



**Jet Propulsion Laboratory**  
California Institute of Technology



# Anomaly Detection and Explanation in Galaxy Observations from the Dark Energy Survey

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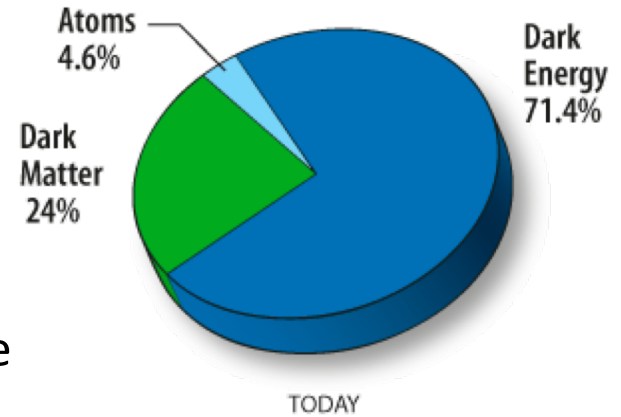
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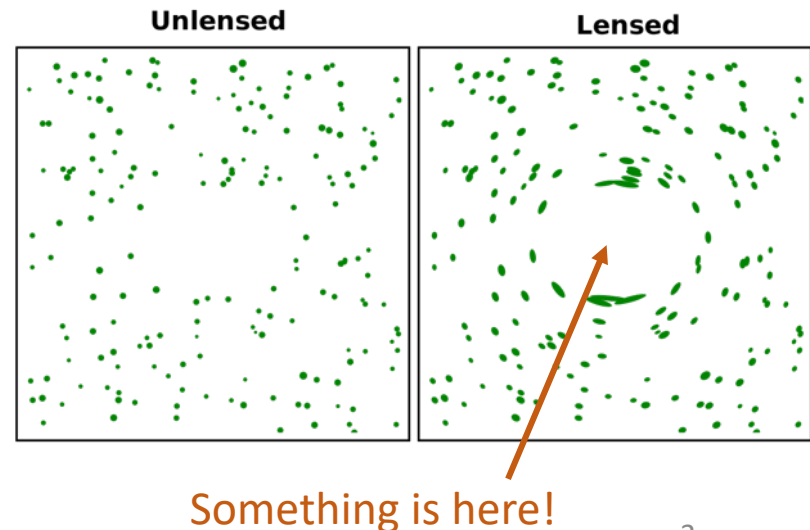
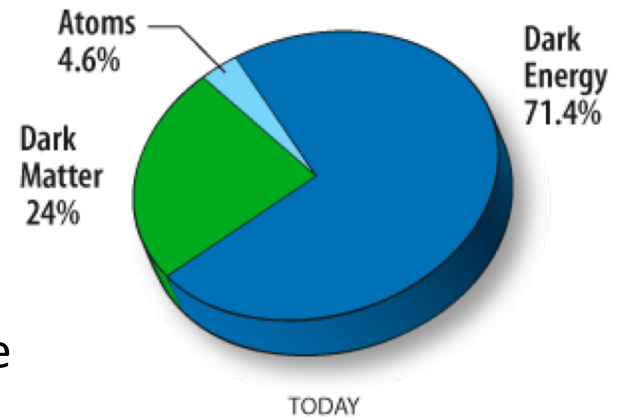
# Dark Energy Survey: Motivation

- Quest: Understand our universe (formation and evolution), using a cosmological model characterized by 6-10 parameters
  - E.g., amount of dark energy, dark matter
  - **Dark energy** drives the expansion of the universe
  - **Dark matter** drives the clustering of galaxies



