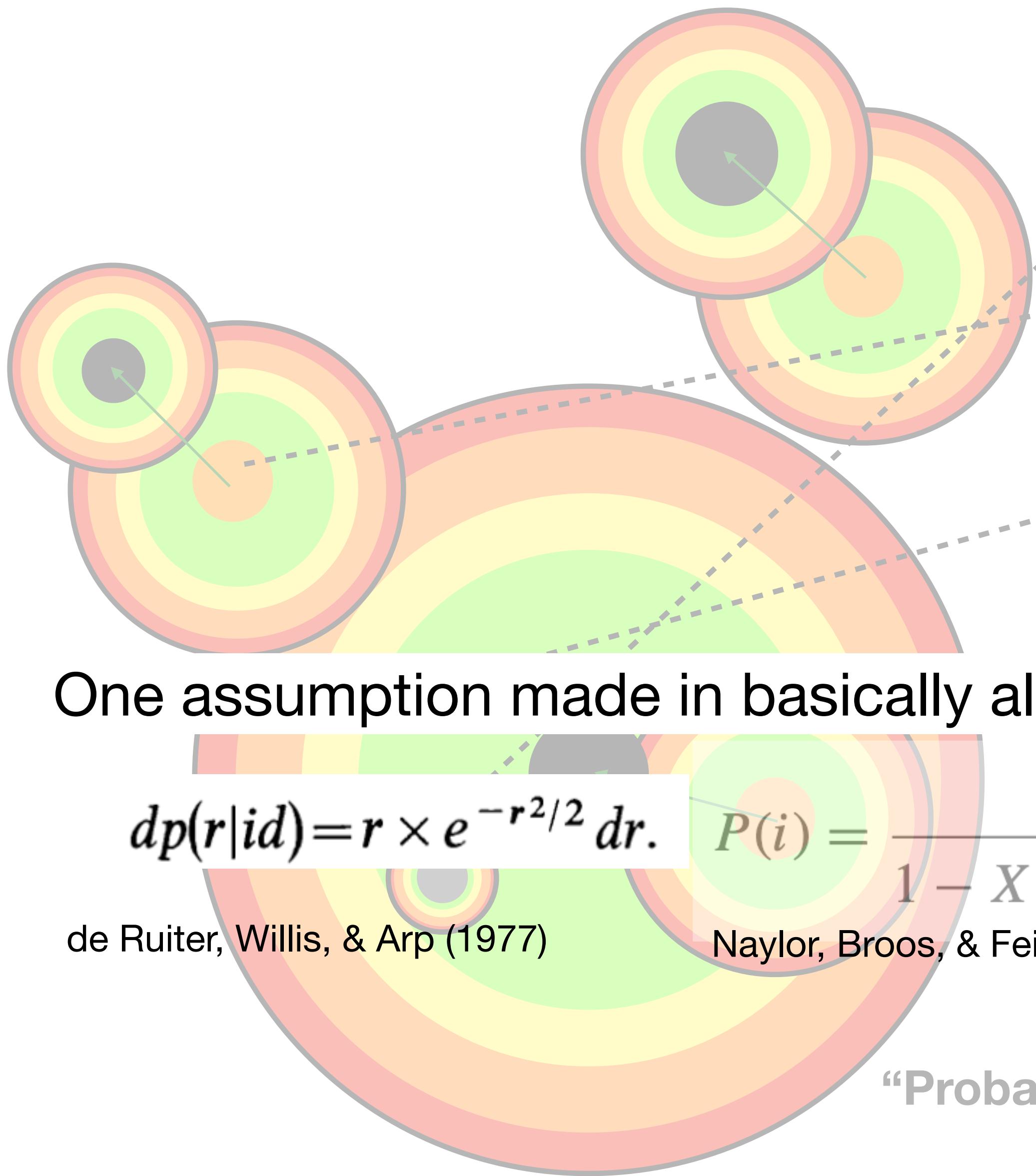
Wilson & Naylor (2018a)

**The photometry-based likelihoods (c and f) allow us to mitigate high false positive rate in crowded fields**

# Probabilistic Cross-Matching: the AUF



# Probabilistic Cross-Matching: the AUF



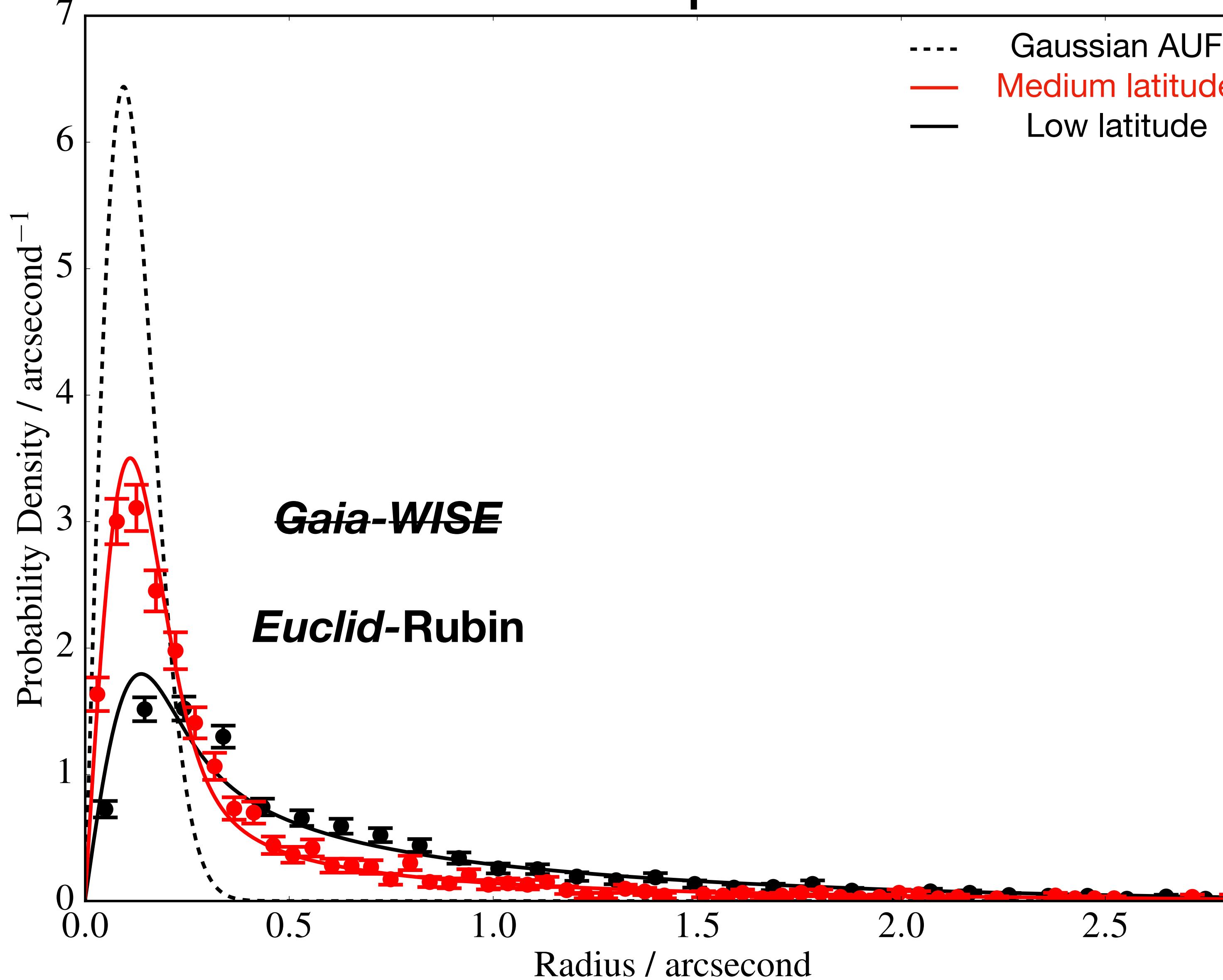
The generalised **Astrometric Uncertainty Function** can be of any form

(cf. the “Astronomy Error Function,” Gauss’s original name for the Gaussian function)

$$p(D|H) = \int p(m|H) \prod_{i=1}^n p_i(x_i|m, H) d^3m$$

Budavári & Szalay (2008)

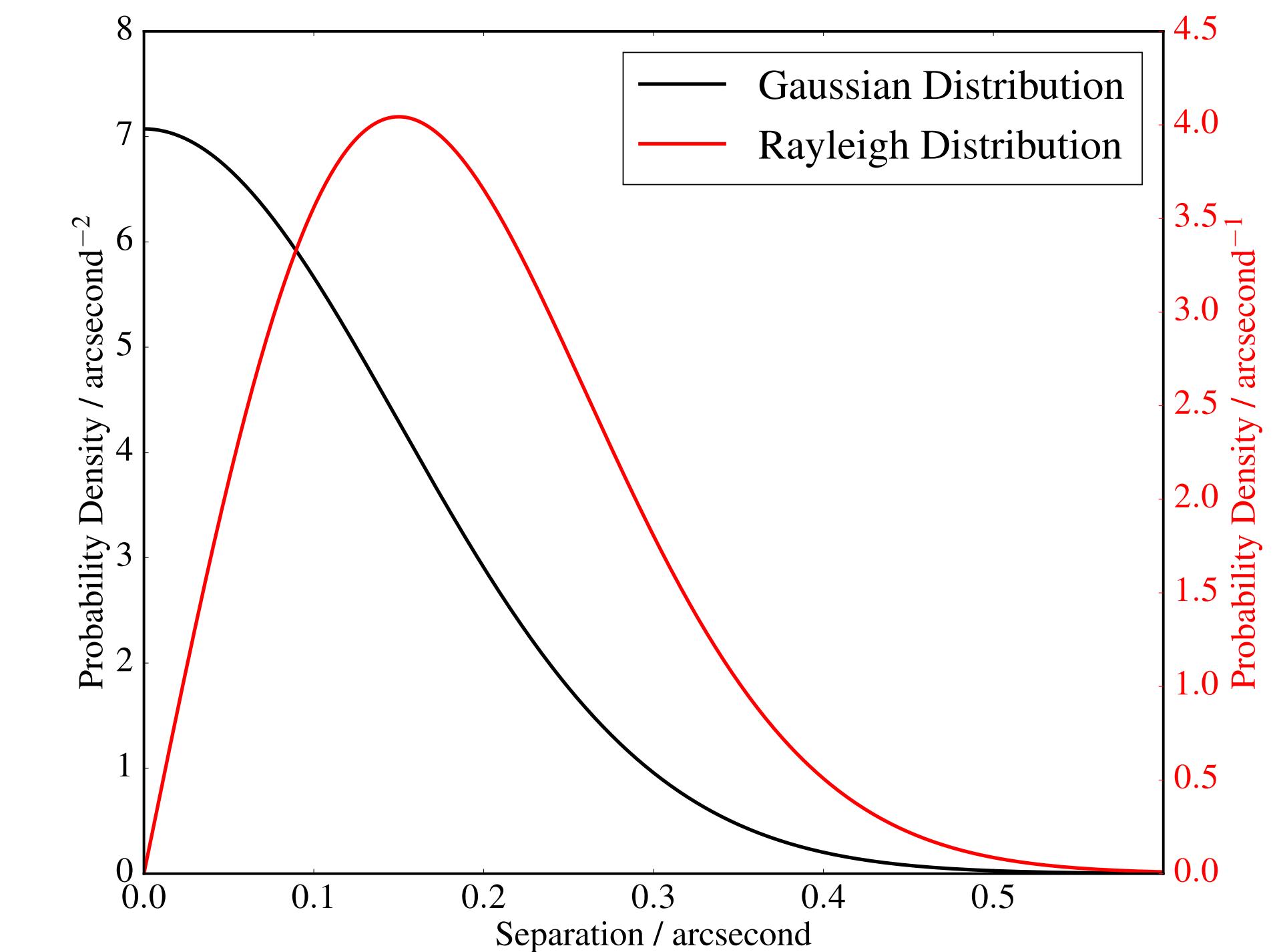
# Additional Components of the AUF



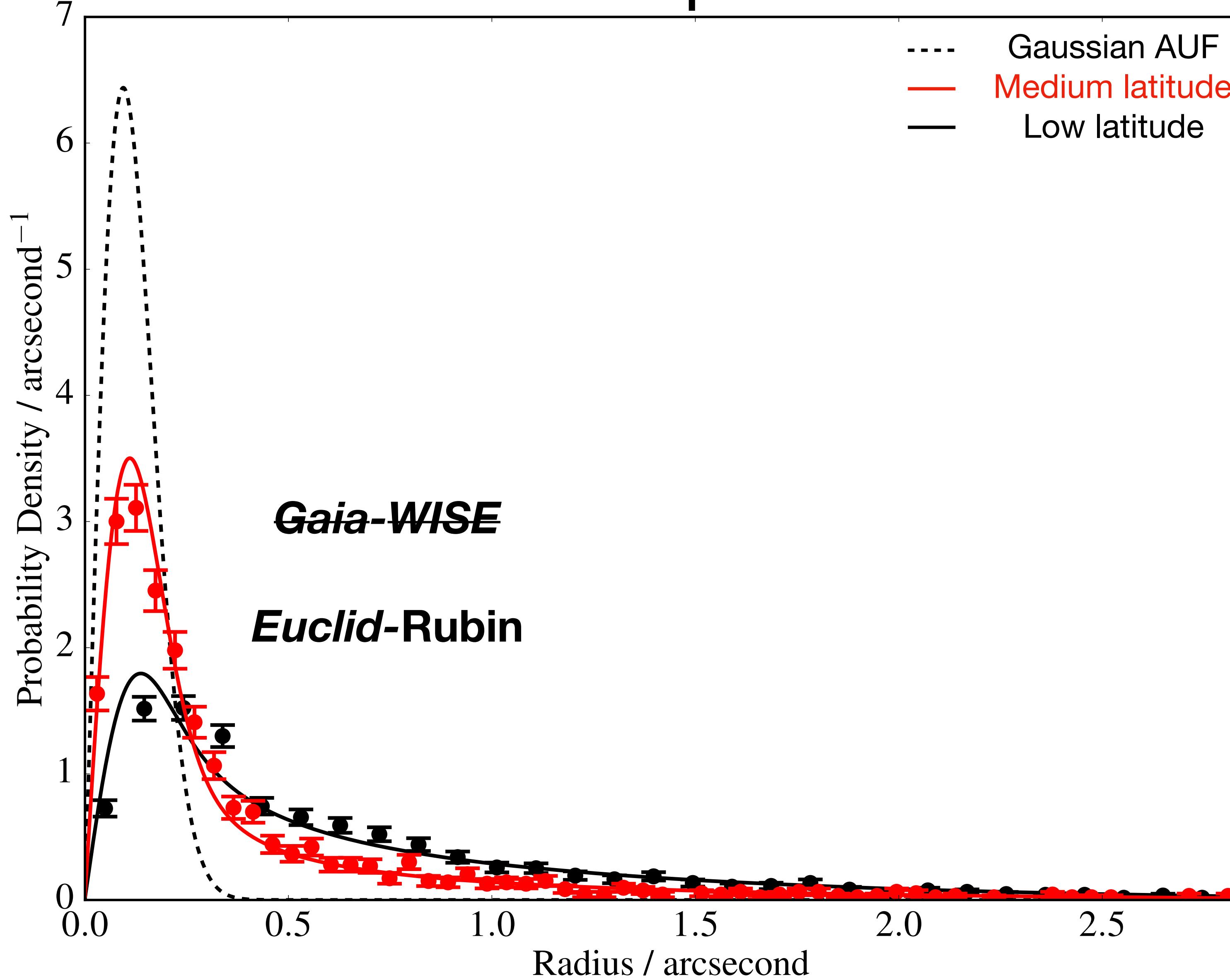
$$g(x, y, \sigma) = (2\pi\sigma^2)^{-1}\exp\left(-\frac{1}{2}\frac{x^2 + y^2}{\sigma^2}\right)$$

↓

$$g(r, \sigma) = \frac{r}{\sigma^2} \exp\left(-\frac{1}{2}\frac{r^2}{\sigma^2}\right)$$

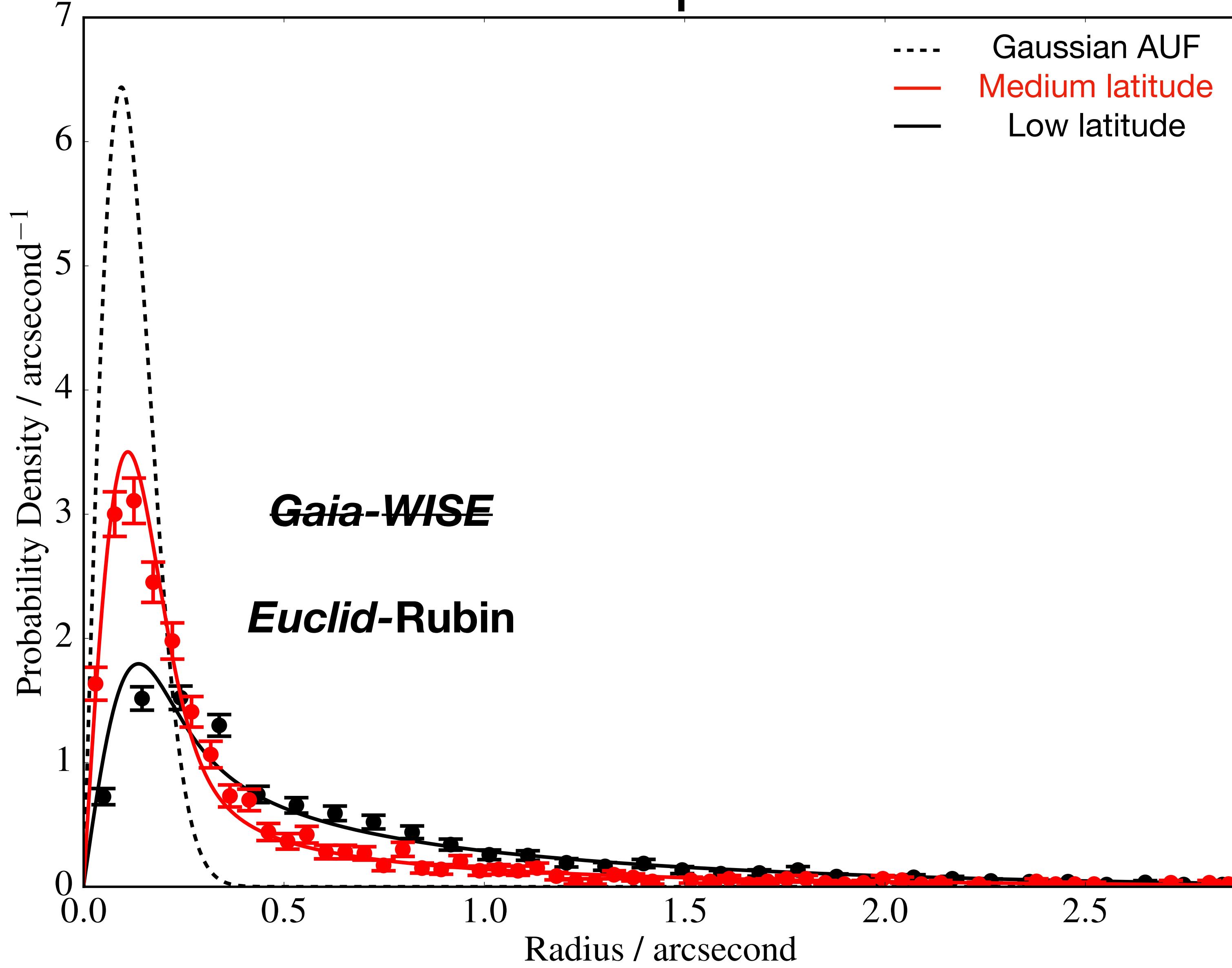


# Additional Components of the AUF



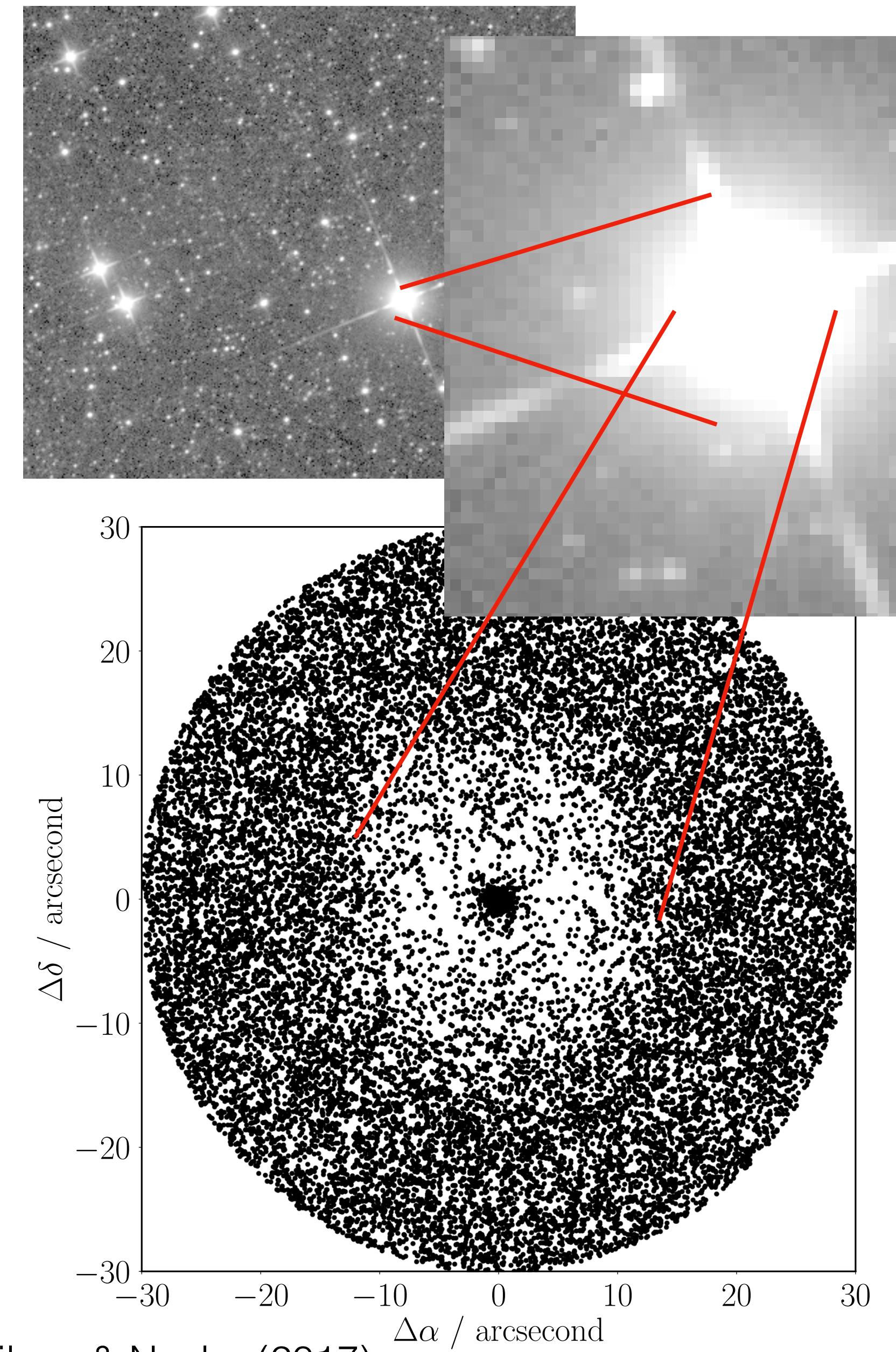
# Additional Components of the AUF

(and any other systematic — e.g. proper motions, cf. Wilson 2023, RASTI)



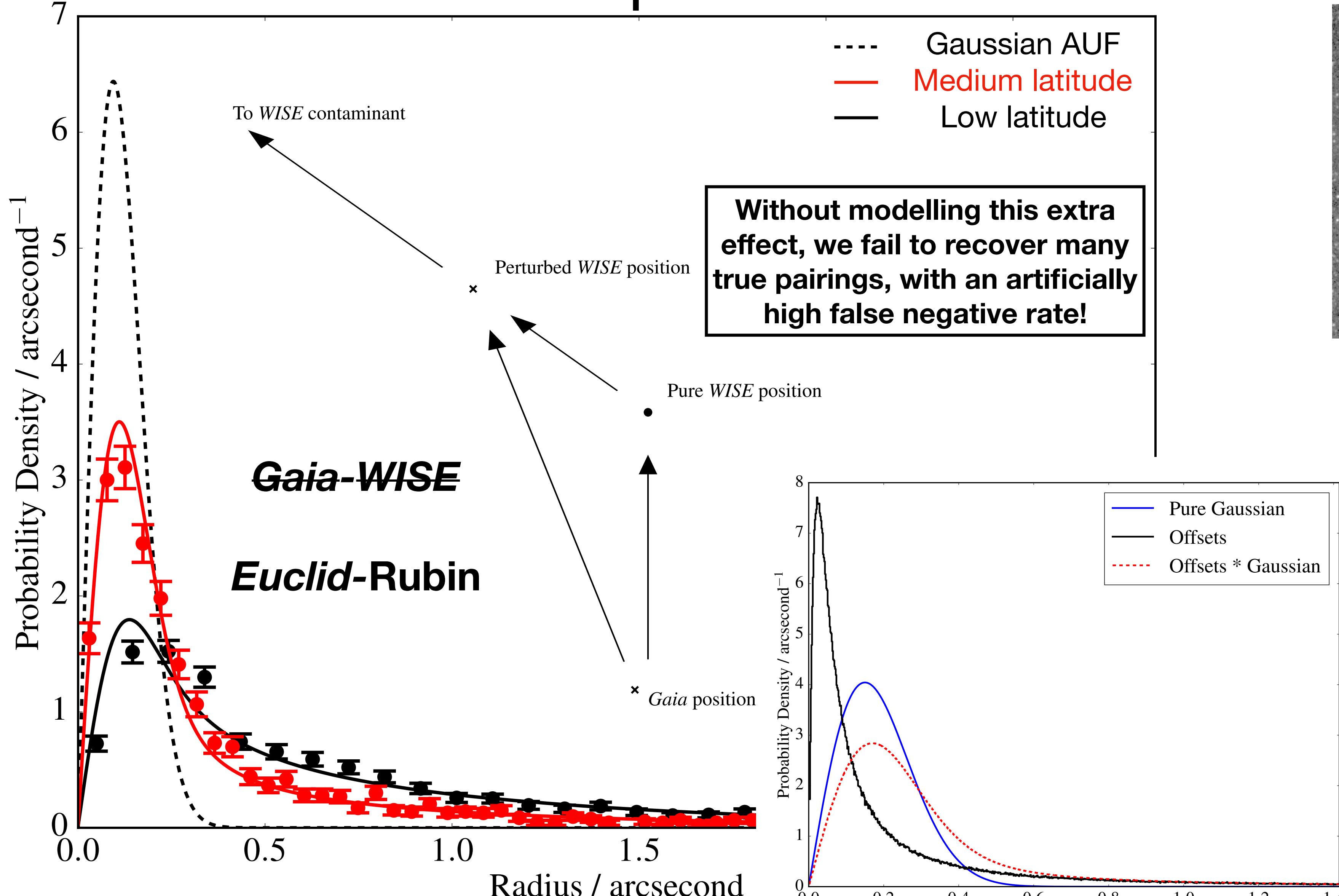
WISE - Wright et al. (2010)

Gaia DR2 - Gaia Collaboration, Brown A. G. A., et al. (2018)



# Additional Components of the AUF

(and any other systematic – e.g. proper motions, cf. Wilson 2023, RASTI)



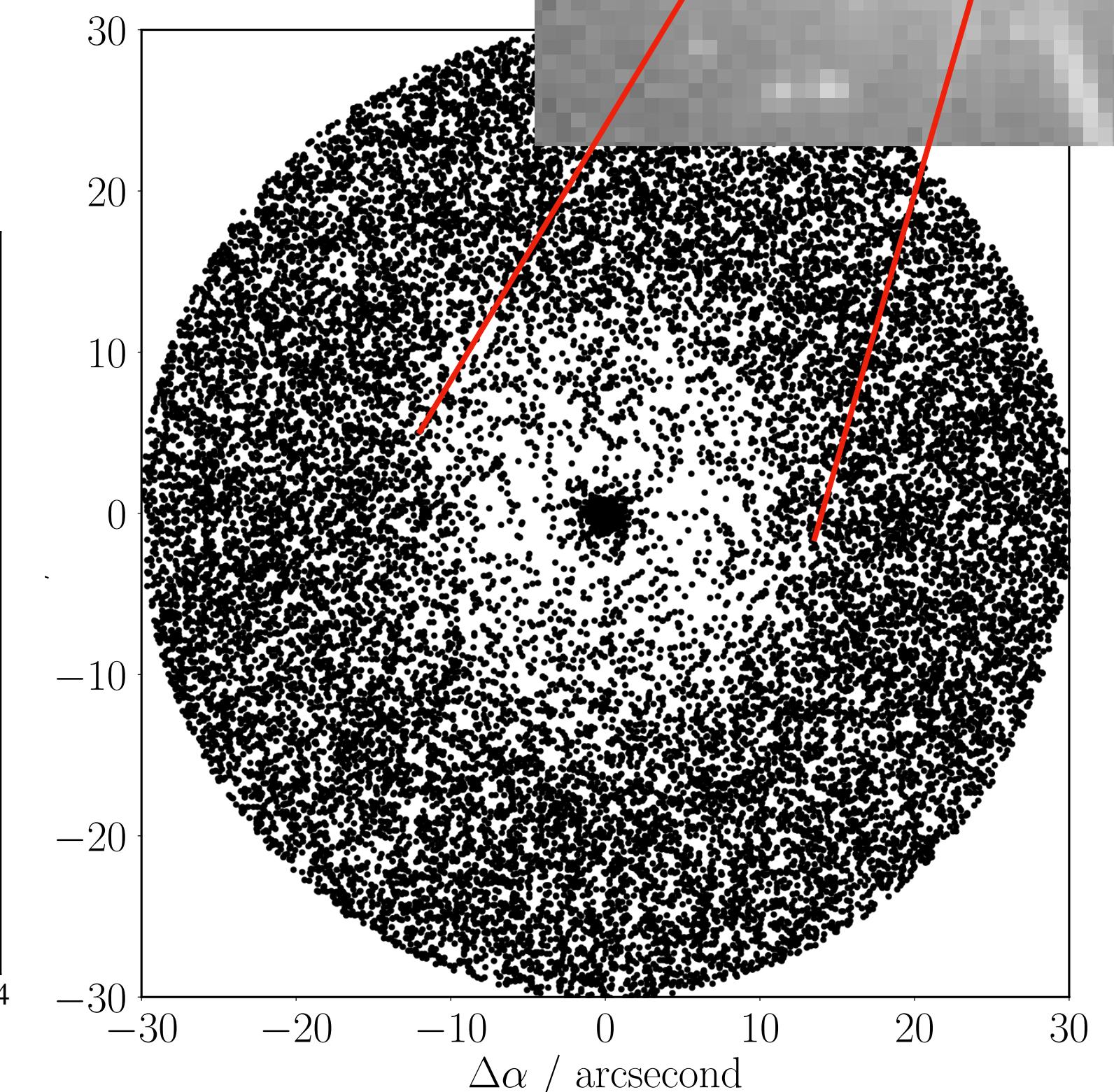
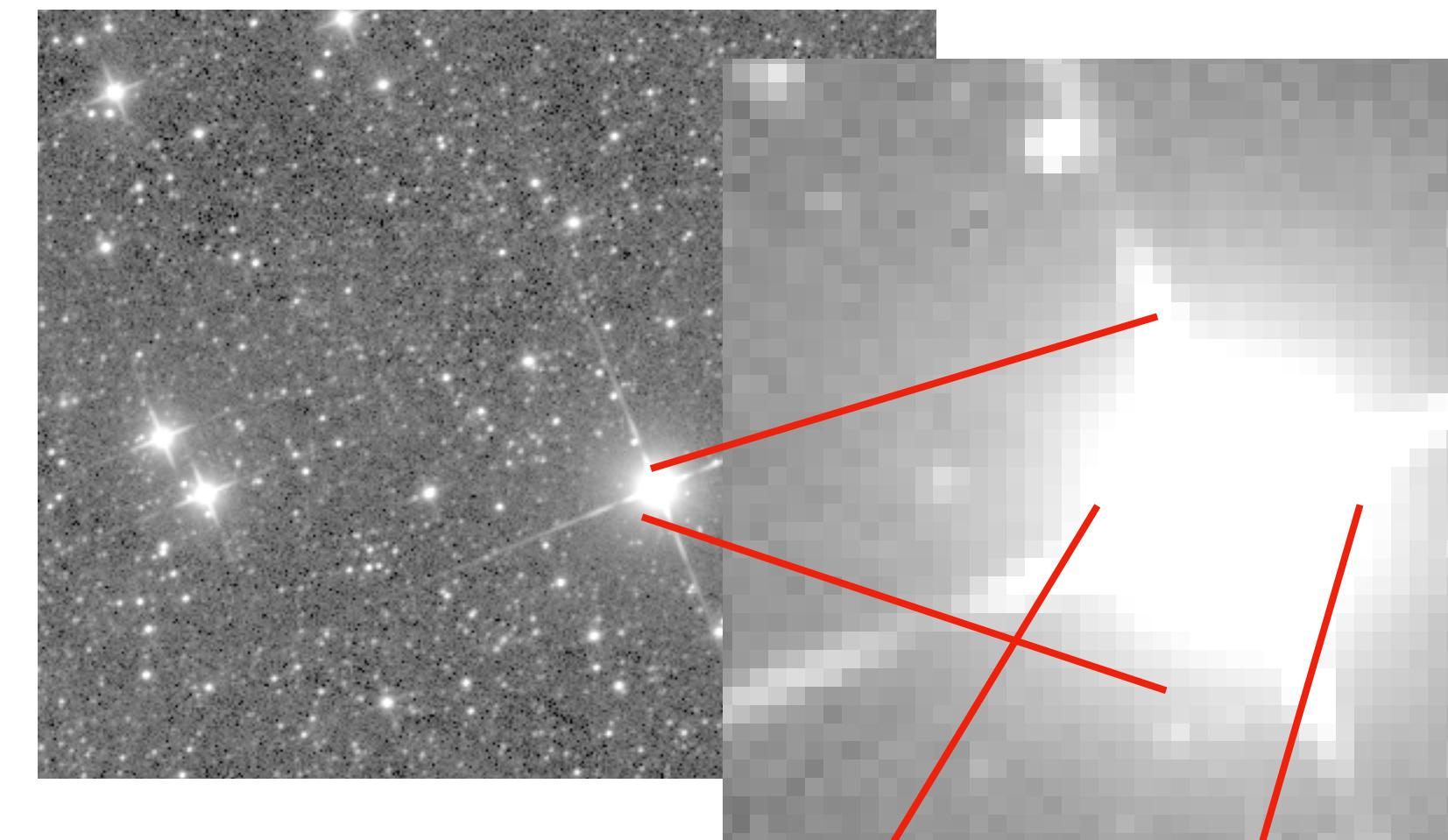
WISE - Wright et al. (2010)

Gaia DR2 - Gaia Collaboration, Brown A. G. A., et al. (2018)

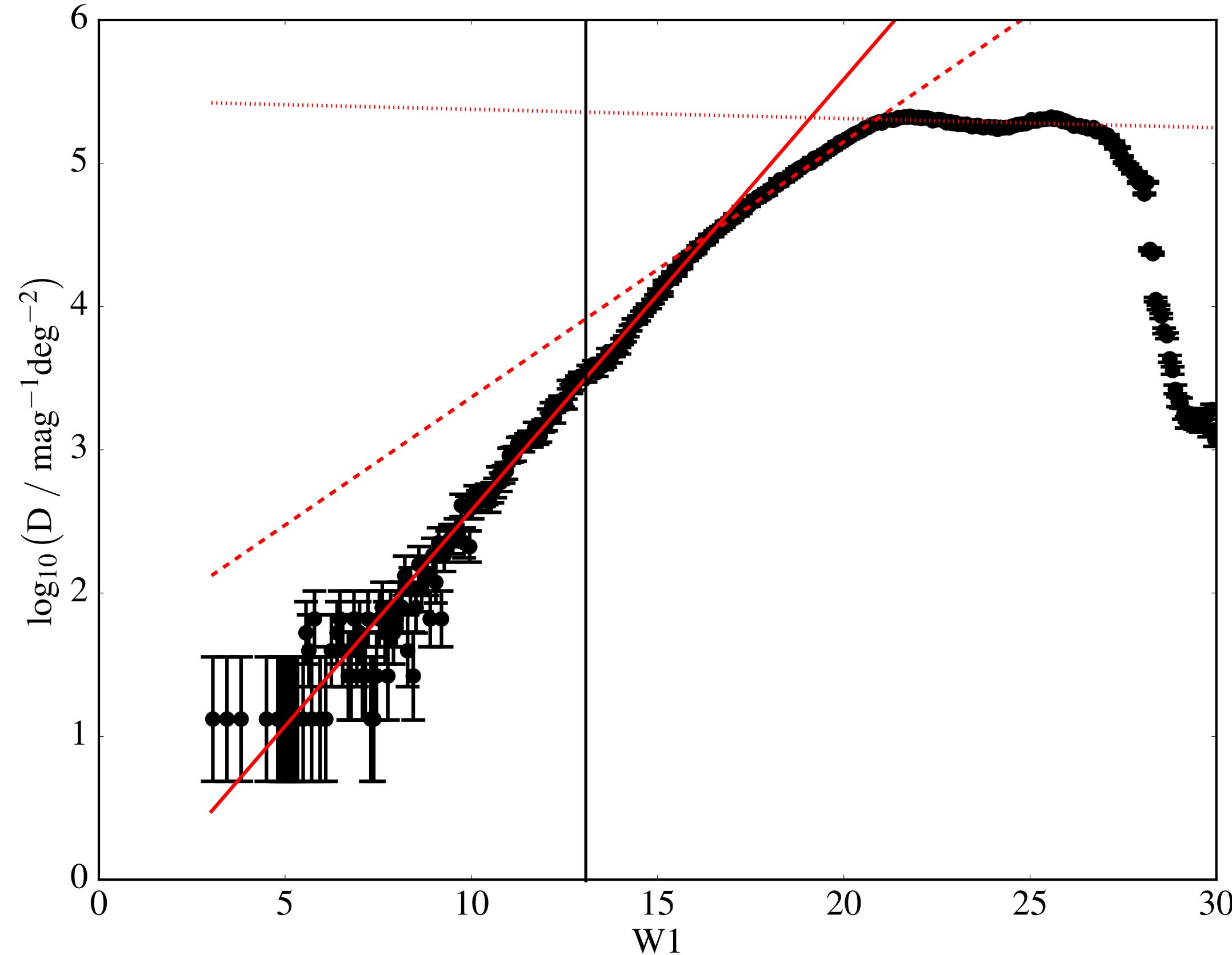
Wilson & Naylor (2018b)

Wilson & Naylor (2017)

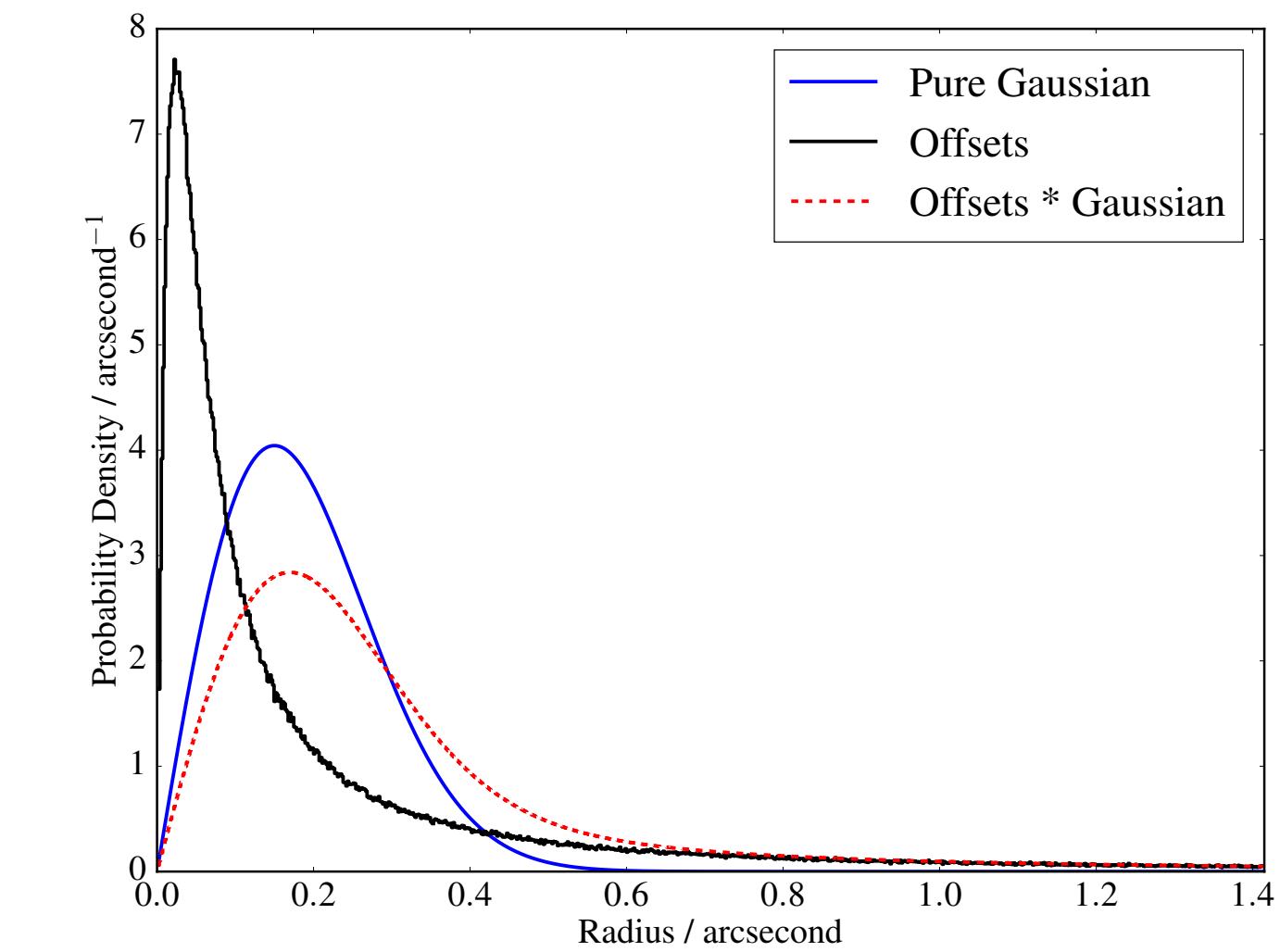
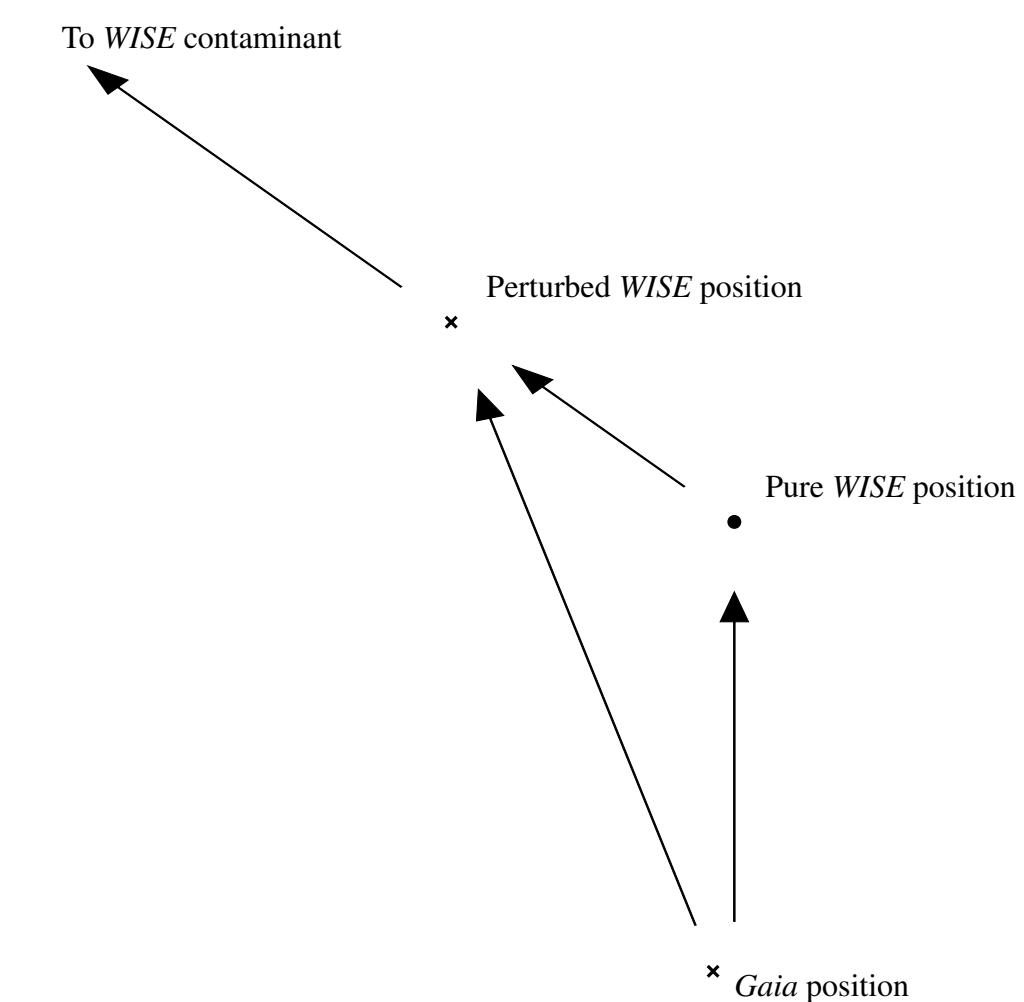
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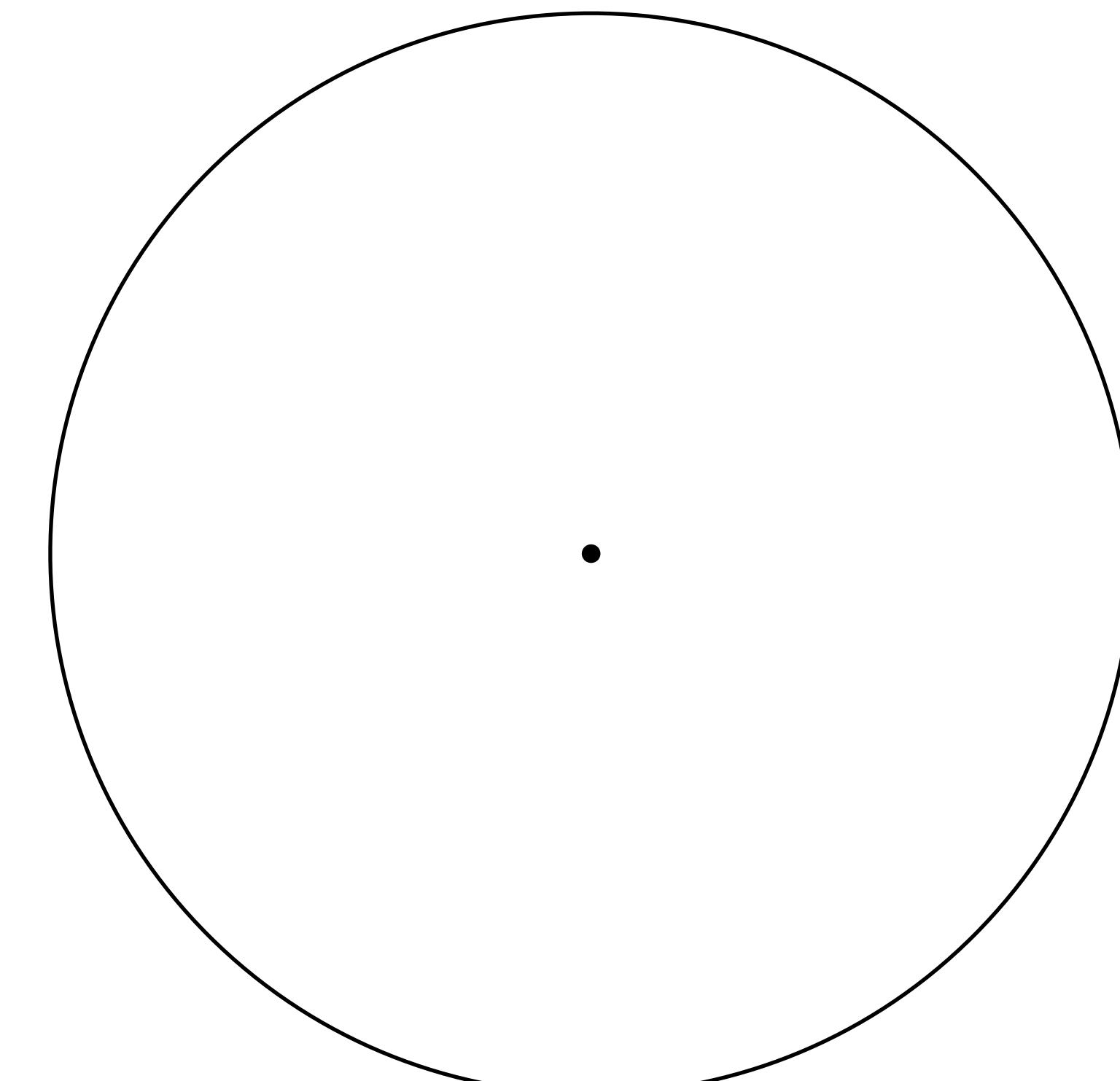
# Building Empirical AUFS