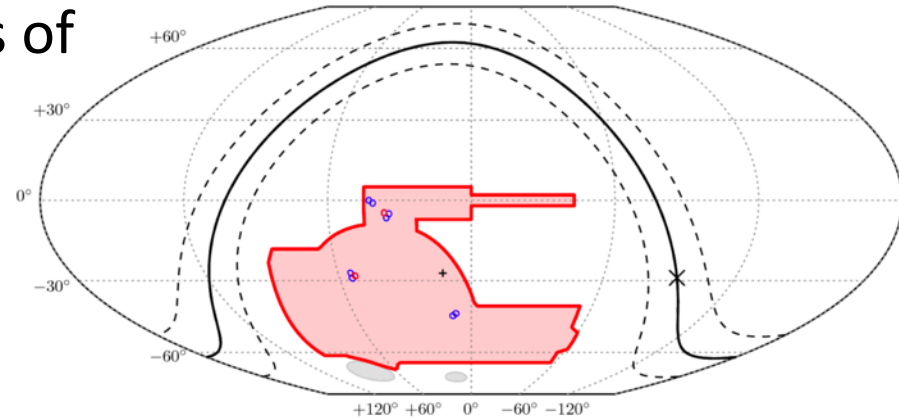
# Dark Energy Survey: Motivation

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  - E.g., amount of dark energy, dark matter
  - **Dark energy** drives the expansion of the universe
  - **Dark matter** drives the clustering of galaxies
- How to determine the amount of dark energy and dark matter? We can't observe them directly.
  - Infer **dark matter** from weak lensing galaxy observations
    - Dark matter magnifies + distorts background galaxy shapes
  - Infer **dark energy** from changes in **dark matter** distribution over time (distance)
  - Subtle effects; require millions of galaxies to reliably estimate



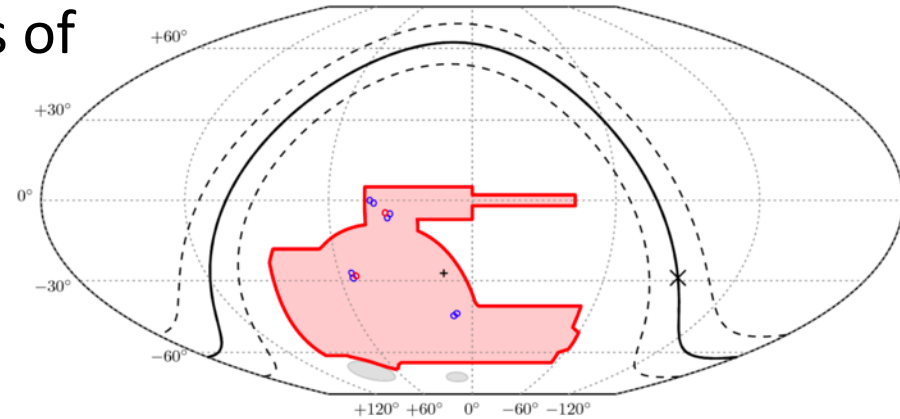
# Dark Energy Survey (DES)

- Surveyed 5000 square degrees of southern sky over 6 years (Aug. 2013 - Jan. 2019)
  - 4-m telescope in Chile
- 400M objects (~310M galaxies)
  - But **noise/artifacts** will pollute **dark energy**, **dark matter** estimates



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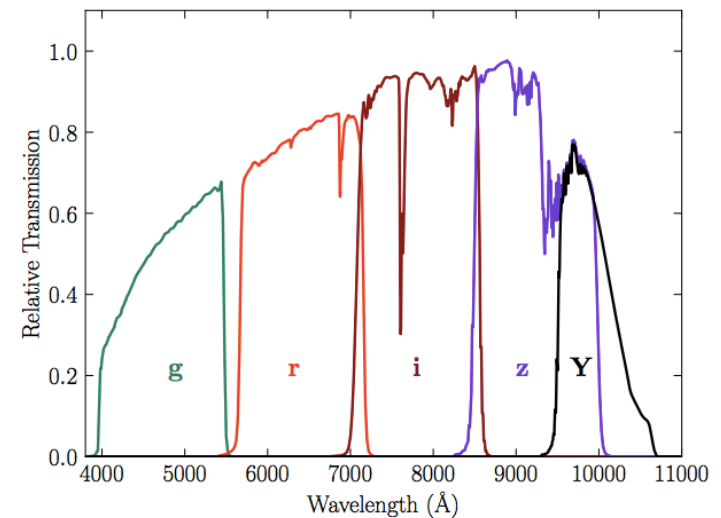


- Our goal: Identify outliers in DES catalog to
  1. Find, filter, and understand **artifacts**, which can
    1. Inform improvements to the DES processing pipeline and
    2. Yield better estimates of cosmological model parameters (e.g., amount of **dark energy** and **dark matter**)
  2. Discover **new scientific phenomena** (what's out there?)