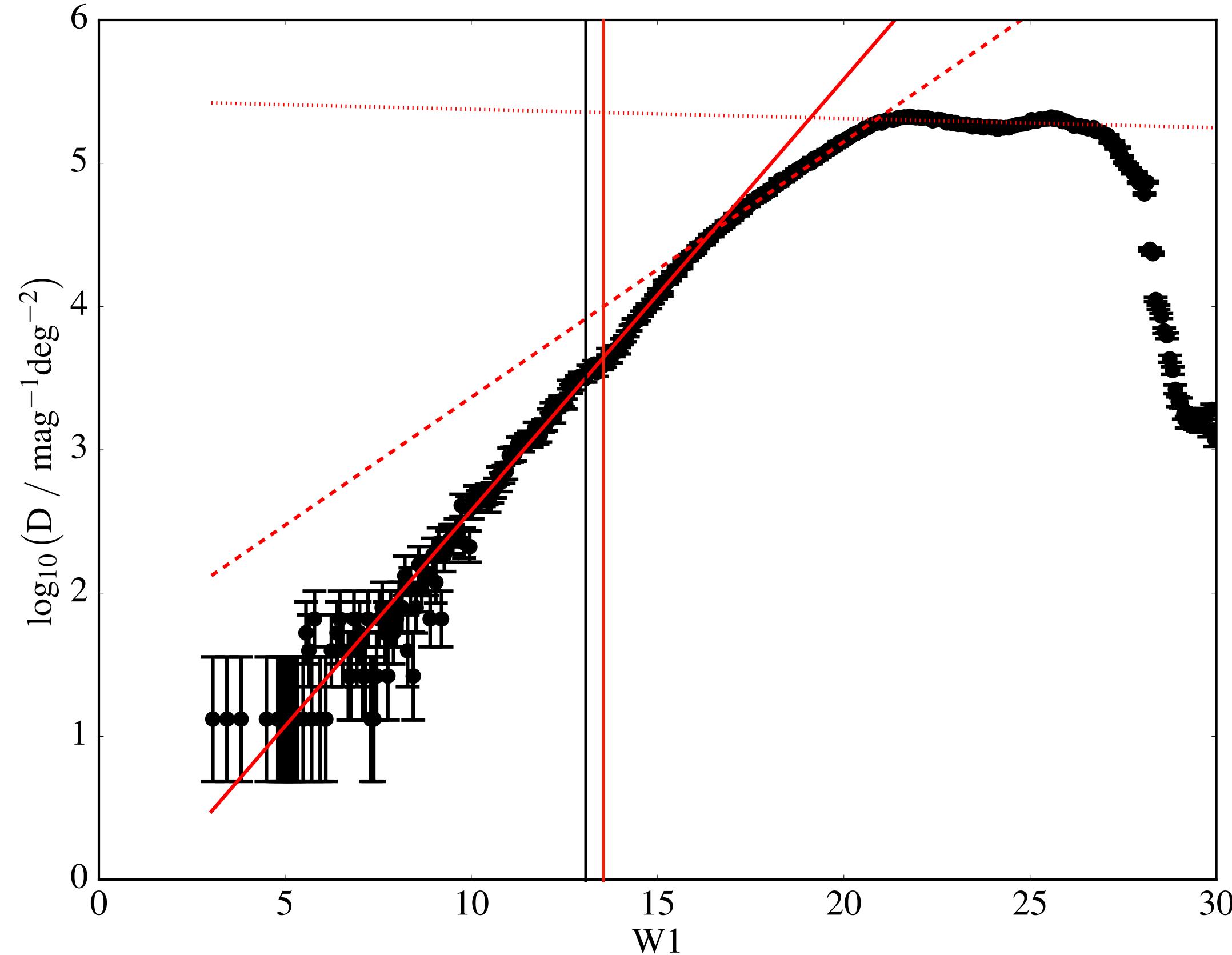
(sources per PSF circle  $\sim 10^{-6}$  sources per mag per sq deg)



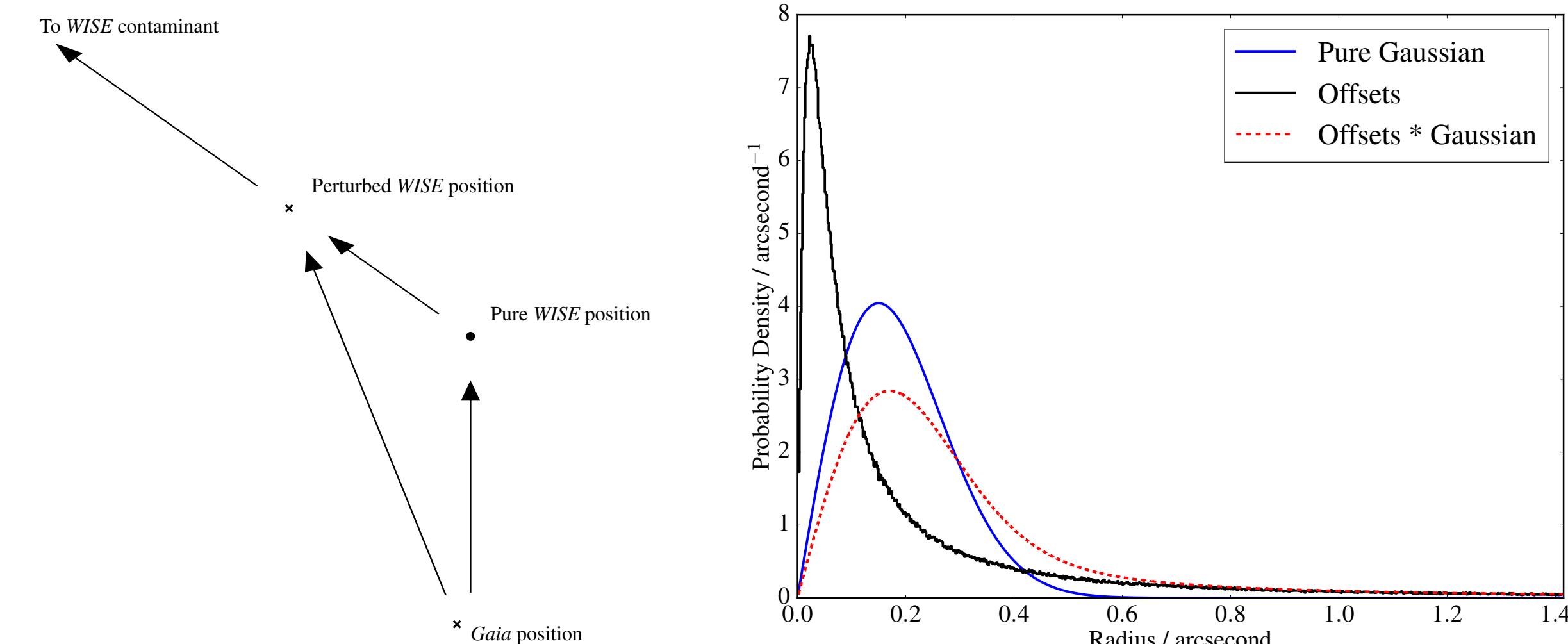
**PSF radius  $\sim 1.2$  FWHM (Rayleigh criterion)**



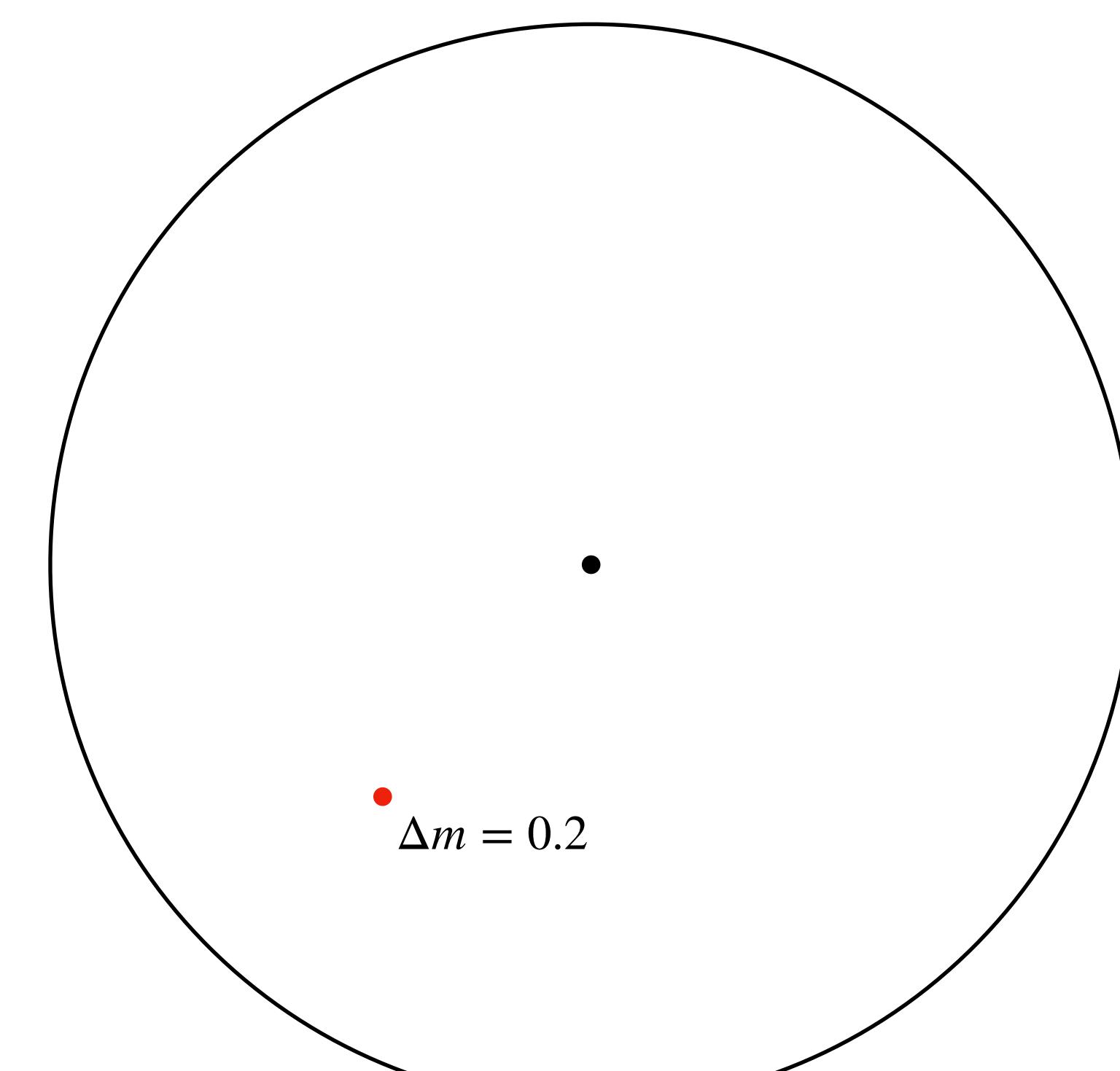
# Building Empirical AUFS



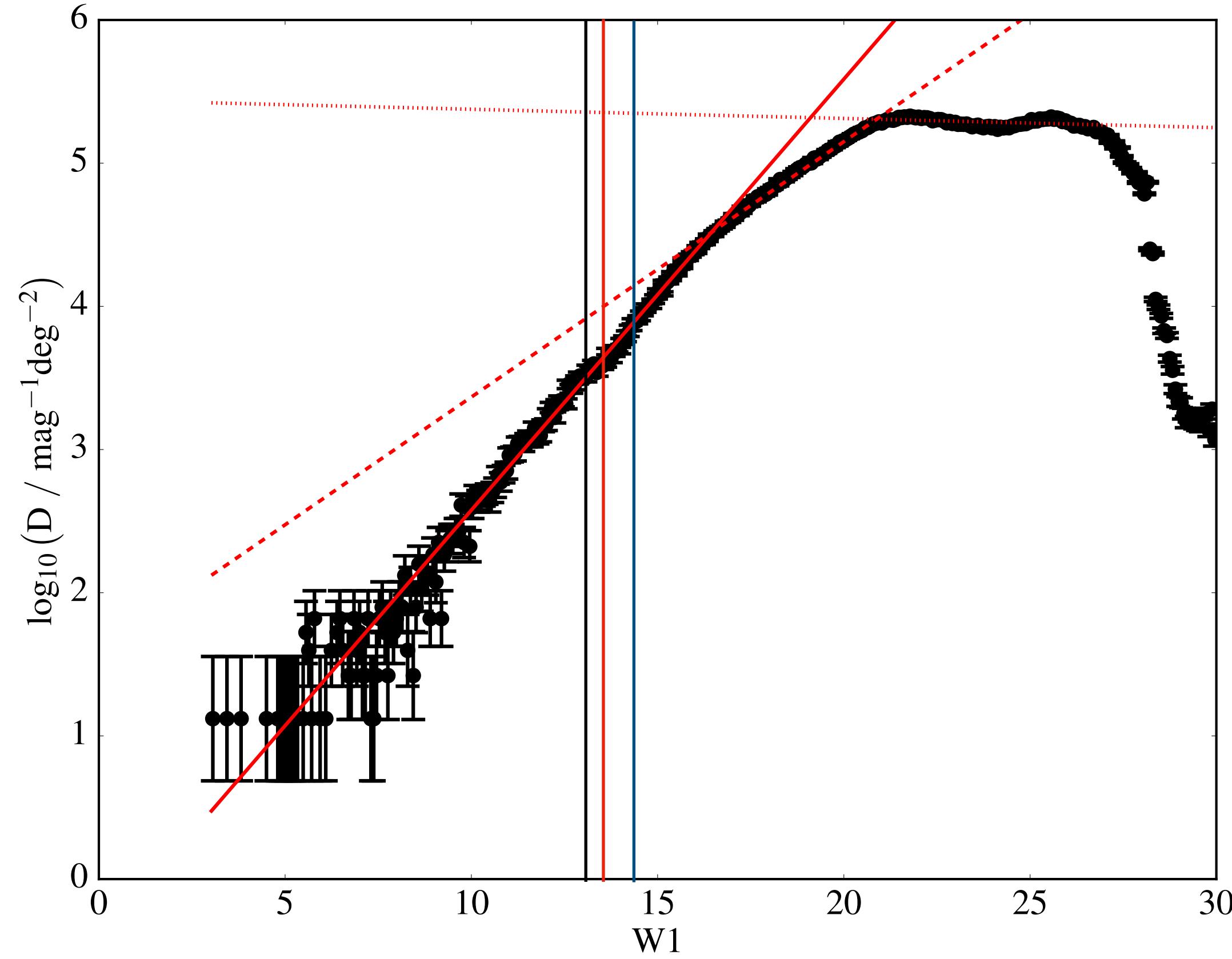
(sources per PSF circle  $\sim 10^{-6}$  sources per mag per sq deg)



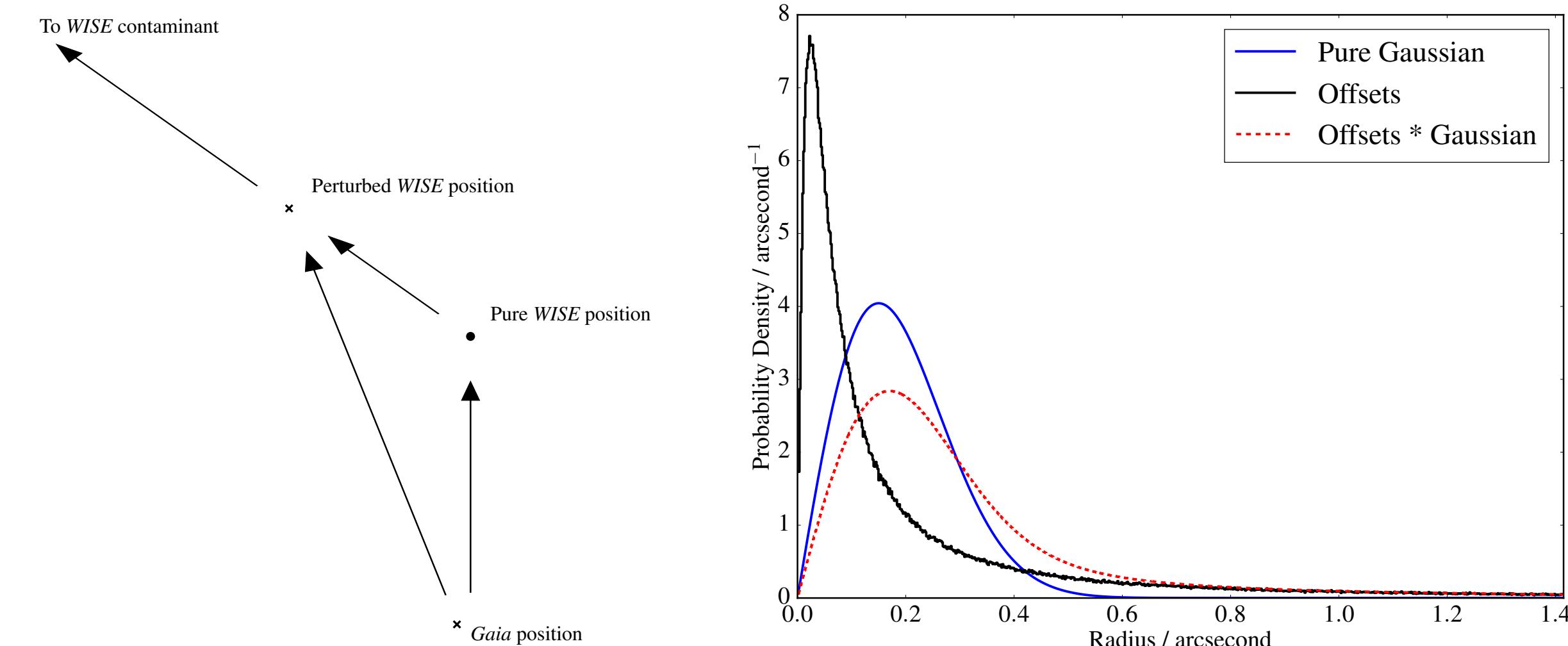
PSF radius  $\sim 1.2$  FWHM (Rayleigh criterion)



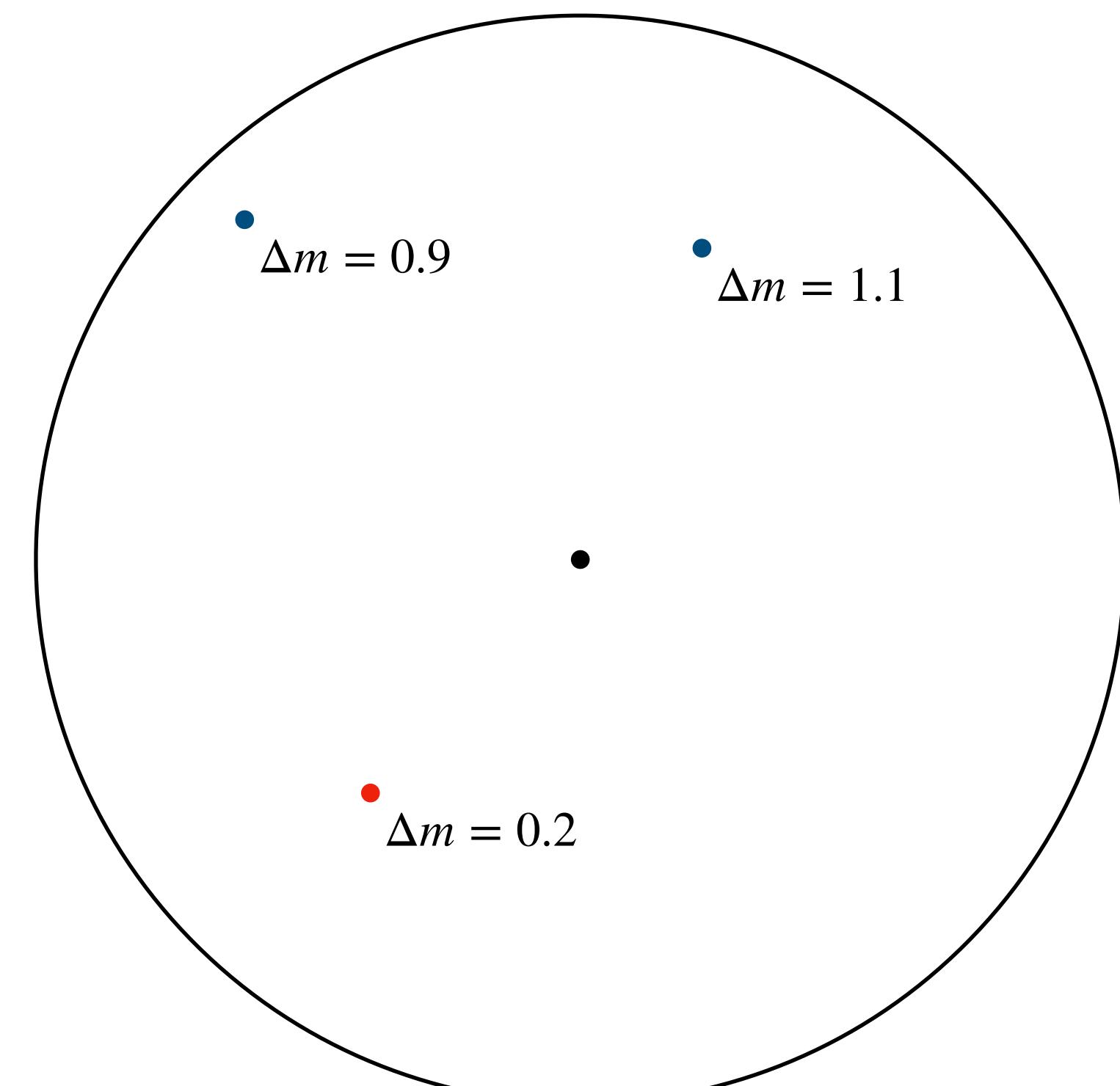
# Building Empirical AUFS



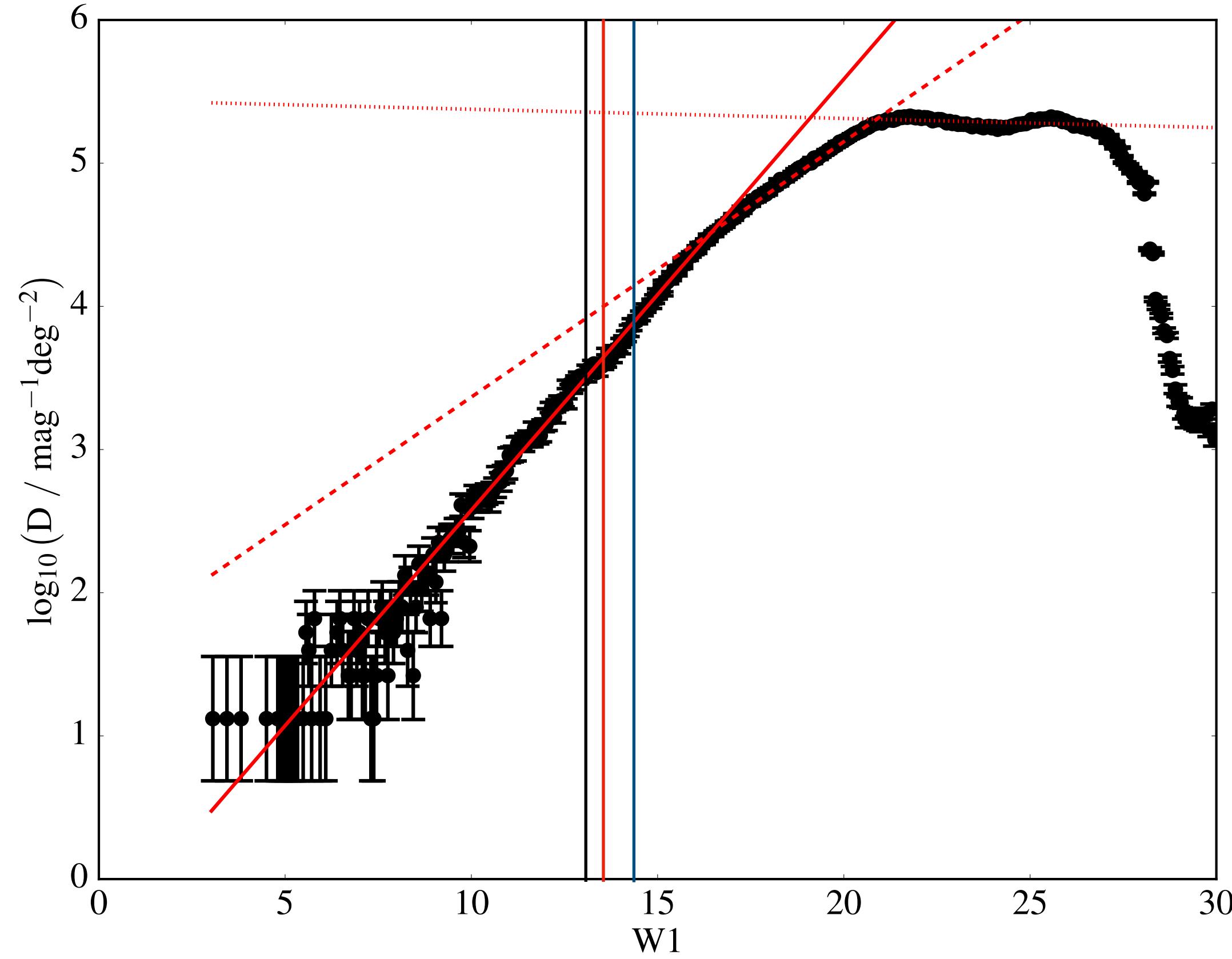
(sources per PSF circle  $\sim 10^{-6}$  sources per mag per sq deg)



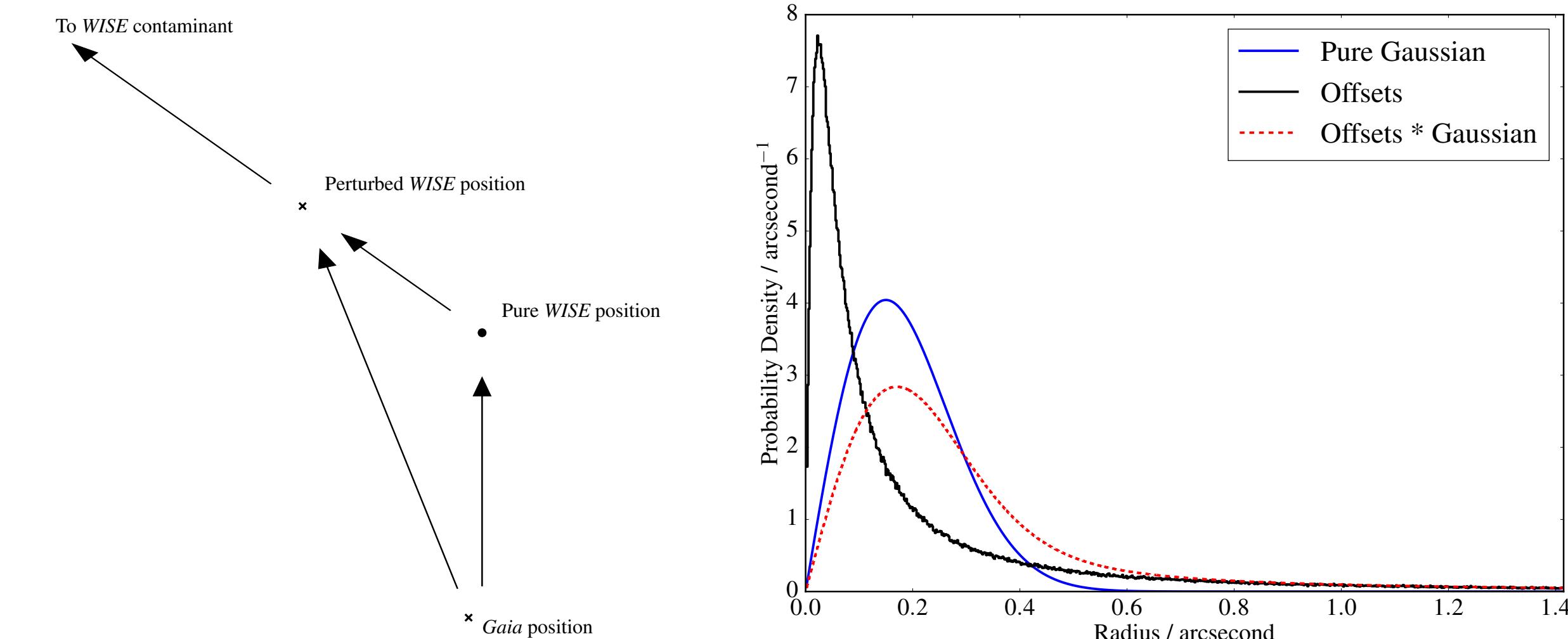
PSF radius  $\sim 1.2$  FWHM (Rayleigh criterion)



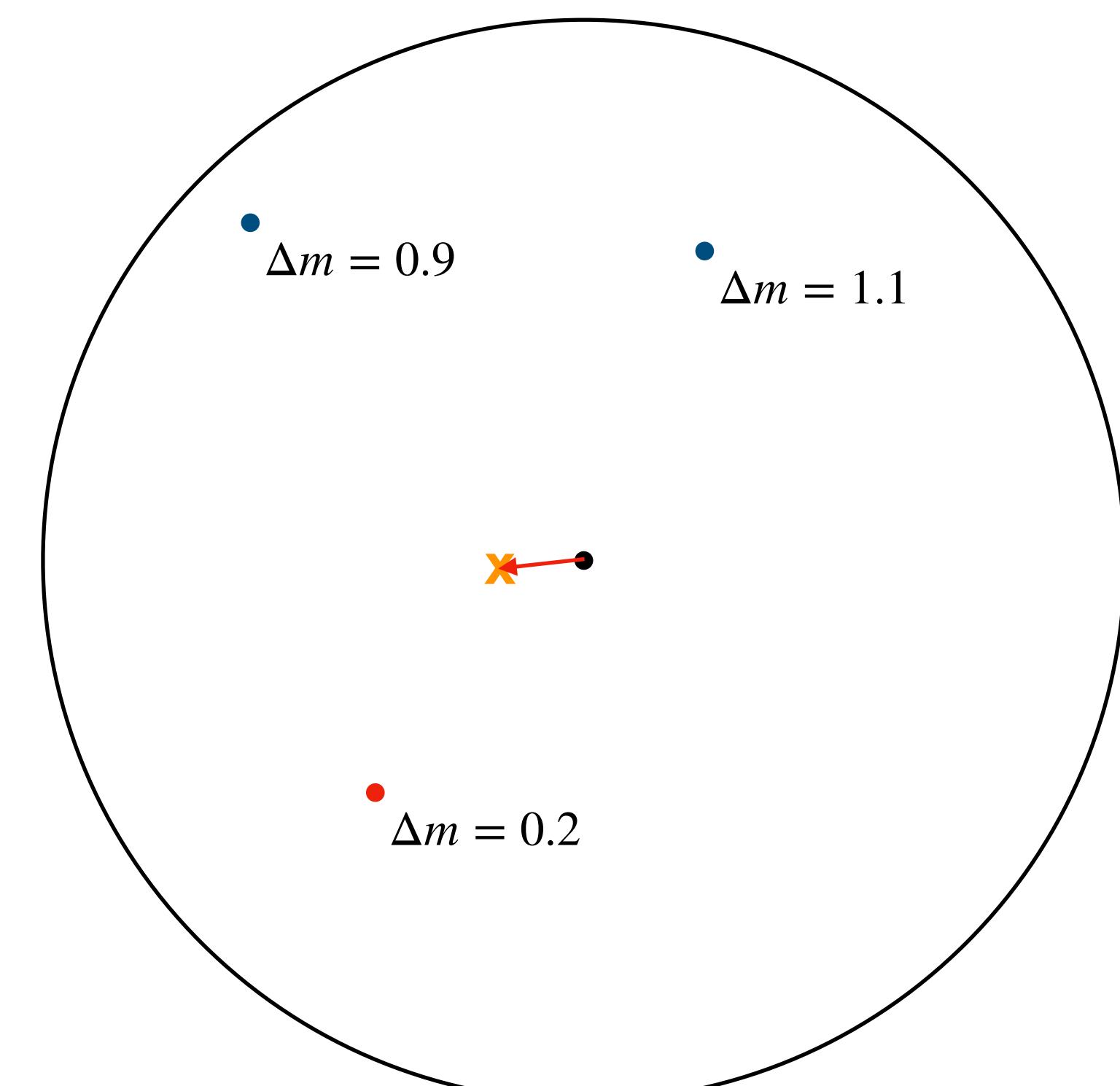
# Building Empirical AUFS



(sources per PSF circle  $\sim 10^{-6}$  sources per mag per sq deg)



PSF radius  $\sim 1.2$  FWHM (Rayleigh criterion)

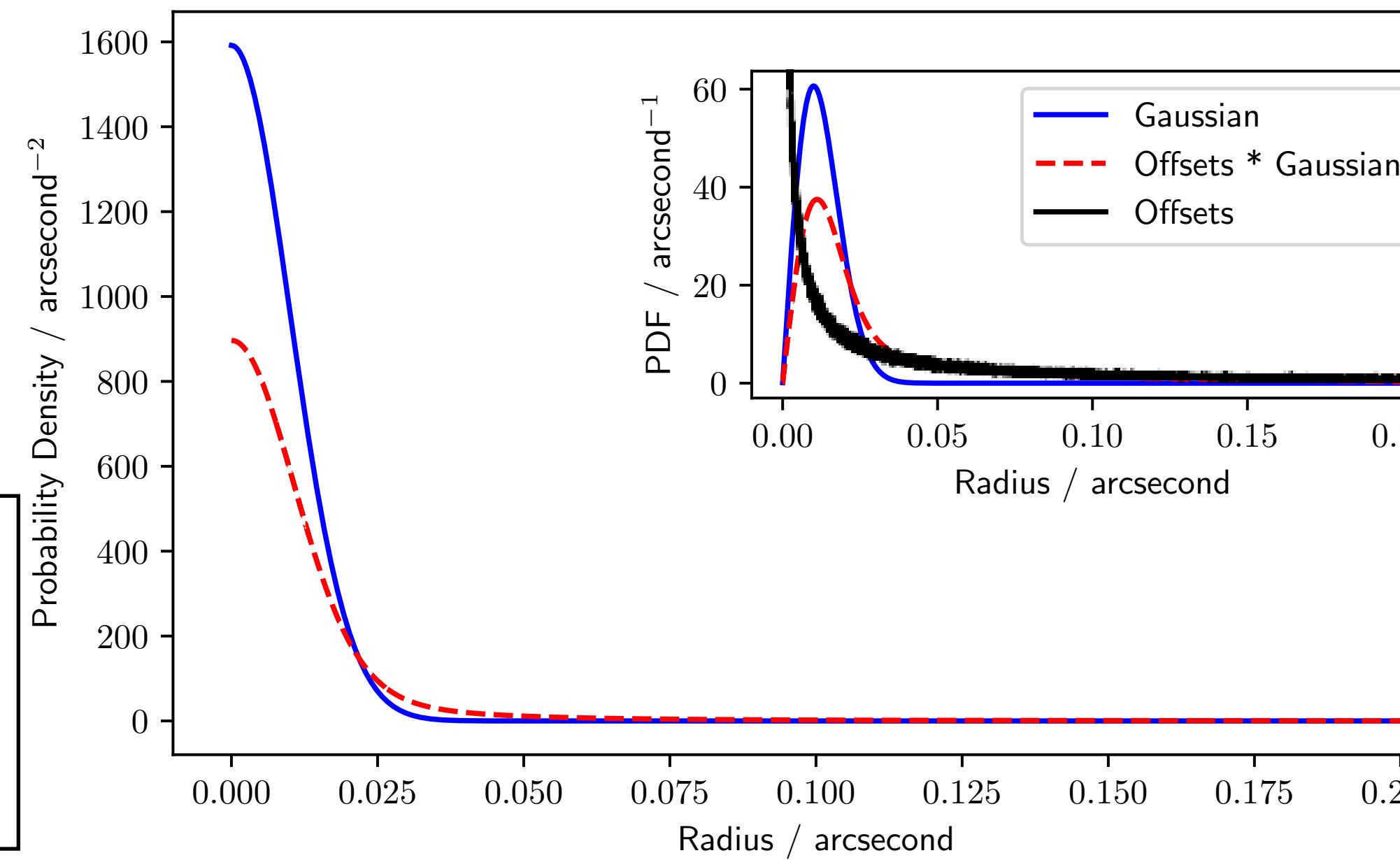


# The Rubin AUF: Galactic Plane

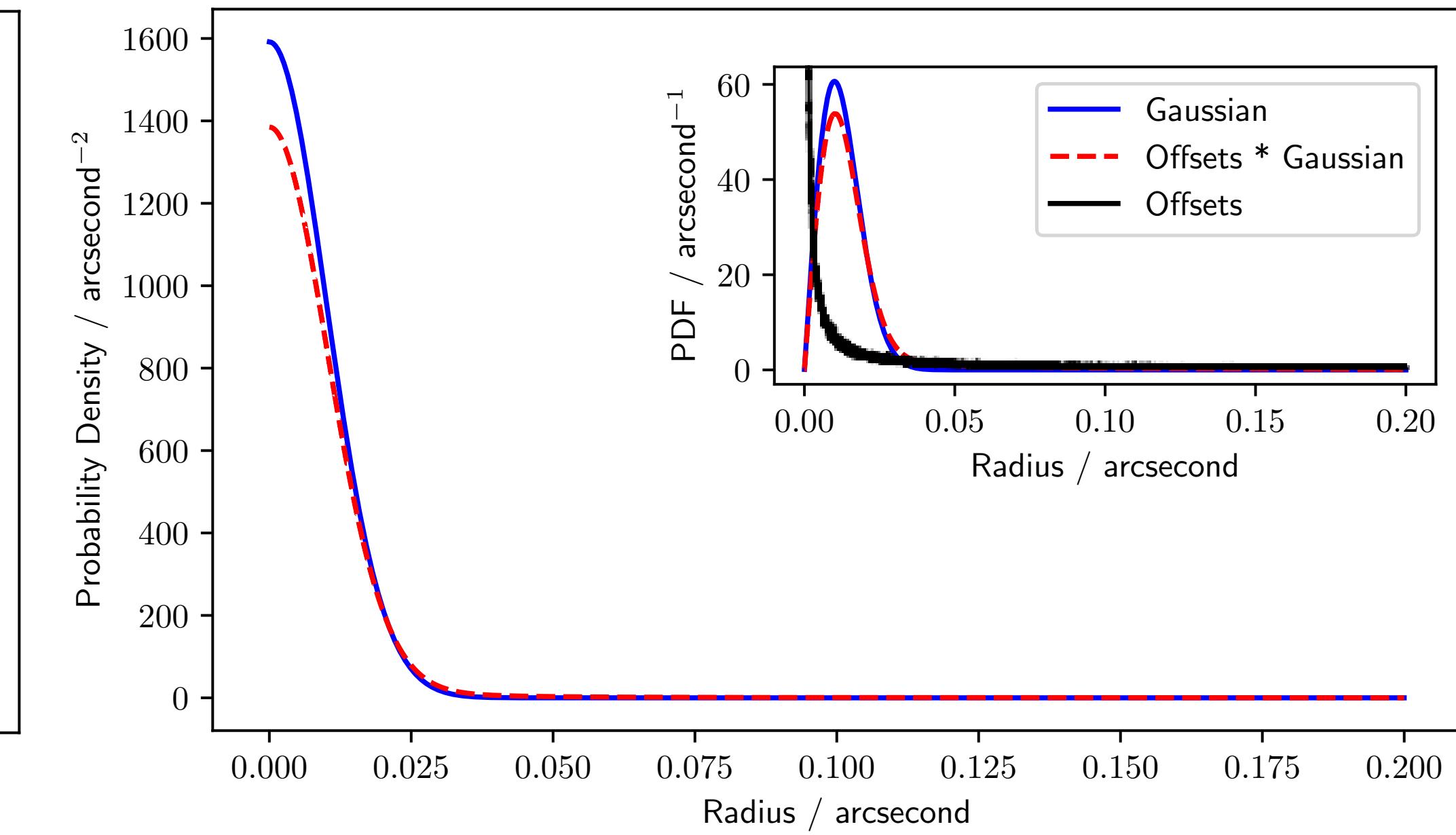
Galactic Centre

Single-visit

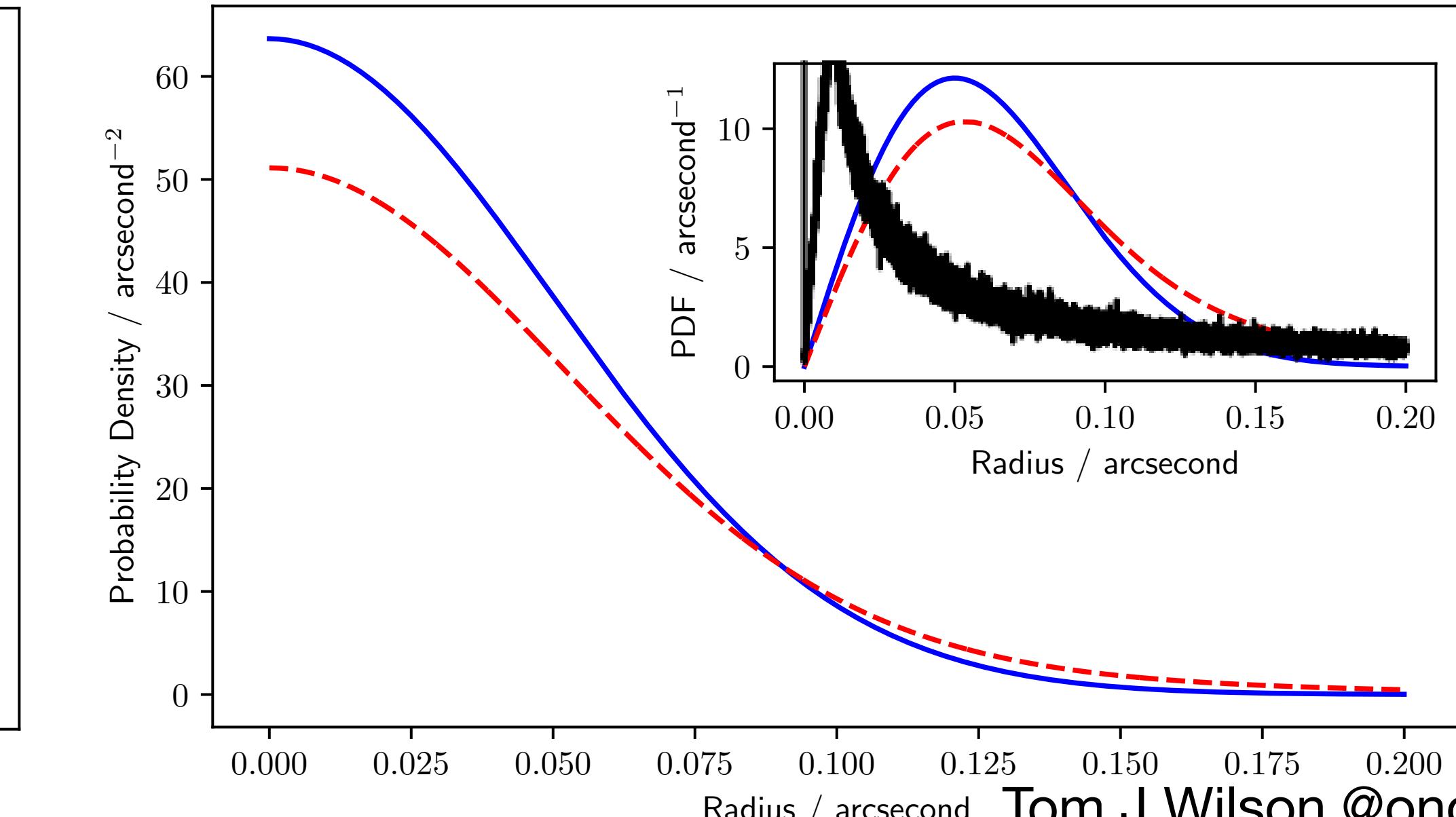
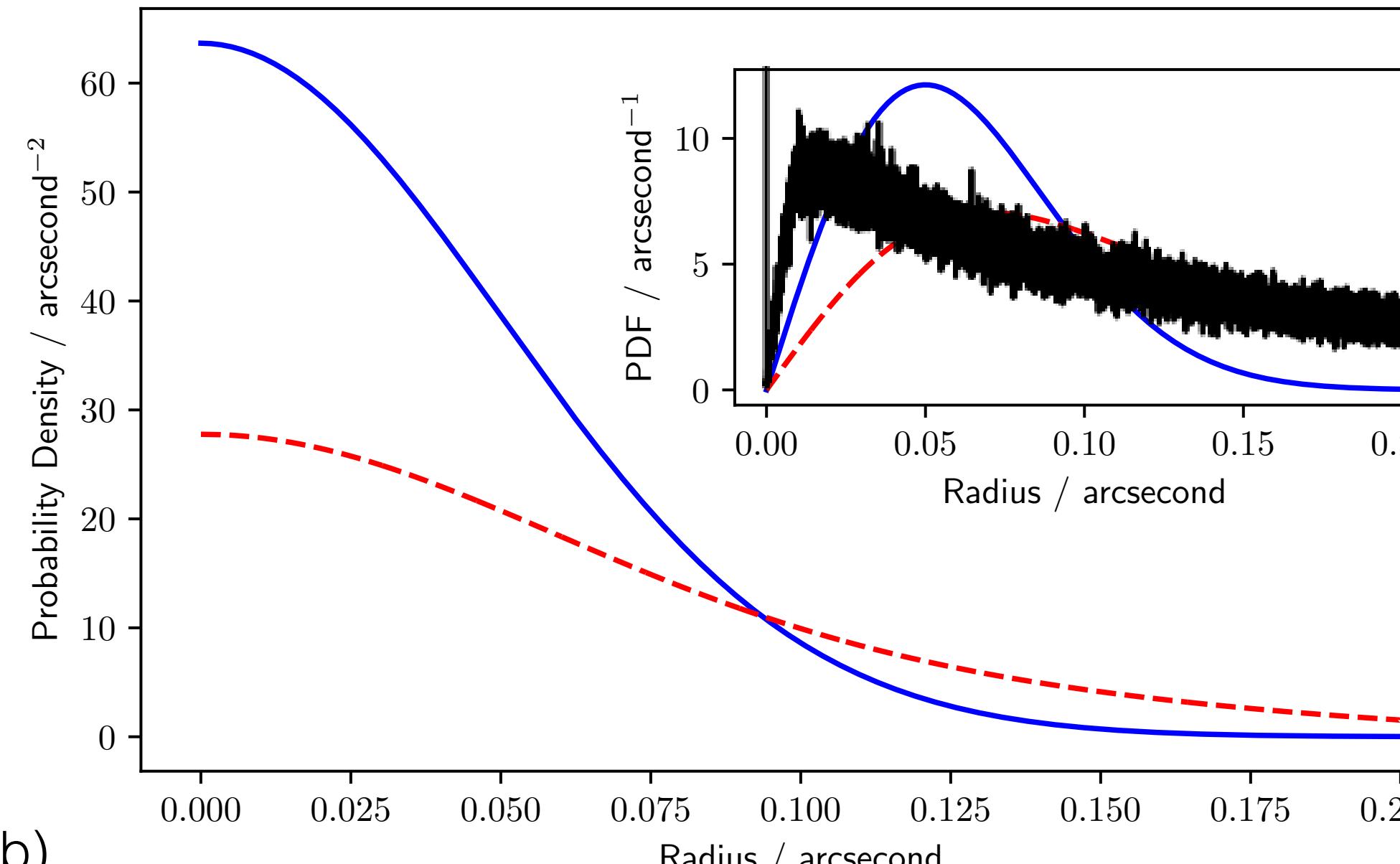
**Without modelling  
this extra effect, we  
fail to recover many  
true pairings, with an  
artificially high false  
negative rate!**