# DES Object Catalog



- Observe: Collect sky images at 4 bands
  - 10 exposures (90 s) per band (different dates)
- Find sources (SExtractor) and match to reference catalogs
- Model sources (NGMIX)
- Extract features:  
id, RA, Dec, G, R, I, Z, etc.
- Apply recommended quality filters (discards 2/3 of objects)
  - And yet... spoiler: **artifacts** remain



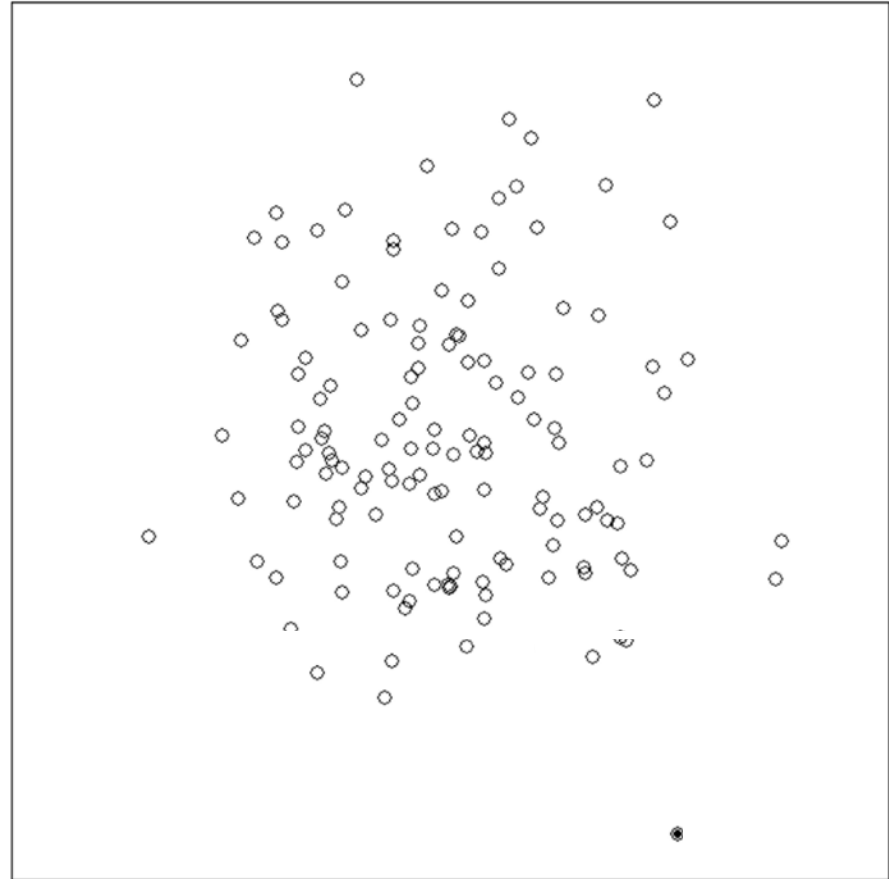
**Figure 1.** The DES *g*, *r*, *i*, *z* and *Y* Standard Bandpasses. These curves include atmospheric transmission and instrumental response. Details can be found in Burke et al. (2018).