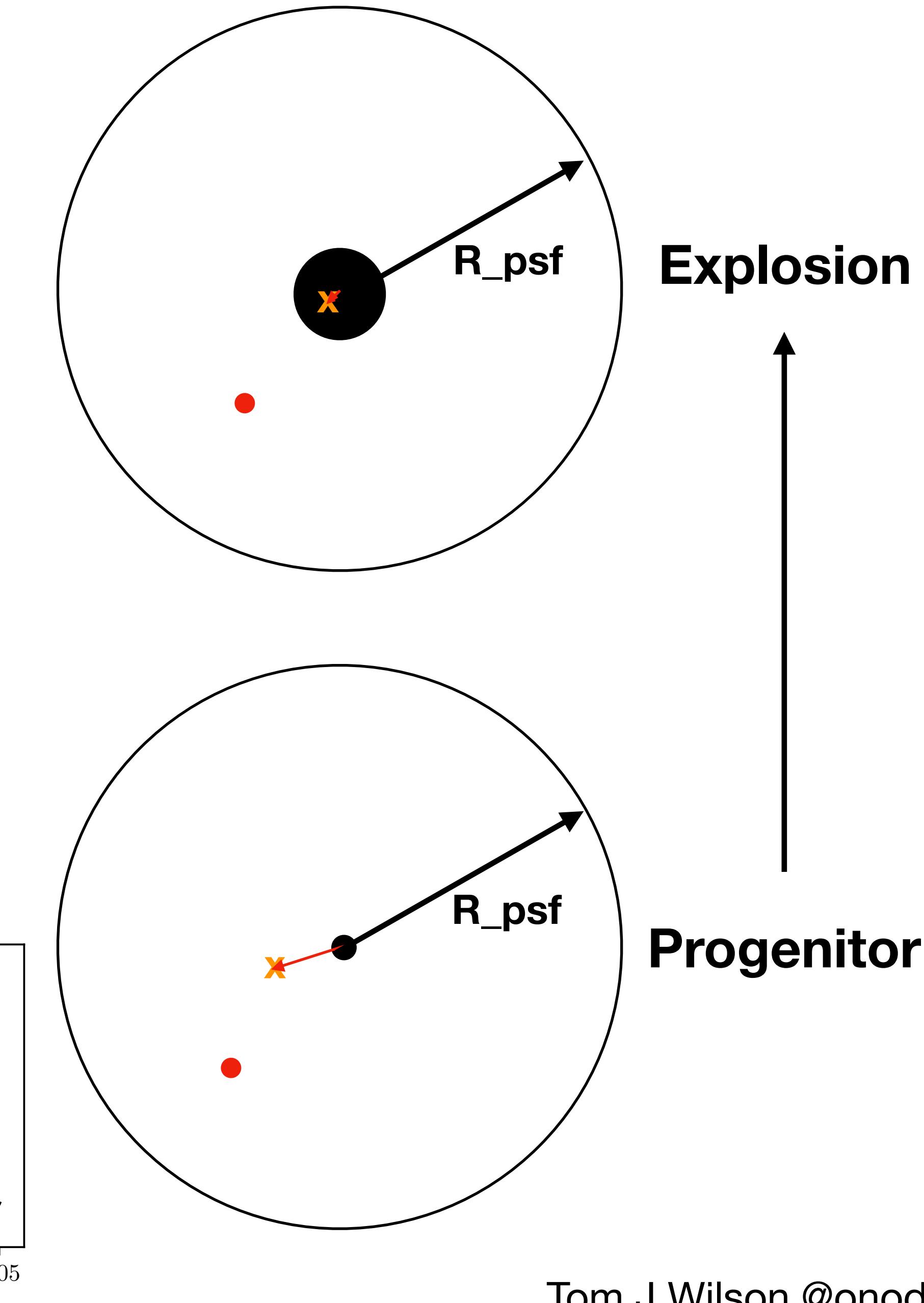
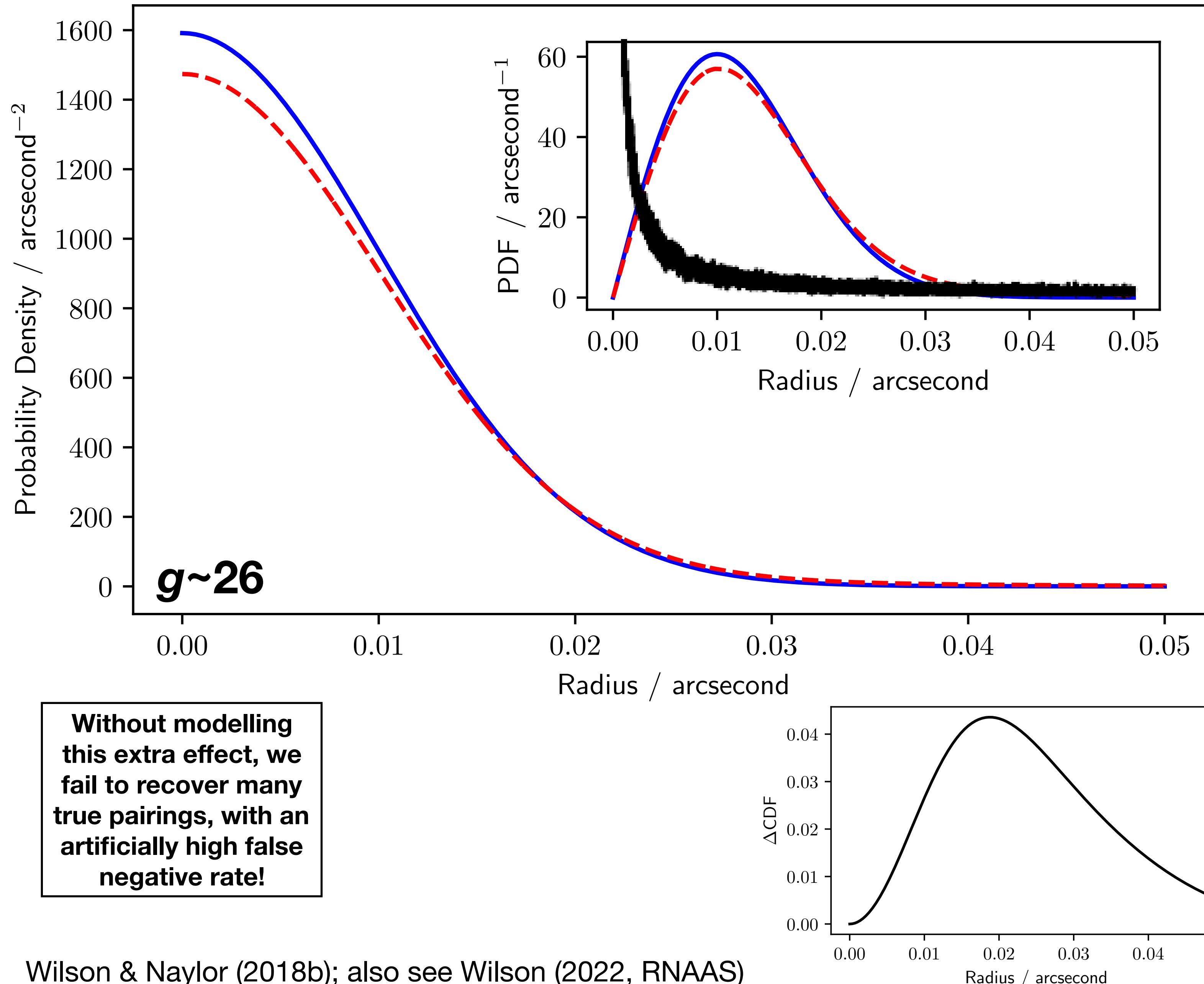
Not the Galactic Centre



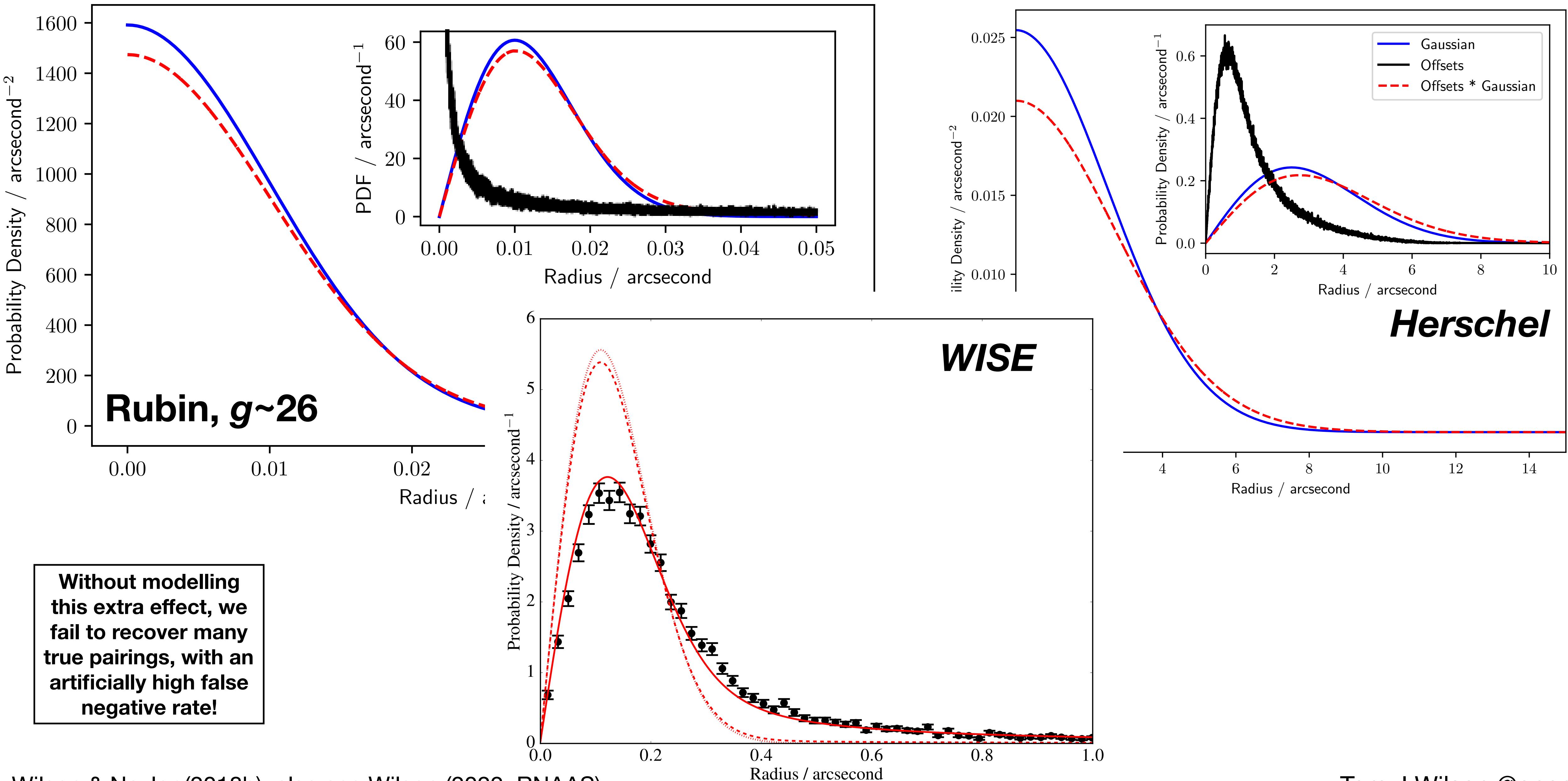
Co-add



# The Rubin AUF: Extra-Galactic, Transients

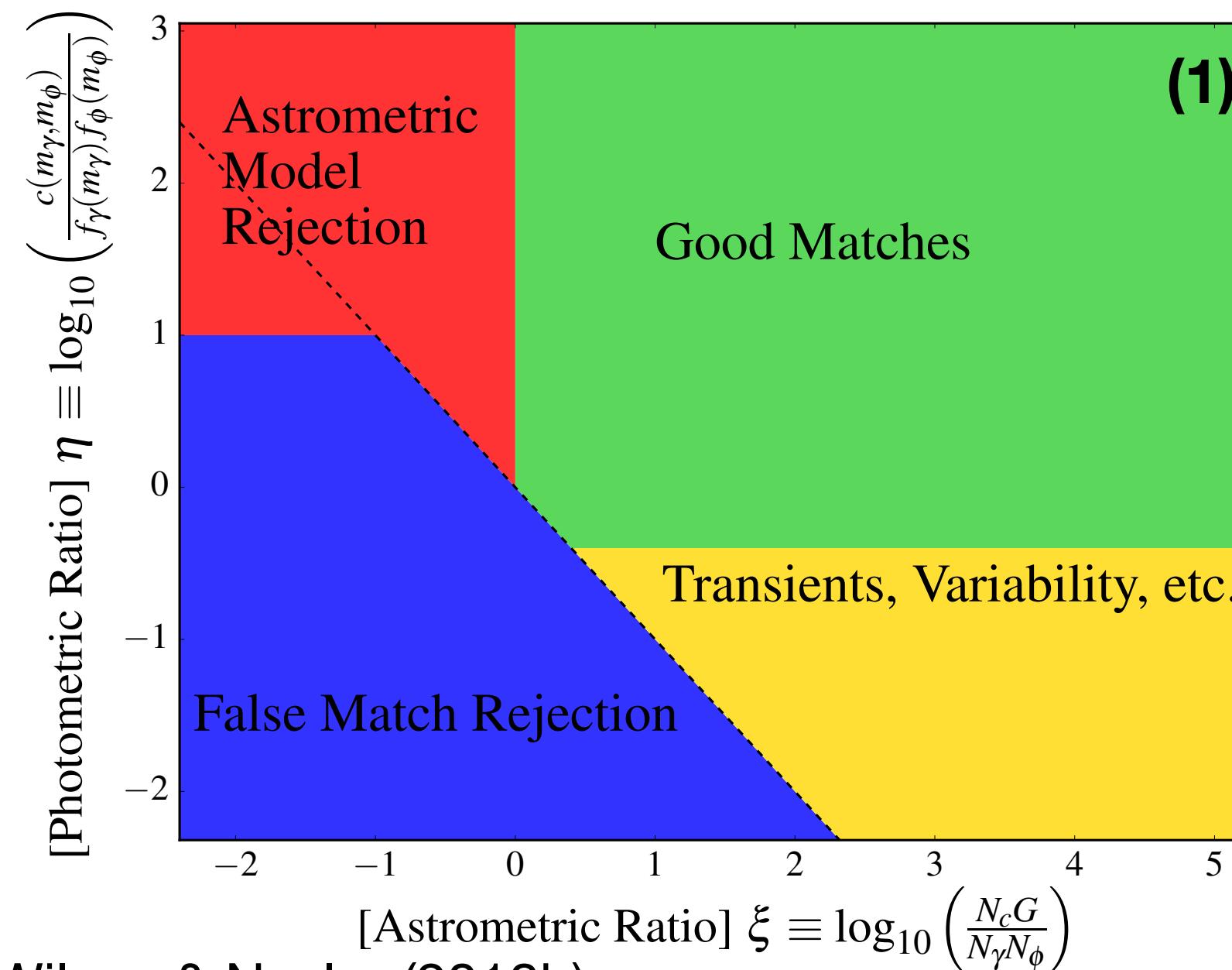


# The Rubin AUF: Extra-Galactic, Transients



# Why Use Macauff's Cross-Matches?

- 0) Getting cross-matches, even for “well behaved” fields
- 1) Finding “odd” objects, either using the inclusion vs non-inclusion of the photometry in the two match runs, or via the likelihood ratio space – separately-planned “real time” matching service for transient objects
- 2) Removing e.g. IR excess or correcting for extinction-like crowding brightening, through Average Contamination; crucial for “1% photometry” in both precision *and* accuracy
- 3) Recovering additional sources missed by other match services – either in crowded fields (we recover up to twice as many *Gaia-WISE* matches than the *Gaia* best neighbour matches), or with our extension to unknown proper motion modelling as an extra systematic

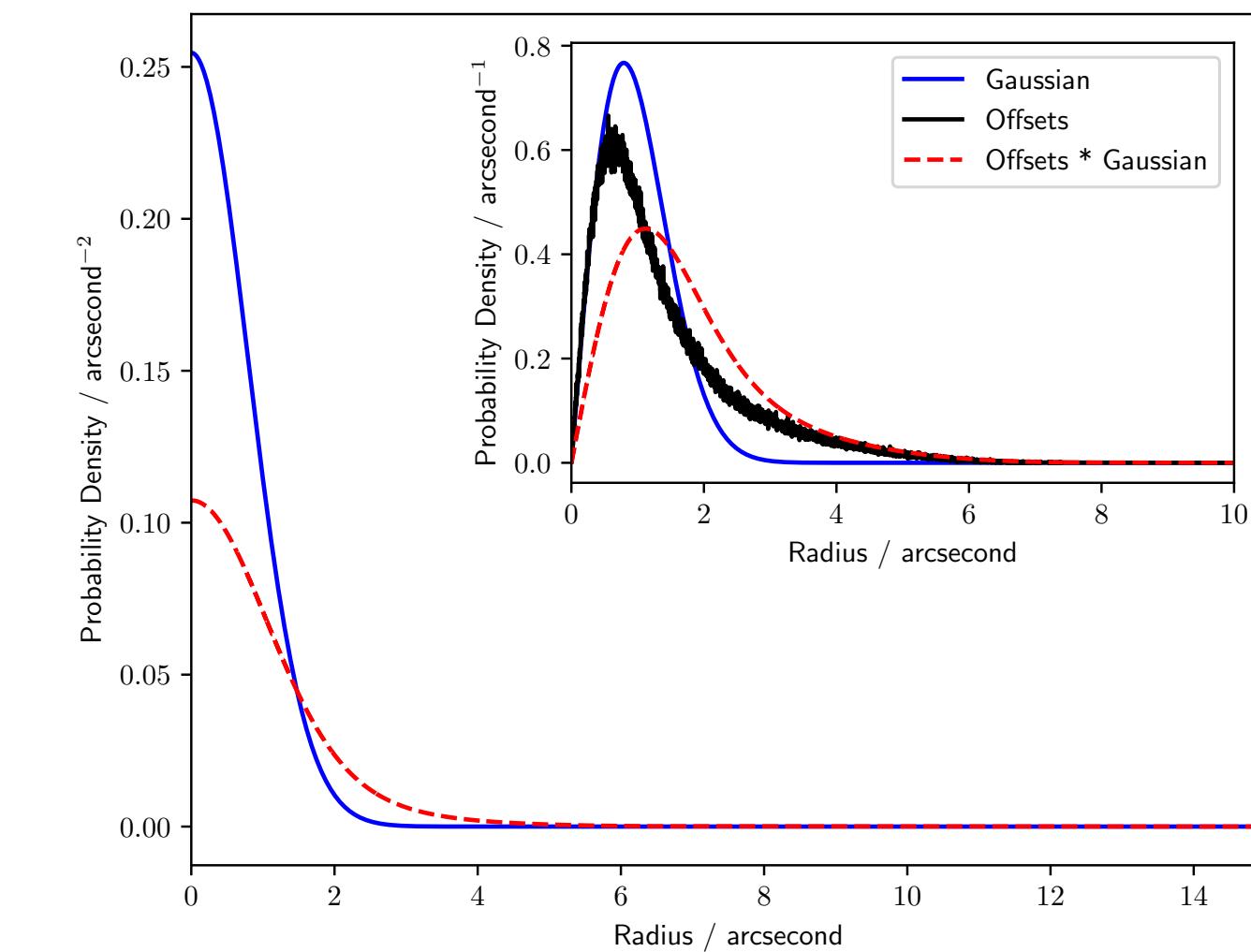
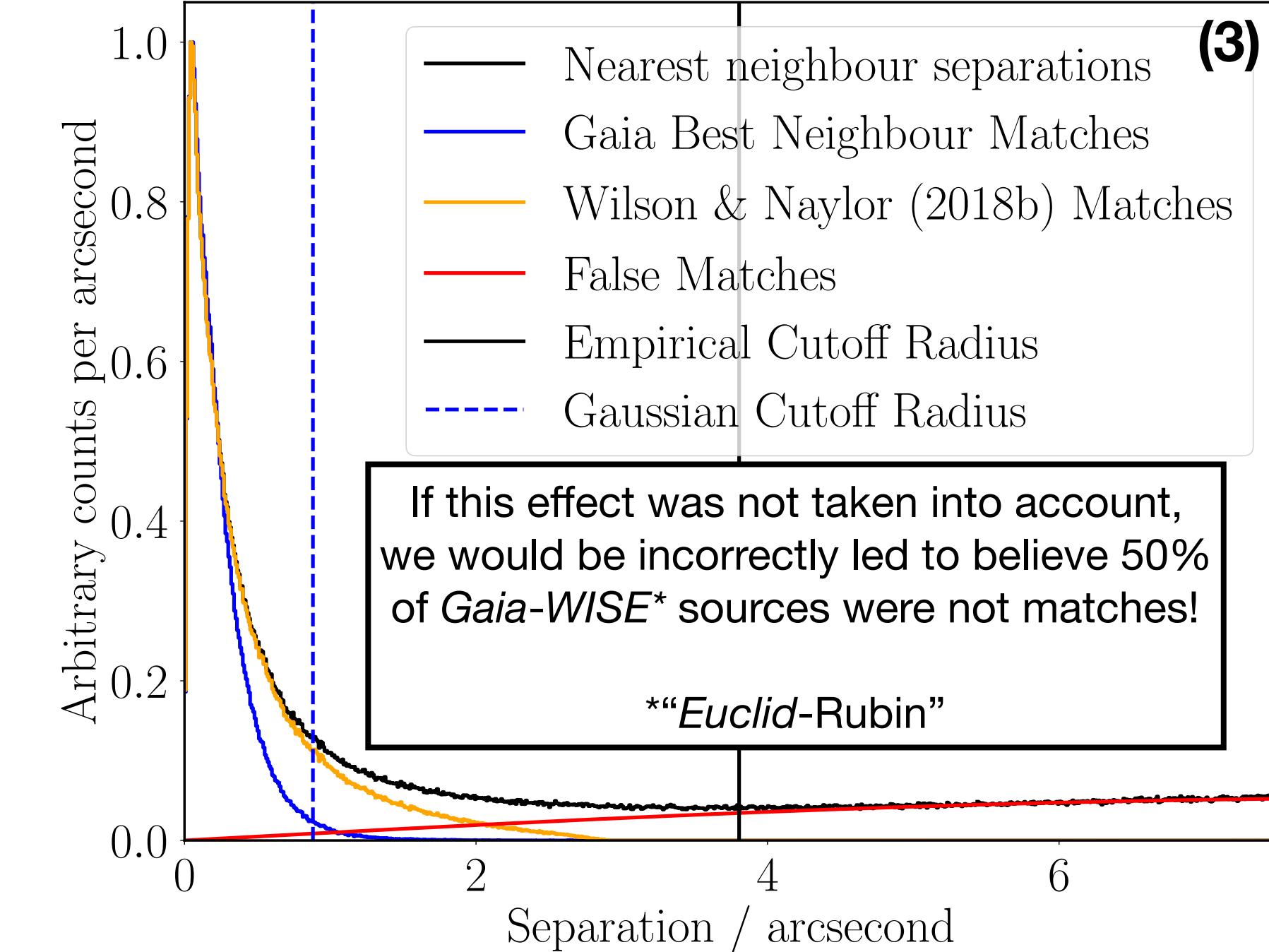
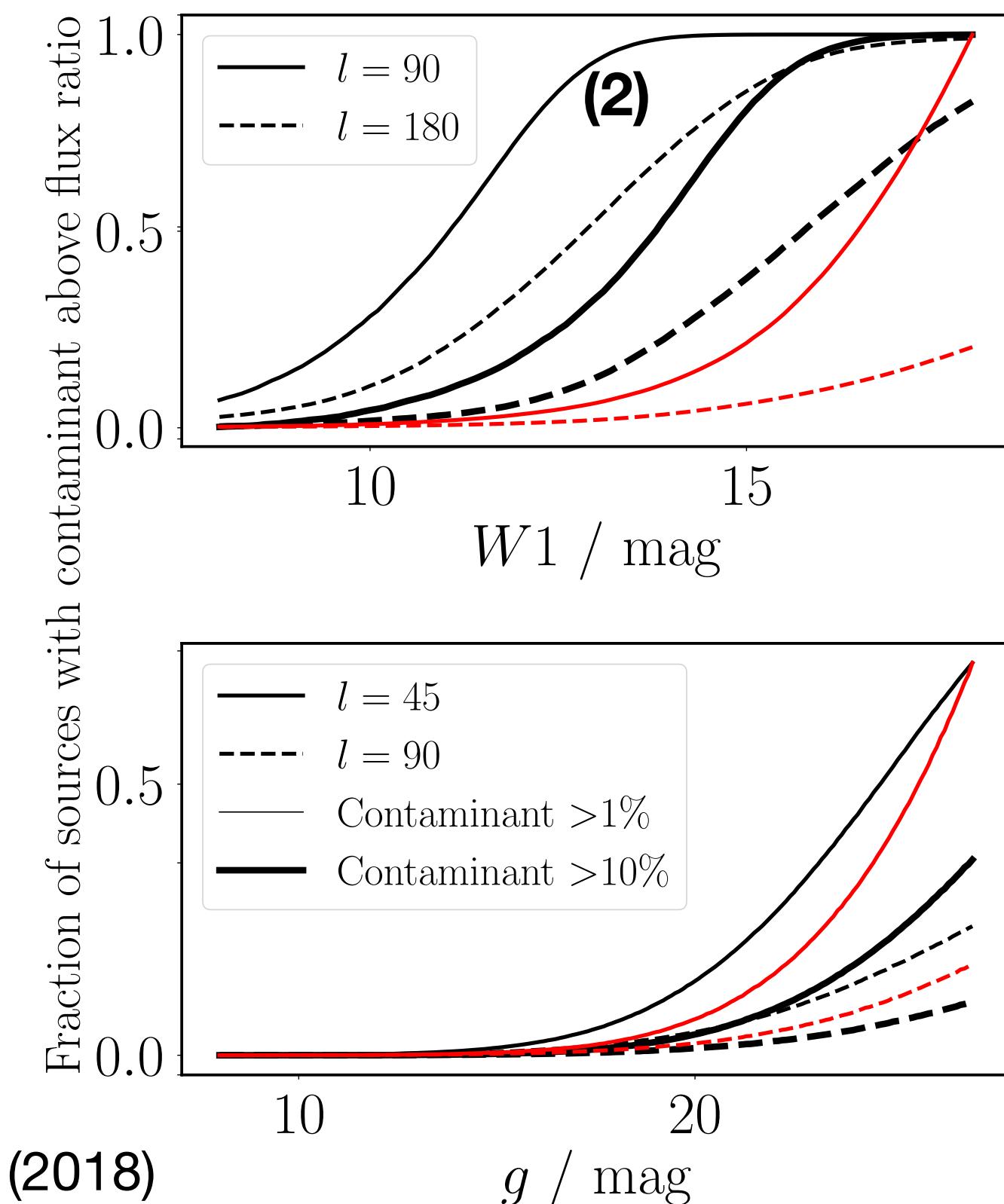