# Outlier Detection Methods

- Isolation Forest [Liu et al., 2008]
  - Rank all items by their isolation scores
- DEMUD: Discovery via Eigenbasis Modeling of Uninteresting Data [Wagstaff et al., 2013]
  - Select diverse set of unusual objects using incremental Singular Value Decomposition (SVD)
  - Provide explanations for each object's selection (e.g., unusual feature values)

# Isolation Forest

- Construct forest of random decision trees
- Compute isolation score for each item: average depth in trees

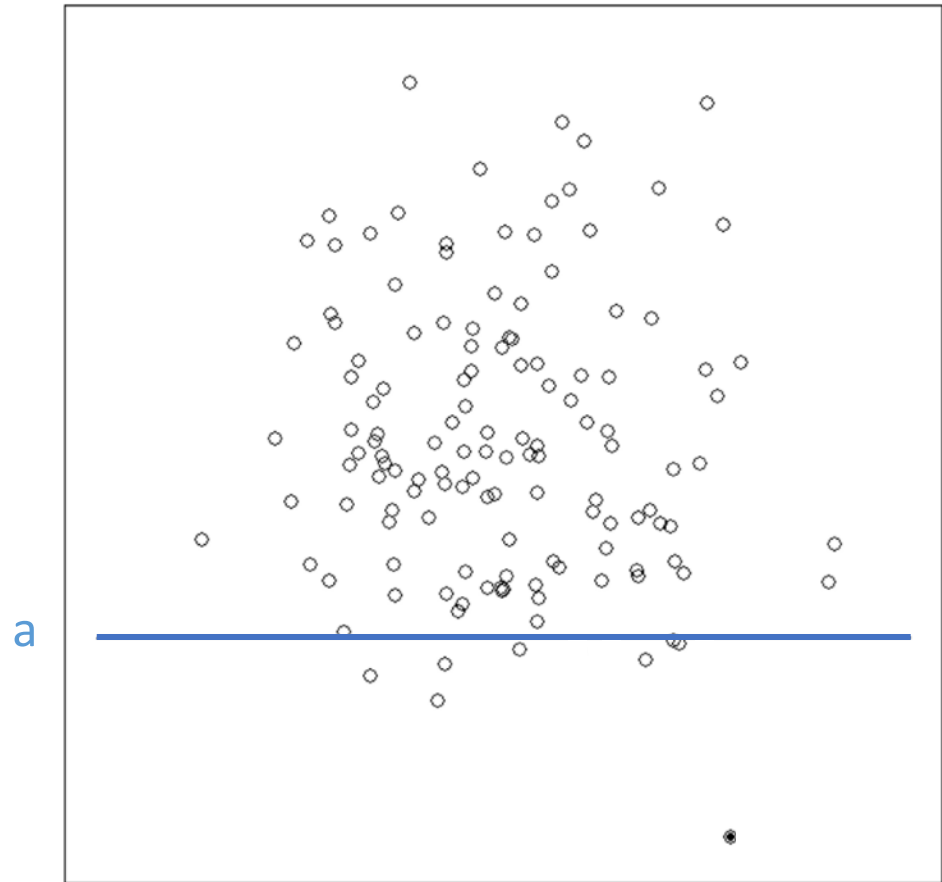
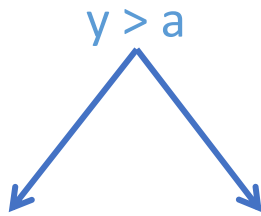


[Liu et al., 2008]