Wilson & Naylor (2018b)

WISE - Wright et al. (2010)

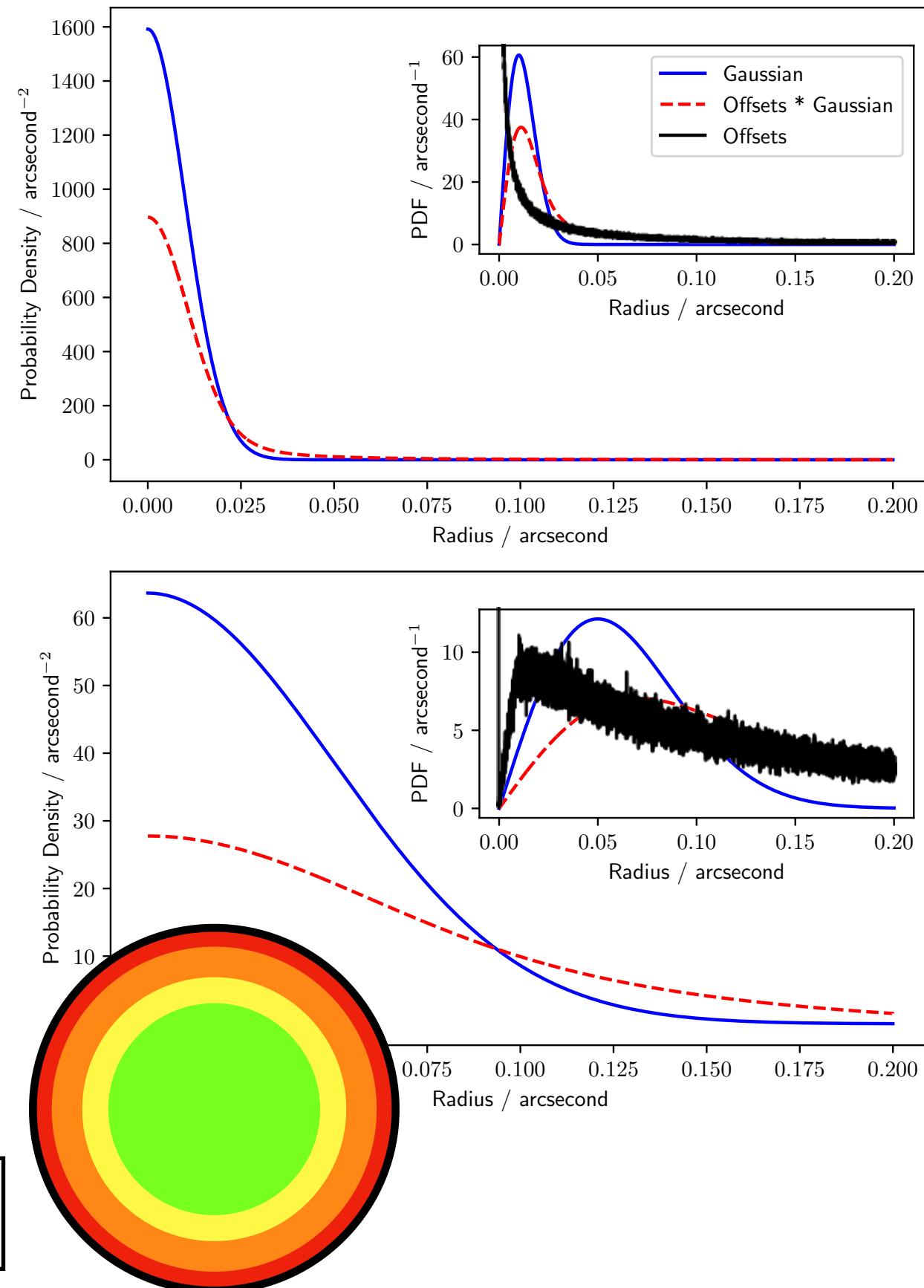
Gaia matches - Marrese et al. (2019)

Gaia DR2 - Gaia Collaboration, Brown A. G. A., et al. (2018)



# macauff: Cross-Matching in the Crowded LSST Sky

- Our cross-match algorithms include two key elements to avoid issues with crowded & confused data
  - A generalised approach to the Astrometric Uncertainty Function allows for the full inclusion of the effects of perturbation due to blended sources – reduce false -ves!
  - Use of (two-sided) photometry to sort out multiple competing matches— reduce false +ves!
- Software package [macauff](#) developed to cross-match catalogues, including the effect of unresolved contaminant sources (and rejection of interloper objects using photometry in the static sky)
  - Developed through an IKC to Rubin/LSST:UK, matches planned to *Gaia*, *WISE*, *VISTA*, *SDSS*, ...
  - We have compute time to cross-match datasets — let me know your favourite combo, and what you need matched (to LSST or otherwise)!
- Incorporating this extension of position uncertainty into real-time matches allows for more robust counterpart identification in the alert stream and a more accurate and precise transient SED
- Furthermore, we can provide *statistical* information on the level of photometric contamination unresolved contaminant sources cause, which can be subtracted in a probabilistic framework!



Nearest-neighbour matching will not work in the era of Rubin!



The AUF does not need to, and in fact quite often should not, be Gaussian!



University  
of Exeter

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Science and  
Technology  
Facilities Council



Wilson & Naylor, 2017, MNRAS, 468, 2517  
Wilson & Naylor, 2018a, MNRAS, 473, 5570  
Wilson & Naylor, 2018b, MNRAS, 481, 2148  
Wilson, 2022, RNAAS, 6, 60  
Wilson, 2023, RASTI, 2, 1

<https://github.com/macauff/macauff>



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**Or, Algorithms Aren't The Whole Problem Anymore**

# lsdb, hipscat, and the problem of 30-billion row tables

The screenshot shows the GitHub repository page for the organization `astronomy-commons`. It lists three projects:

- hipscat** (Public): Hierarchical Progressive Survey Catalog. Python library, 7 stars, BSD-3-Clause license, 10 issues, updated 16 minutes ago.
- lsdb** (Public): Large Survey DataBase. Python library, 3 stars, BSD-3-Clause license, 48 issues, updated 39 minutes ago.
- hipscat-import** (Public): HiPSCat import - generate HiPSCat-partitioned catalogs. Python library, 4 stars, BSD-3-Clause license, 20 issues, updated 3 days ago.

The screenshot shows the `LSDB` project page on `ReadTheDocs`. It includes:

- Template LINCC Frameworks Python Project Template**
- Build status: pypi v0.1.4, build passing, codecov 99%, docs passing, benchmarks passing.
- LSDB - Large Survey DataBase**
- A brief description: A framework to facilitate and enable spatial analysis for extremely large astronomical databases (i.e. querying and crossmatching O(1B) sources). This package uses dask to parallelize operations across multiple HiPSCat partitioned surveys.
- A note: Check out our [ReadTheDocs site](#) for more information on partitioning, installation, and contributing.
- See related projects:
  - HiPSCat ([on GitHub](#)) ([on ReadTheDocs](#))
  - HiPSCat Import ([on GitHub](#)) ([on ReadTheDocs](#))

The screenshot shows the `HiPSCat` project page on `ReadTheDocs`. It includes:

- LINCC** logo.
- HiPSCat**
- Hierarchical Progressive Survey Catalog**
- Template LINCC Frameworks Python Project Template**
- Build status: pypi v0.2.7, build passing, codecov 100%, docs passing, benchmarks passing.
- A description: A HiPSCat catalog is a partitioning of objects on a sphere. Its purpose is for storing data from large astronomy surveys, but could probably be used for other use cases where you have large data with some spherical properties.
- A note: Check out our [ReadTheDocs site](#) for more information on partitioning, installation, and contributing.
- See related projects:
  - HiPSCat Import ([on GitHub](#)) ([on ReadTheDocs](#))
  - LSDB ([on GitHub](#)) ([on ReadTheDocs](#))

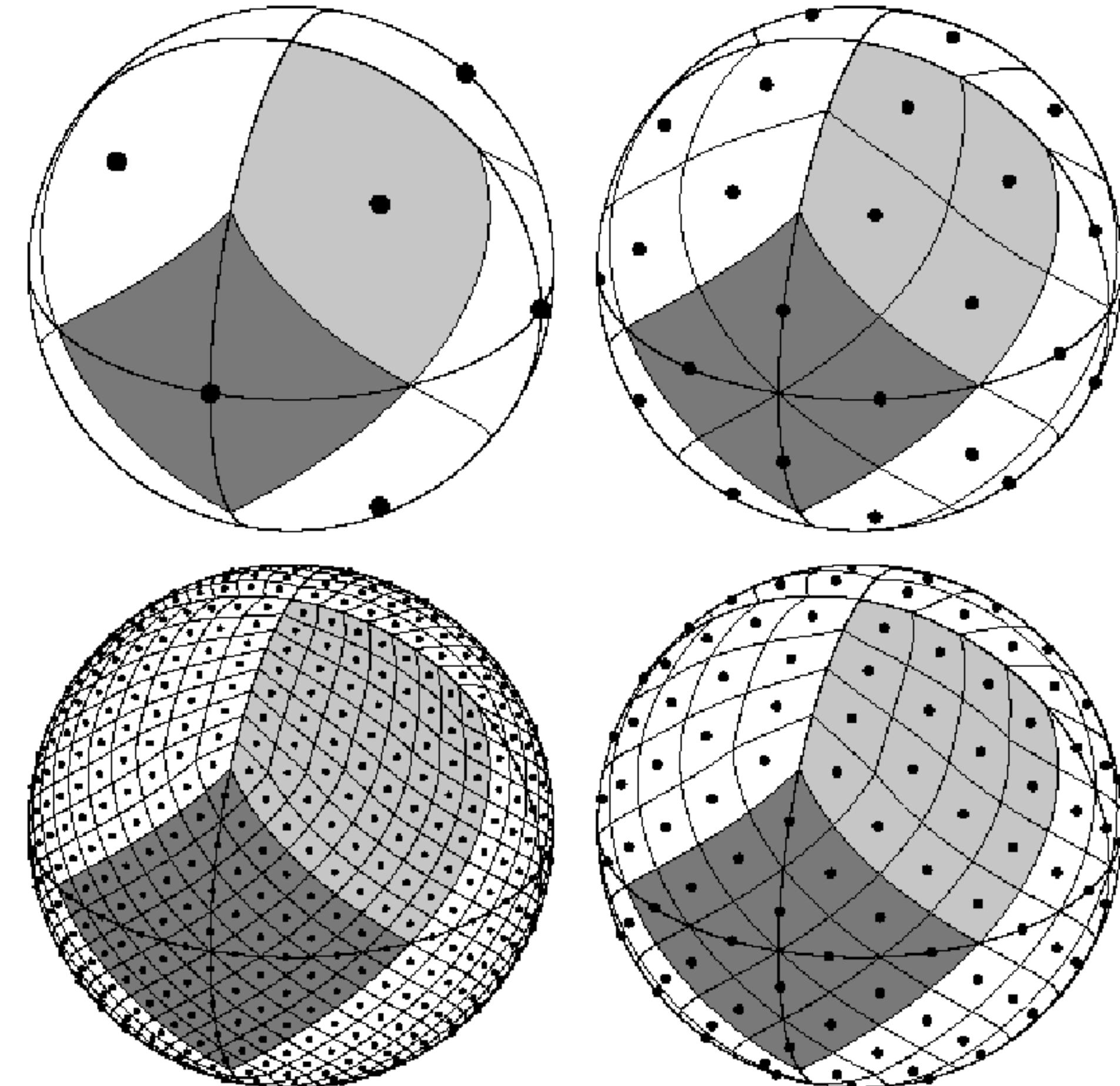
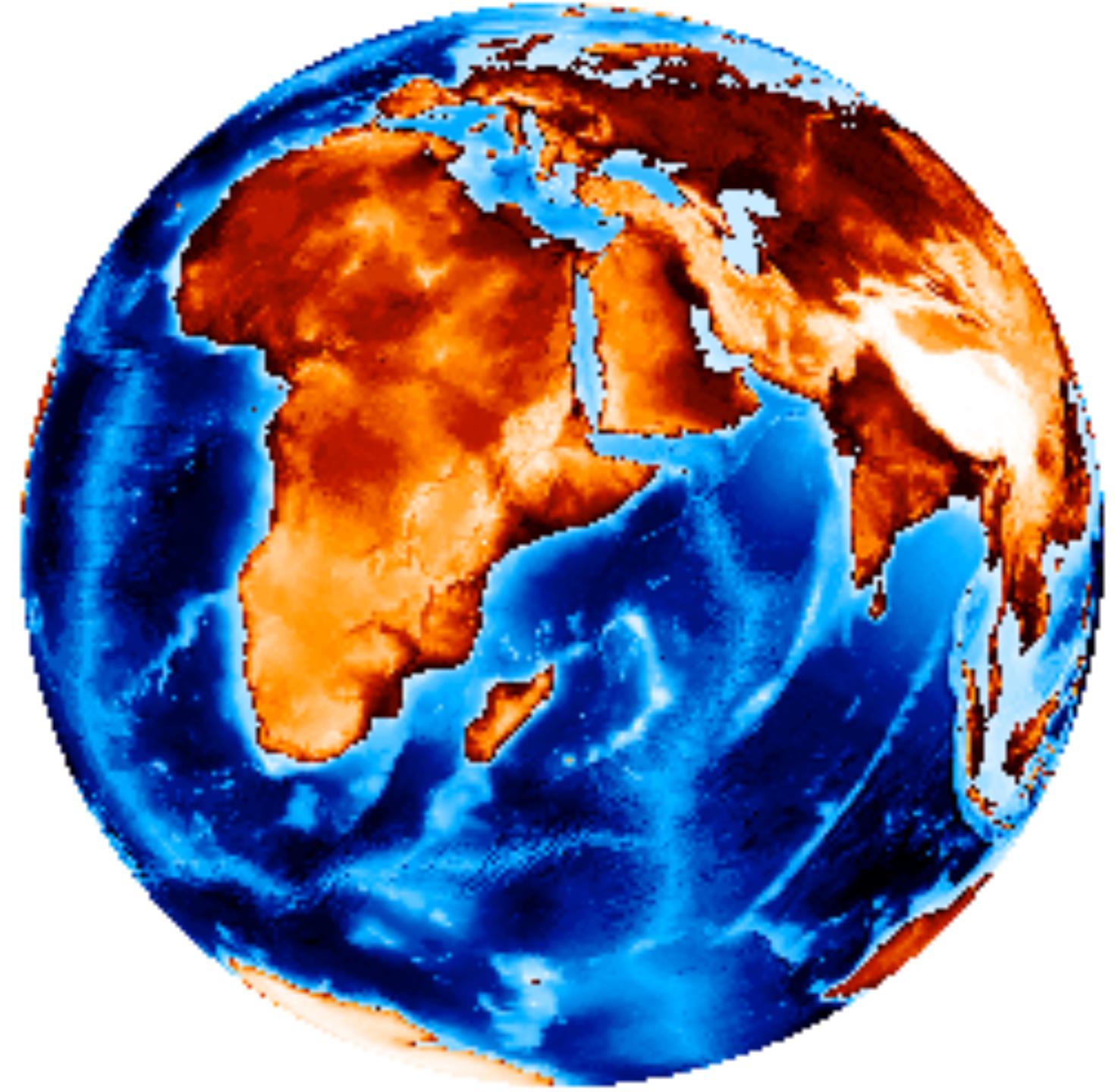
The screenshot shows the `hipscat-import` project page on `ReadTheDocs`. It includes:

- Template LINCC Frameworks Python Project Template**
- Build status: pypi v0.2.5, build passing, codecov, docs passing.
- HiPSCat import - Utility for ingesting large survey data into HiPSCat structure.**
- A note: Check out our [ReadTheDocs site](#) for more information on partitioning, installation, and contributing.
- See related projects:
  - HiPSCat ([on GitHub](#)) ([on ReadTheDocs](#))
  - LSDB ([on GitHub](#)) ([on ReadTheDocs](#))

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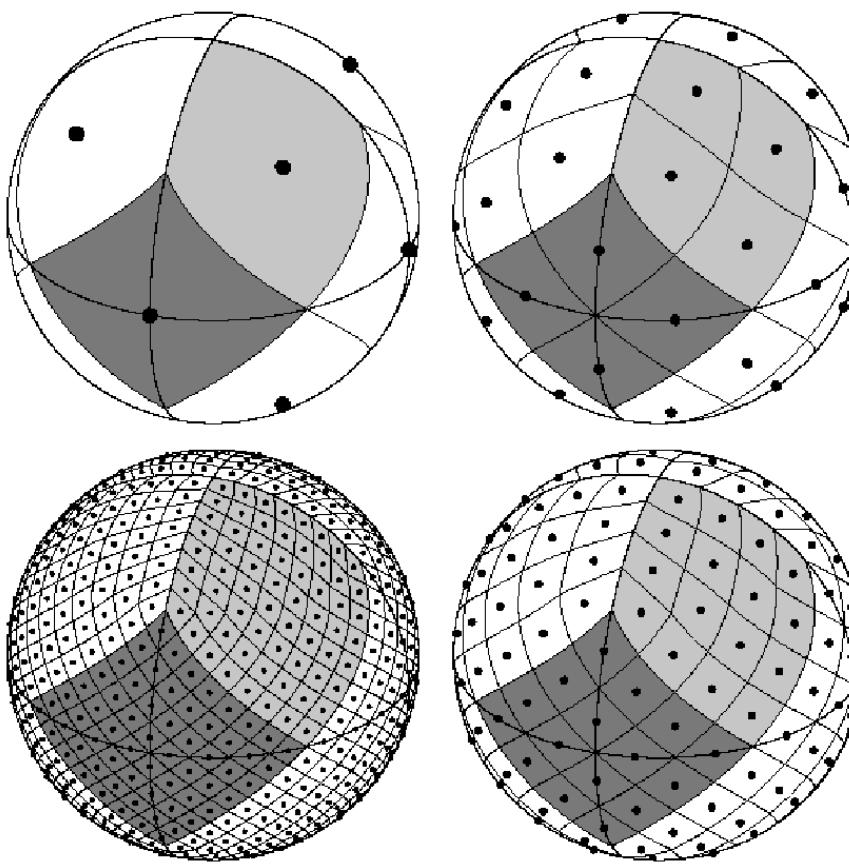
# High-Speed, Robust Spatial Analysis

lsdb does astronomy on hipscat-formatted surveys, with hipscat built on healpix



# Importing catalogues, doing science

## 1. (Optional) Use hipscat-import to generate some valid catalogues



```
__ /path/to/catalogs/<catalog_name>,
|__ catalog_info.json
|__ partition_info.csv
|__ Norder=1/
|   |__ Dir=0/
|     |__ Npix=0.parquet
|     |__ Npix=1.parquet
|__ Norder=J/
|   |__ Dir=1000/
|     |__ Npix=K.parquet
|     |__ Npix=M.parquet
```

```
import pandas as pd

import hipscat_import.pipeline as runner
from hipscat_import.catalog.arguments import ImportArguments
from hipscat_import.catalog.file_readers import CsvReader

# Load the column names and types from a side file.
type_frame = pd.read_csv("neowise_types.csv")
type_map = dict(zip(type_frame["name"], type_frame["type"]))

args = ImportArguments(
    output_artifact_name="neowise_1",
    input_path="/path/to/neowiser_year8/",
    file_reader=CsvReader(
        header=None,
        separator="|",
        column_names=type_frame["name"].values.tolist(),
        type_map=type_map,
        chunksize=250_000,
    ).read,
    ra_column="RA",
    dec_column="DEC",
    pixel_threshold=2_000_000,
    highest_healpix_order=9,
    use_schema_file="neowise_schema.parquet",
    sort_columns="SOURCE_ID",
    output_path="/path/to/catalogs/",
)
runner.run(args)
```

# Importing catalogues, doing science

## 2. Having imported your datasets, do some spatial analysis

```
[1]: import hipscat
import healpy as hp
import numpy as np

## Fill in these variables with what's relevant in your use case:

### Change this path!!!
catalog_path = ".../tests/data/small_sky_order1"

ra = 0 # degrees
dec = -80 # degrees
radius_degrees = 10 # degrees

[2]: ## Load catalog
catalog = hipscat.read_from_healpix(catalog_path)

[3]: ## Plot catalog pixels
hipscat.inspection.plot_pixels(catalog)
```

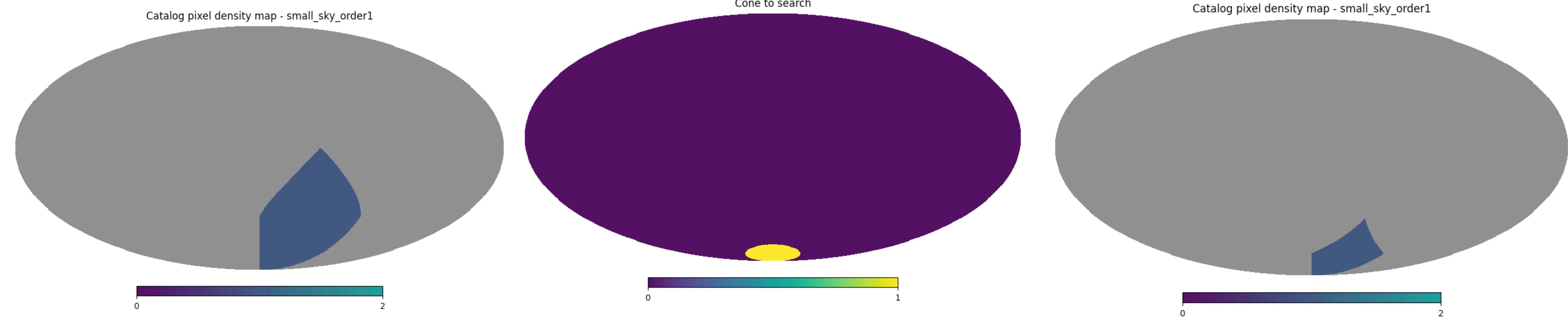
```
[4]: ## Plot the cone using healpy for demonstration

NSIDE = 256
NPIX = hp.nside2npix(NSIDE)
m = np.zeros(NPIX)
center_vec = hp.ang2vec(ra, dec, lonlat=True)
radius_radians = np.radians(radius_degrees)
cone_pixels = hp.query_disc(NSIDE, center_vec, radius_radians)
m[cone_pixels] = 1
hp.mollview(m, title="Cone to search")
```

```
[5]: ## Filter catalog and plot filtered pixels

radius_arcseconds = radius_degrees * 3600
filtered_catalog = catalog.filter_by_cone(ra, dec, radius_arcseconds)

hipscat.inspection.plot_pixels(filtered_catalog)
```



# Importing catalogues, doing science

## 3. Finally, do some science with lsdb, building off hipscat

### Example use-case: cross-match ZTF BTS and NGC

Here we demonstrate how to cross-match [Zwicky Transient Facility](#) (ZTF) Bright Transient Survey (BTS) and [New General Catalogue](#) (NGC) using LSDB.

```
[5]: %%time
ztf_bts = lsdb.from_dataframe(df_ztf_bts, ra_column="ra_deg", dec_column="dec_deg")
ngc = lsdb.from_dataframe(df_ngc, ra_column="ra_deg", dec_column="dec_deg", margin_threshold=1200)

ztf_bts = ztf_bts.query("redshift < 0.01")

matched = ztf_bts.crossmatch(ngc, radius_arcsec=1200, suffixes=("_ztf", "_ngc"))
matched
```

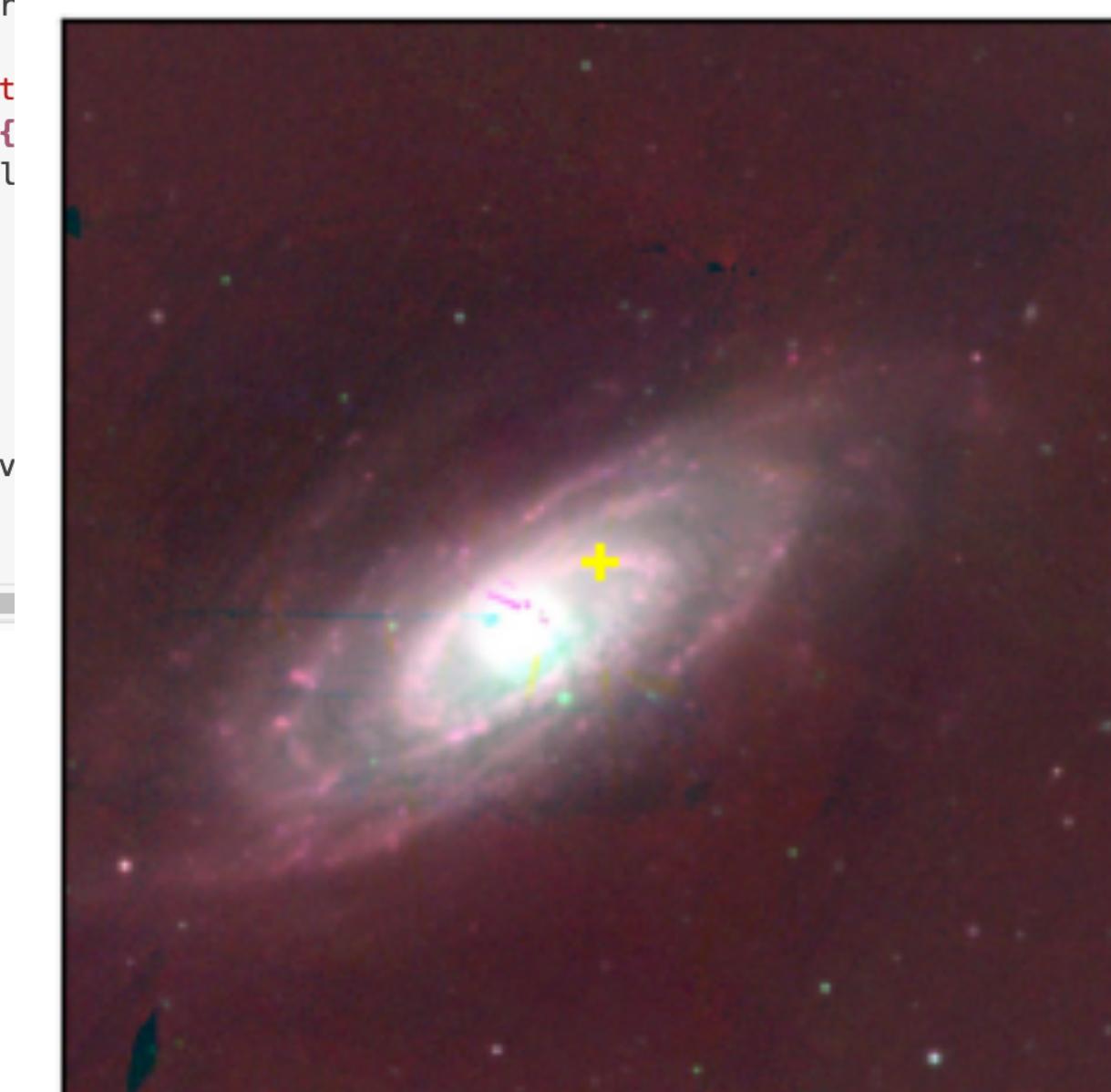
```
[6]: %%time
# Create default local cluster
with Client():
    matched_df = matched.compute()

# Let's output transient name, NGC name and angular distance between them
matched_df = matched_df[["IAUID_ztf", "Name_ngc", "_dist_arcsec", "RA_ztf", "Dec_ztf"]].sort_values(by=["_dist_arcsec"])
)
matched_df
```

[6]:	IAUID_ztf	Name_ngc	_dist_arcsec	RA_ztf	Dec_ztf
_hipscat_index					
	7828968065004994560	SN2022xxf	3705	2.985601	11:30:05.93 +09:16:57.2
	7200132046067335168	SN2020vg	1738	8.931140	11:48:54.43 -04:40:53.8
	3231460713012658176	SN2022pgf	5894	12.223285	15:11:41.90 +59:49:12.2

```
[8]: c = SkyCoord(matched_df["RA_ztf"].values[0], matched_df["Dec_ztf"].values[0], unit="hourarcmin")
ra = c.ra.degree
dec = c.dec.degree
oid = matched_df["IAUID_ztf"].values[0]
table = getimages(ra, dec, size=1200, filter="r")
url = (
    "https://ps1images.stsci.edu/cgi-bin/fit"
    "ra={}&dec={}&size=1200&format=jpg&red={"
).format(ra, dec, table["filename"][0], table["filter"][0])
im = get_ps1_image(url)
fig, ax = plt.subplots(figsize=(7, 3))
if im is not None:
    ax.imshow(im)
    ax.set_xticks([])
    ax.set_yticks([])
    ax.scatter(np.average(plt.xlim()), np.average(plt.ylim()))
    ax.set_title(oid)
plt.show()
```

SN2022xxf



# Importing catalogues, doing science

## 3. Finally, do some science with lsdb, building off hipscat

### Example use-case: cross-match ZTF BTS and NGC

Here we demonstrate how  
(BTS) and New General Cat

```
[5]: %%time
ztf_bts = lsdb.from_dataframe(df_ztf_bts, ra_column="ra_deg", dec_column="dec_deg")
ngc = lsdb.from_dataframe(df_ngc, ra_column="ra_deg", dec_column="dec_deg", margin_threshold=10)

ztf_bts = ztf_bts.query("redshift < 0.01")

matched = ztf_bts.crossmatch(ngc, radius_arcsec=1200, suffixes=("_ztf", "_ngc"))
matched
```

#### Args:

`algorithm (BuiltInCrossmatchAlgorithm | Type[AbstractCrossmatchAlgorithm]):` The algorithm to use to perform the crossmatch. Can be either a string to specify one of the built-in cross-matching methods, or a custom method defined by subclassing `AbstractCrossmatchAlgorithm`.

#### Built-in methods:

- `kd\_tree`: find the k-nearest neighbors using a kd\_tree

**Nearest-neighbour matching will not work in the era of Rubin!**

Tom J Wilson @

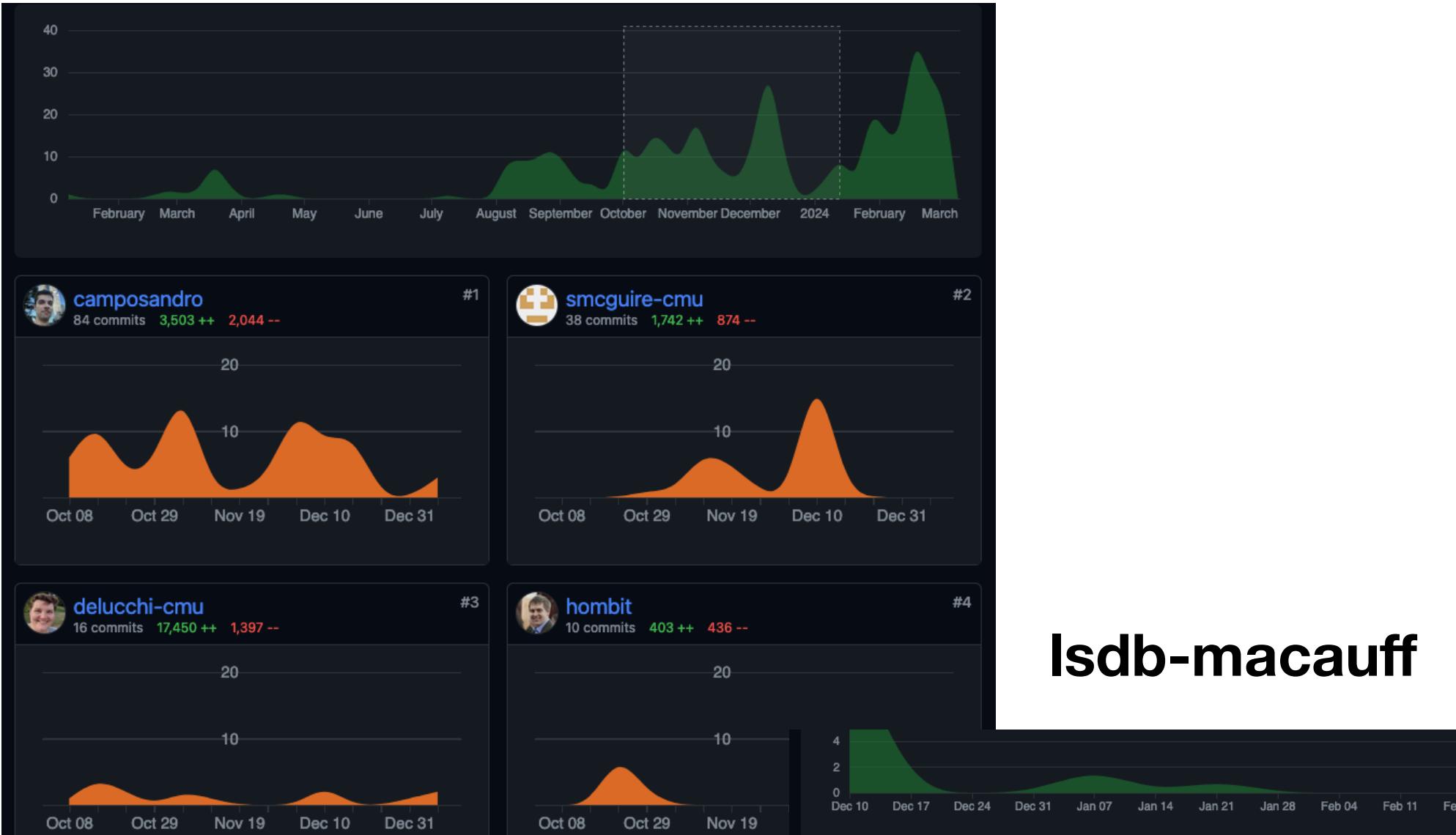


Or, The Actual LINCC Incubator!

# lsdb-macauff: The Best of Both Worlds

The LINCC Incubator's goal was simple: combine lsdb and macauff.  
In practice, this was quite involved, with lots of codebase activity!

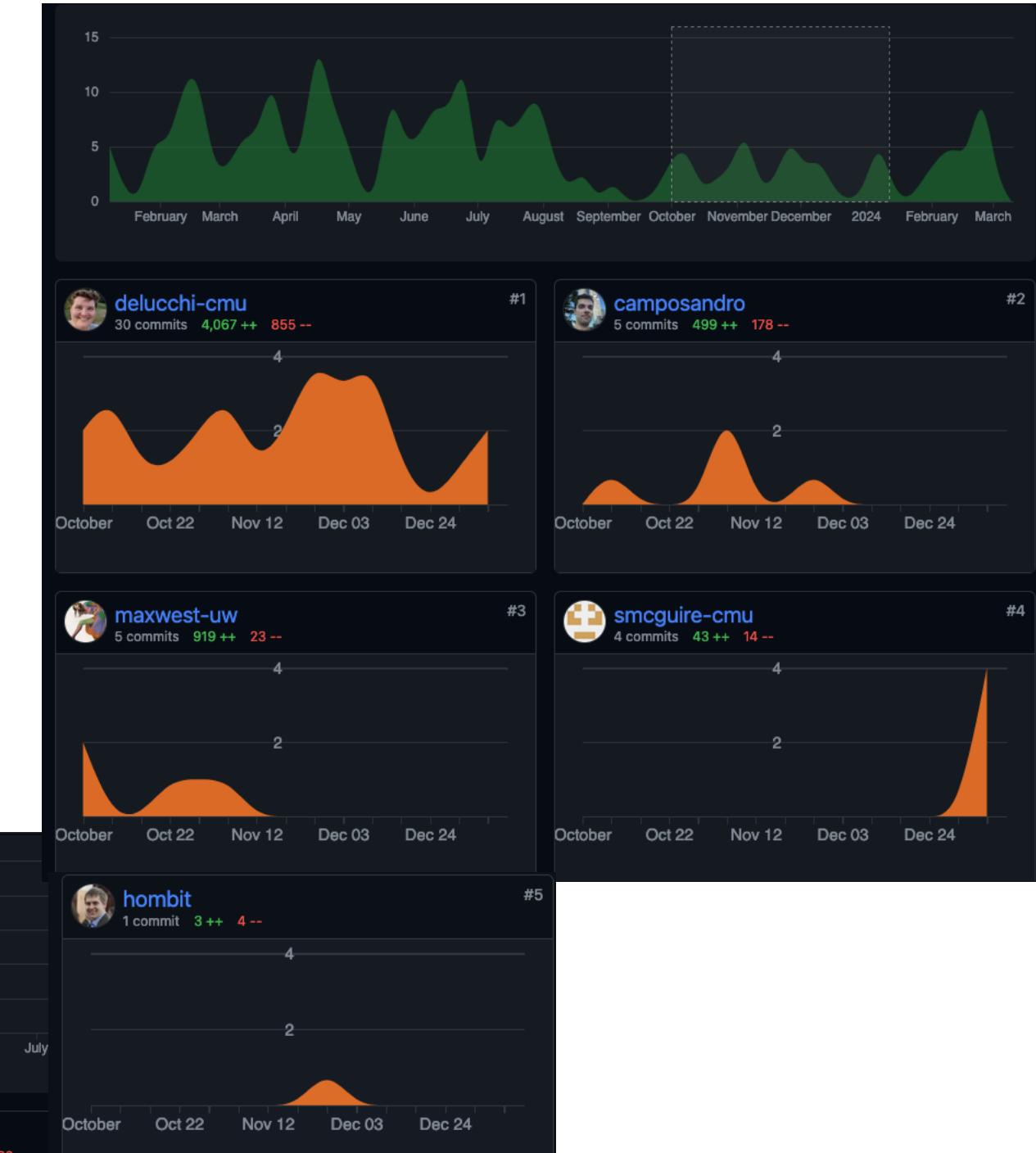
lsdb\*



hipscat\*



hipscat-import\*



# lsdb-macauff: The Best of Both Worlds

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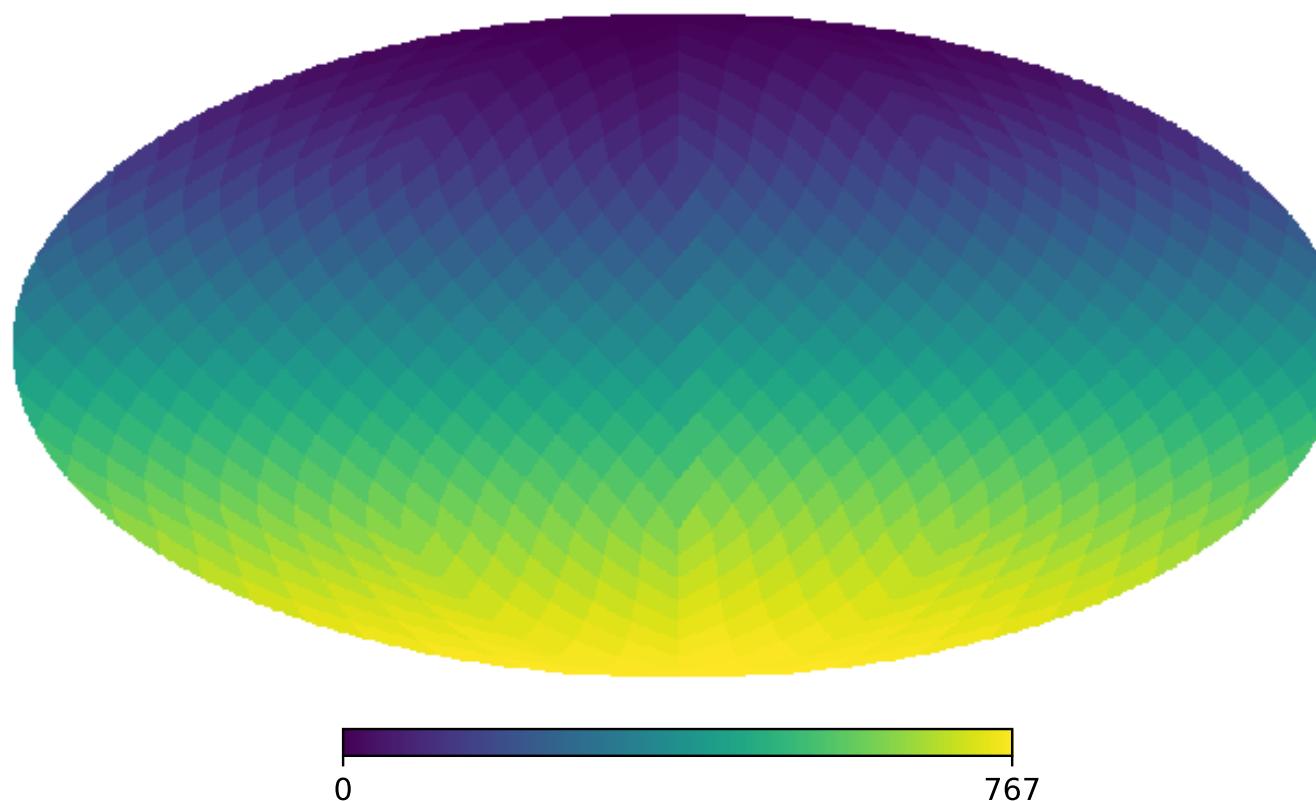
macauff



## Improvements to macauff's algorithms:

- Better algorithms that handle more complex match arrangements, like healpix
  - Current IKC work built on rectilinear grid; relaxing this assumption improves use cases
- Split out inner loop from I/O
  - macauff-internal algorithms (i.e., code-versions of the first half of this talk) are independent of how you load input catalogues and output counterparts
  - Pass various arrays and variables around in memory, necessary for lsdb's dask functionality
- Allow for certain variables to be pre-calculated ahead of time, and others to be loaded from memory ahead of time, required for lsdb workflows

Mollweide view

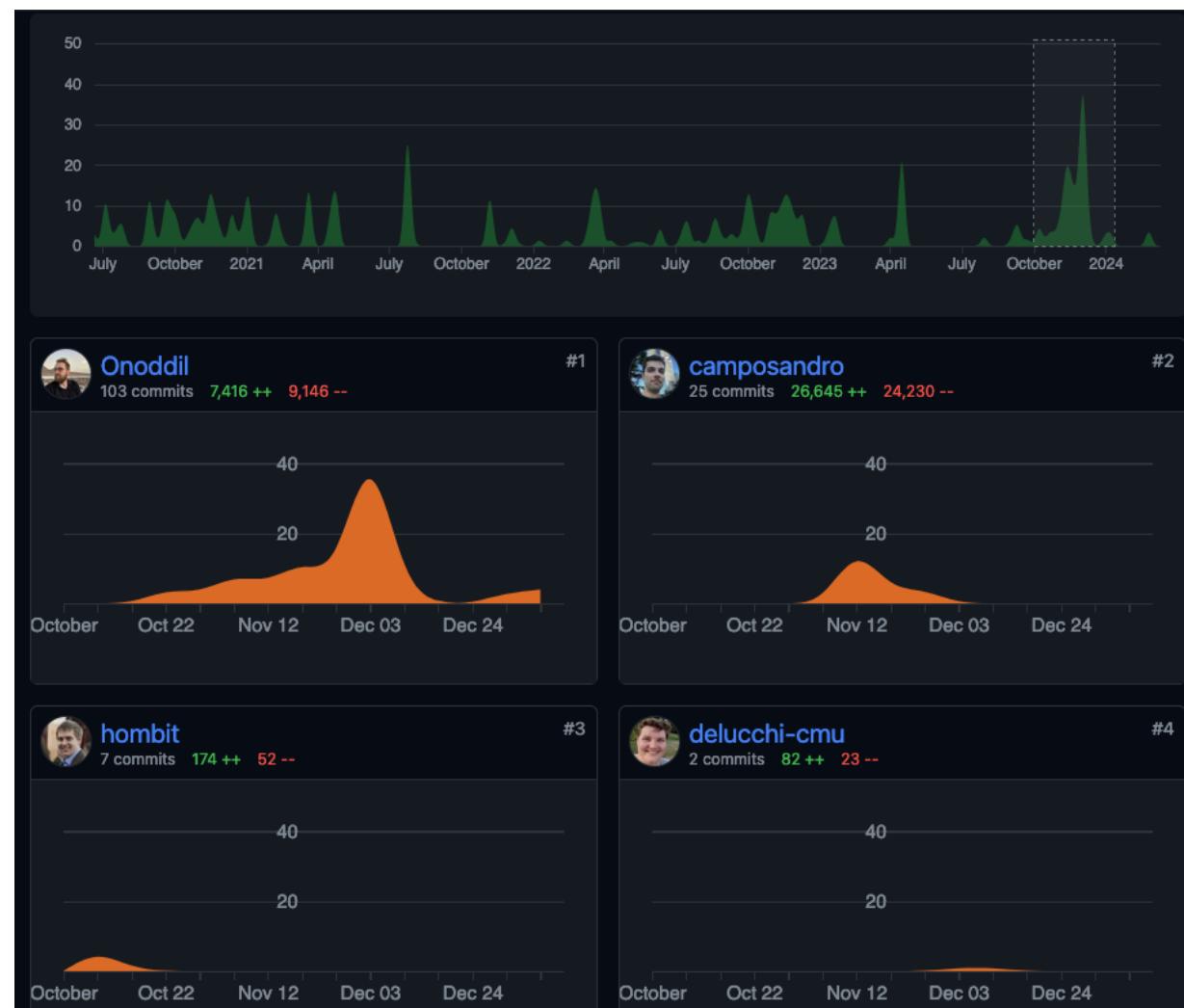


```
20 v  class Macauff():
21      ...
22      Class to perform the catalogue-catalogue association determination, on two
23      datasets which are already pre-processed and set up for cross-matching.
24
25      Parameters
26      -----
27      cm : Class
28          Input "IO" class, with the necessary parameters and datasets configured
29          for cross-matching.
30      ...
```