# Isolation Forest

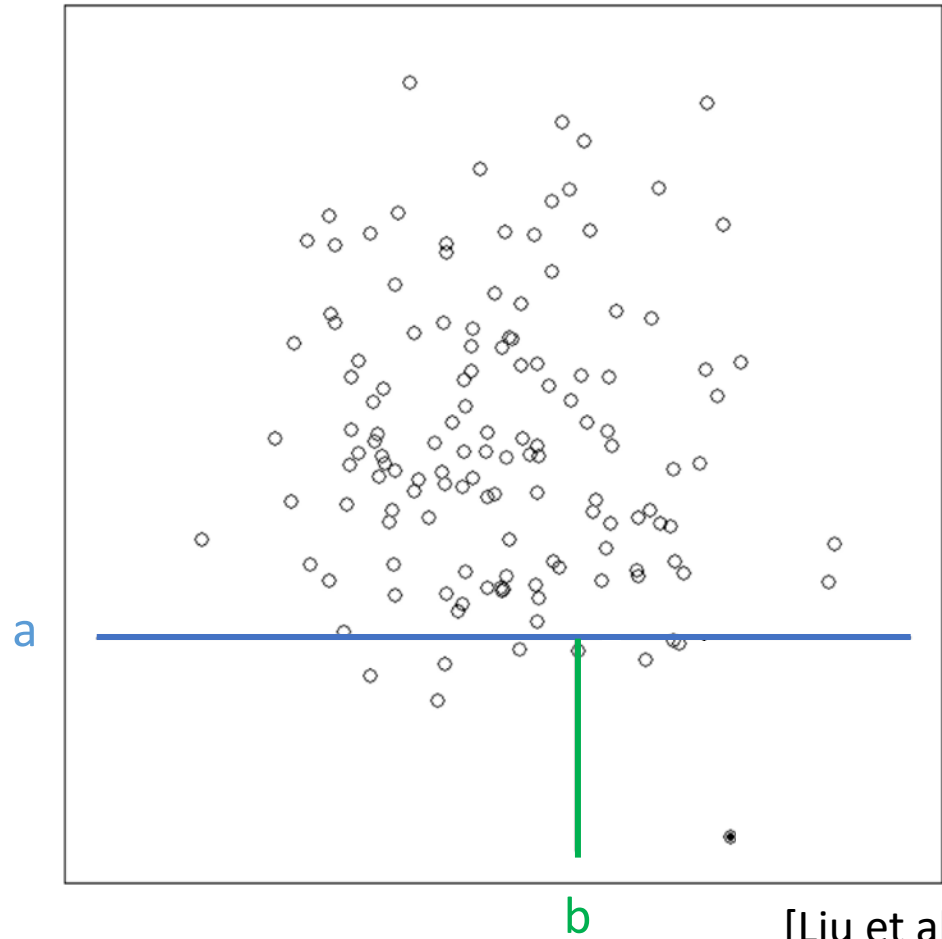
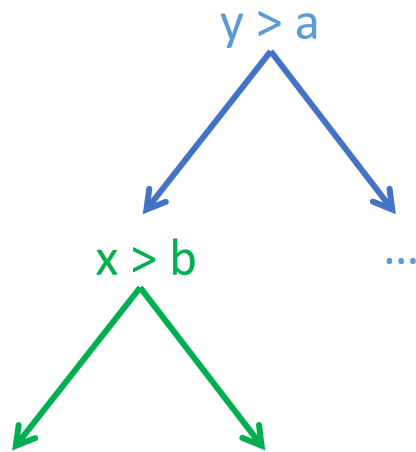
Random decision tree



[Liu et al., 2008]