# lsdb-macauff: The Best of Both Worlds

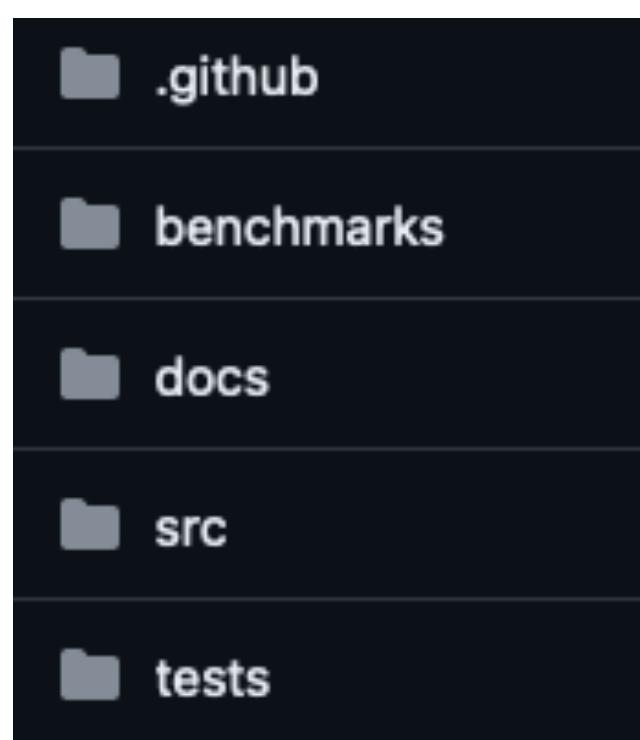
The LINCC Incubator's goal was simple: combine lsdb and macauff.  
In practice, this was quite involved!

macauff



Improvements to macauff's codebase:

- New code layout, for better security and test reproduction
- New build system
  - As with almost every software package of recent years, macauff was compiled using `setup.py`, which is deprecated. Moved to a future-proofed CMake build, allowing for “modern” python packaging with Fortran code.
- Apply the LINCC Python Project Template, a very easy way to get good packaging
  - Linting, package builds, benchmarking, pip installing, automated version tags, etc.
  - A good stress-test of the PPT for an already-mature codebase as well!
- Helped set up a readthedocs account for documentation, which I had been putting off getting done...



Template LINCC Frameworks Python Project Template

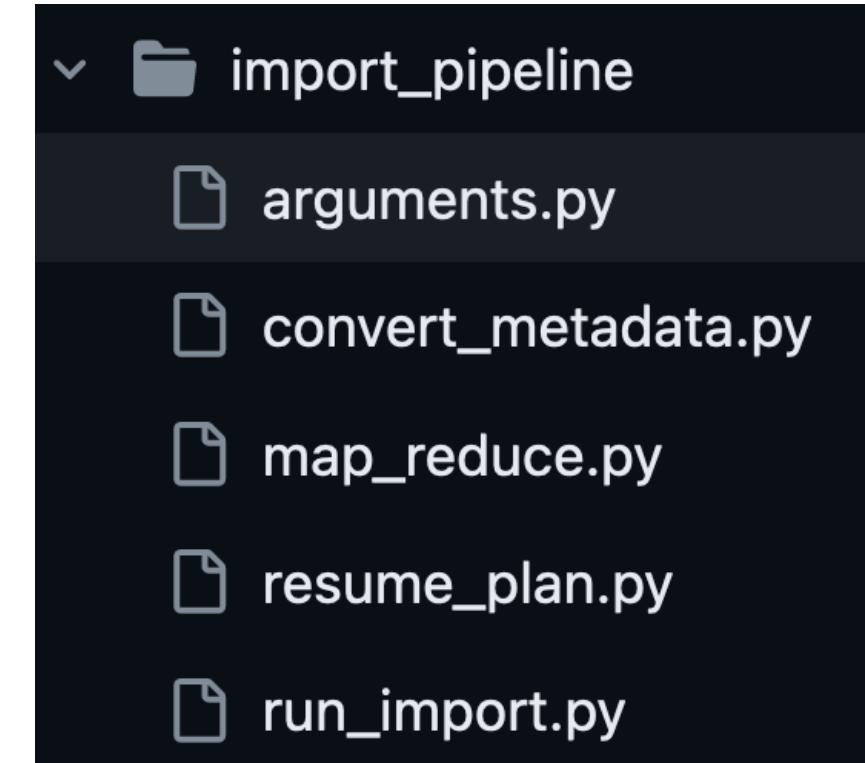
<https://macauff.readthedocs.io/en/latest/>

# lsdb-macauff: The Best of Both Worlds

The LINCC Incubator's goal was simple: combine lsdb and macauff.  
In practice, this was quite involved!



- Various extensions/changes to hipscat, hipscat-import that kicking the tyres in a new way revealed
- Added new functionality to allow for the loading of pre-computed macauff associations as a hipscat files



```
def run(args, client):
    """run macauff cross-match import pipeline"""\n\n
```

```
def from_yaml(input_file, output_directory):
    """Read YAML file with column metadata for the various cross-match files from macauff.\n\n
```

```
assoc_frame = pd.read_parquet(single_path)

assoc_frame.head(5)[["gaia_source_id", "catwise_name", "match_p", "separation"]]

gaia_source_id      catwise_name   match_p   separation
0  1488120269370752  J025039.37+021935.2  0.999997  0.117720
```

```
single_path = '/macauff_association/Norder=2/Dir=0/Npix=0.parquet'

pq.read_metadata(single_path).schema

<pyarrow._parquet.ParquetSchema object at 0x7f52db1542c0>
required group field_id=-1 schema {
    optional int64 field_id=-1 gaia_source_id;
    optional double field_id=-1 gaia_ra;
```

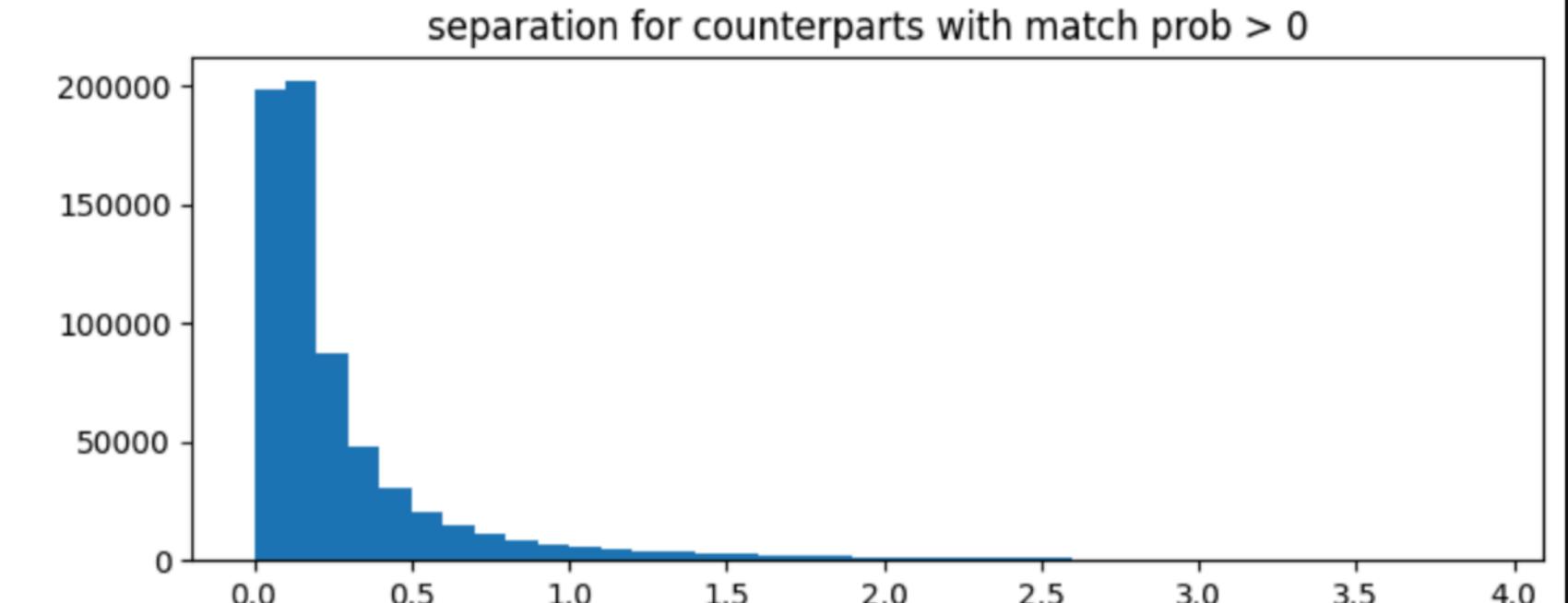
  

```
sep_bins = np.arange(0, 4, .1)

for threshold in [0, 0.5, 0.85, 0.95, 0.99]:
    hist, bins = np.histogram(assoc_frame["separation"][assoc_frame["match_p"] > threshold], bins=sep_bins)

    width = np.diff(bins)
    center = (bins[:-1] + bins[1:]) / 2

    fig, ax = plt.subplots(figsize=(8,3))
    ax.bar(center, hist, align='center', width=width)
    plt.title(f"separation for counterparts with match prob > {threshold}")
    plt.show()
```



# lsdb-macauff: The Best of Both Worlds

The LINCC Incubator's goal was simple: combine lsdb and macauff.  
In practice, this was quite involved!

lsdb\*



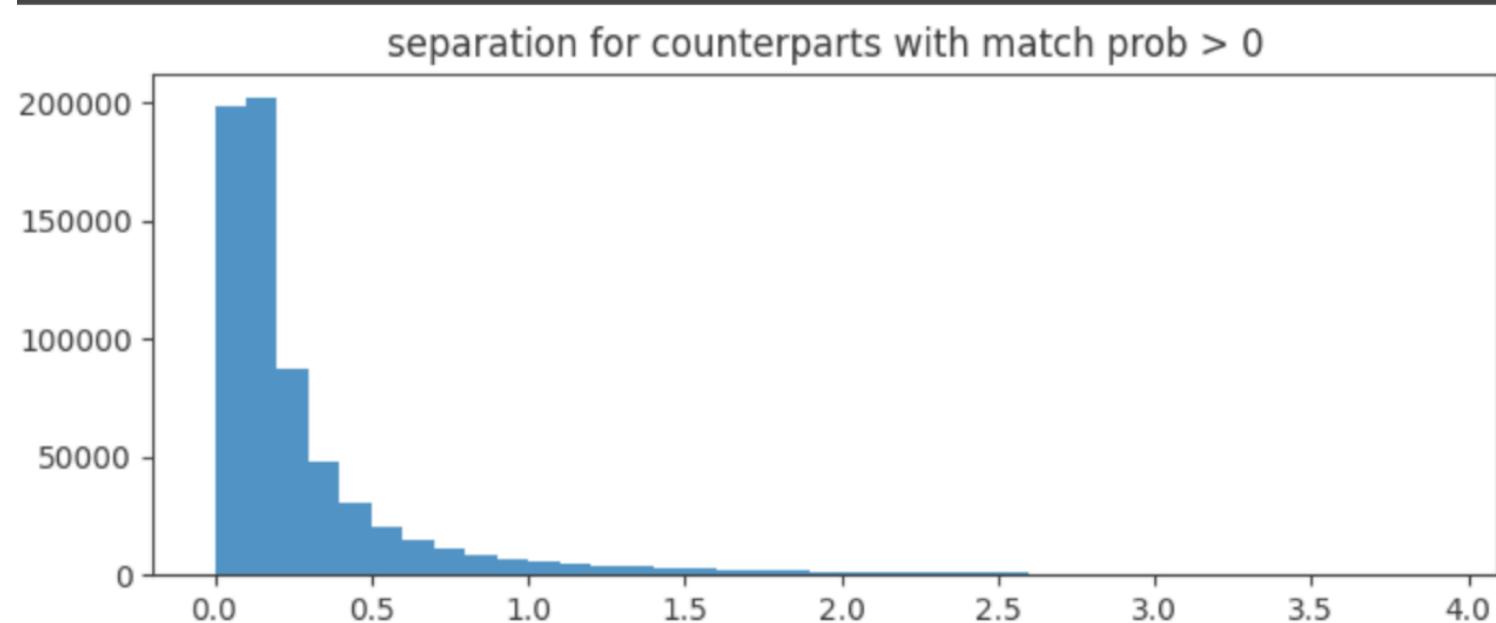
- When results from macauff are imported into lsdb (through `hipscat!`), you will now be able to do much more flexible cross-match refining than with nearest neighbour matching, using all of the “extras” macauff will produce, basically for free!

```
import lsdb
from dask.distributed import Client

client = Client(n_workers=6, memory_limit='20GB', local_directory="",
client
```

Each catalog is loaded using the `lsdb.read_hipscat` method. First the macauff association table, and then the gaia and wise object catalogs. The loading is done lazily, so at this stage the results show just the column names and types.

```
macauff_association = lsdb.read_hipscat("macauff_association/")
macauff_association
center = (bins[:-1] + bins[1:]) / 2
fig, ax = plt.subplots(figsize=(8,3))
ax.bar(center, hist, align='center', width=width)
plt.title(f"separation for counterparts with match prob > {threshold}")
plt.show()
```



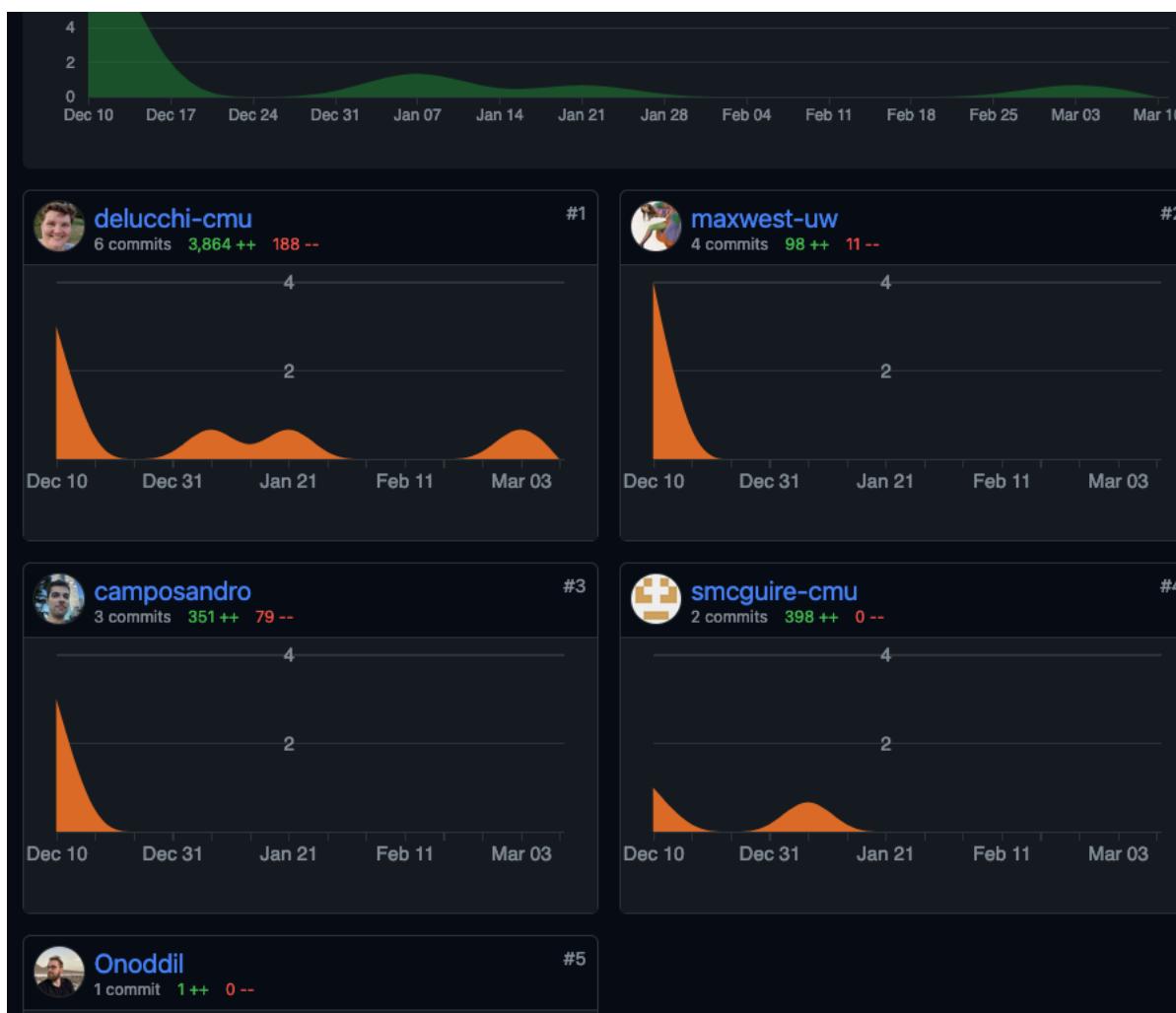
```
joined = gaia.join(catwise, through=macauff_association)
joined
```

```
joined.query("match_p > 0.999")._ddf.partitions[0].compute()
```

# lsdb-macauff: The Best of Both Worlds

The LINCC Incubator's goal was simple: combine lsdb and macauff.  
In practice, this was quite involved!

## lsdb-macauff



- New shell that talks to both macauff and lsdb – hence lsdb-macauff!
- Allows macauff to be called within lsdb, for smaller-scale, individual cross-match runs
- Will provide all of the same advantages that using pre-join tables does, but for other science cases

```
def test_macauff_crossmatch(
    catalog_a_csv, catalog_b_csv, all_sky_params, gaia_all_sky_params, wise_all_sky_params
):
    catalog_a = Catalog(CatalogInfo({"catalog_name": "catalog_a"}, [HealpixPixel(0, 0)])
    catalog_b = Catalog(CatalogInfo({"catalog_name": "catalog_b"}, [HealpixPixel(0, 0)])

    algo = MacauffCrossmatch(
        left=pd.read_csv(catalog_a_csv),
        right=pd.read_csv(catalog_b_csv),
        left_order=0,
        left_pixel=0,
        right_order=0,
        right_pixel=0,
        left_metadata=catalog_a,
        right_metadata=catalog_b,
        suffixes=("a", "b"),
        right_margin_hc_structure=None,
    )
    algo.crossmatch(all_sky_params, gaia_all_sky_params, wise_all_sky_params, None, None)
```

Args:

```
algorithm (BuiltInCrossmatchAlgorithm | Type[AbstractCrossmatchAlgorithm])
    algorithm to use to perform the crossmatch. Can be either a string
    the built-in cross-matching methods, or a custom method defined by
    AbstractCrossmatchAlgorithm.
```

Built-in methods:

```
-`kd_tree`: find the k-nearest neighbors using a kd_tree
```



- Macauff is great, lsdb is too.
- Now they can talk to each other! Either in using pre-generated all-sky association tables (such as those we are making through LSST:UK!), or through individual use-cases with the lsdb-macauff wrapper.
  - Still some work left to do — there's always more to be done in software development!
- Extends lsdb-scale catalogue analysis to probabilistic cross-matching, much-needed in the era of LSST!



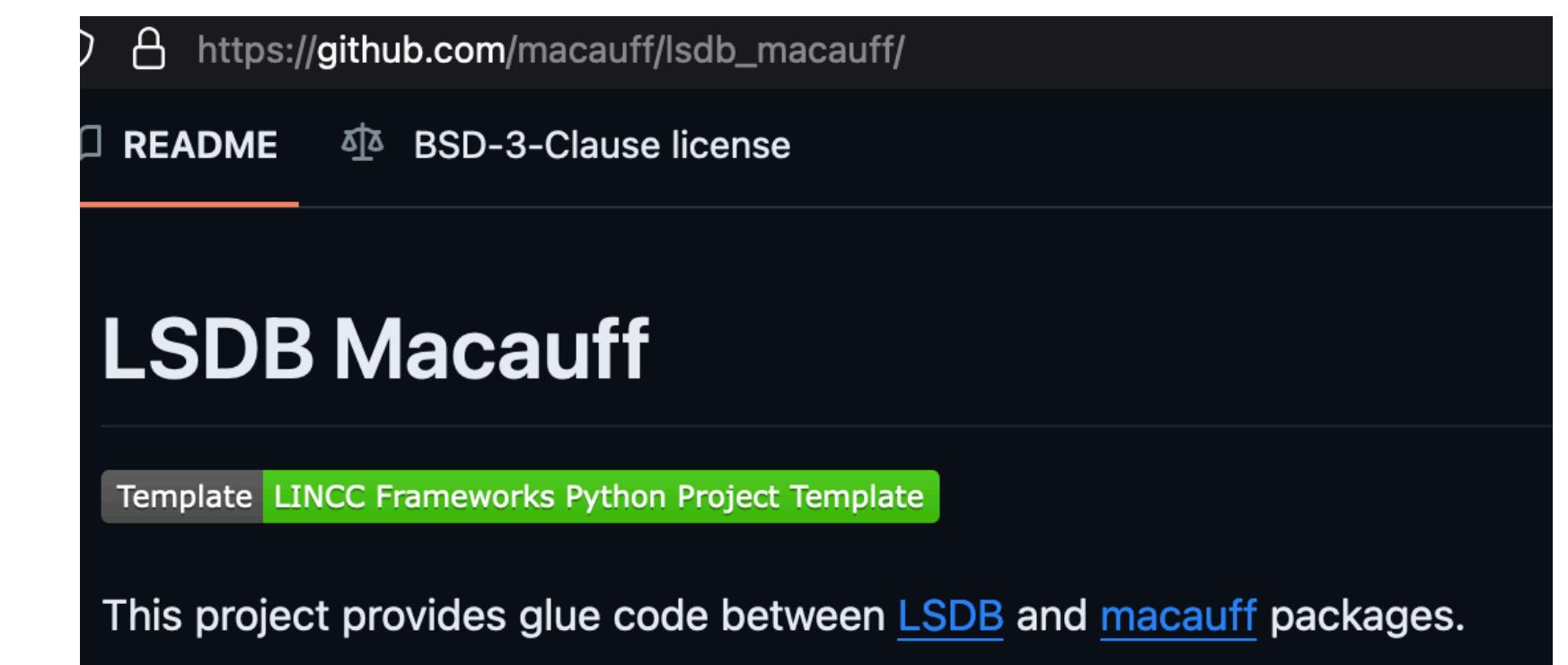
University  
of Exeter



Science and  
Technology  
Facilities Council



@pm.me  
@Onoddil.github.io  
[www.onoddil.com](http://www.onoddil.com)



A screenshot of a GitHub repository page for 'lsdb\_macauff'. The page title is 'LSDB Macauff'. It shows the README file and a BSD-3-Clause license file. A note at the bottom states: 'This project provides glue code between [LSDB](#) and [macauff](#) packages.'

Tom J Wilson @onoddil