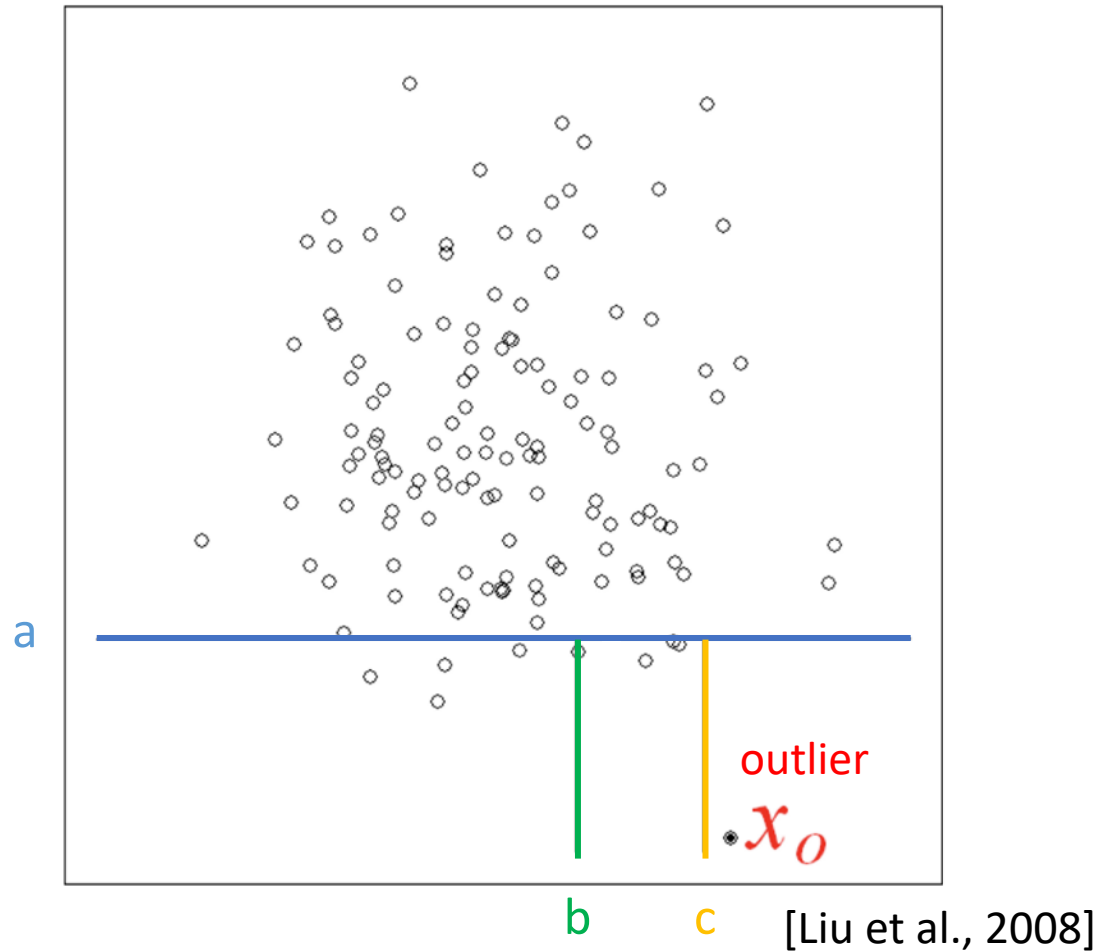
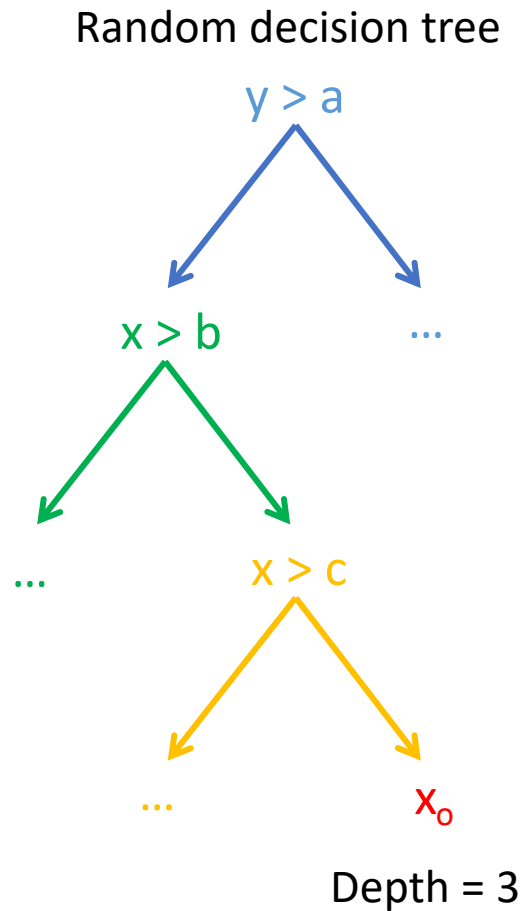
# Isolation Forest

Random decision tree



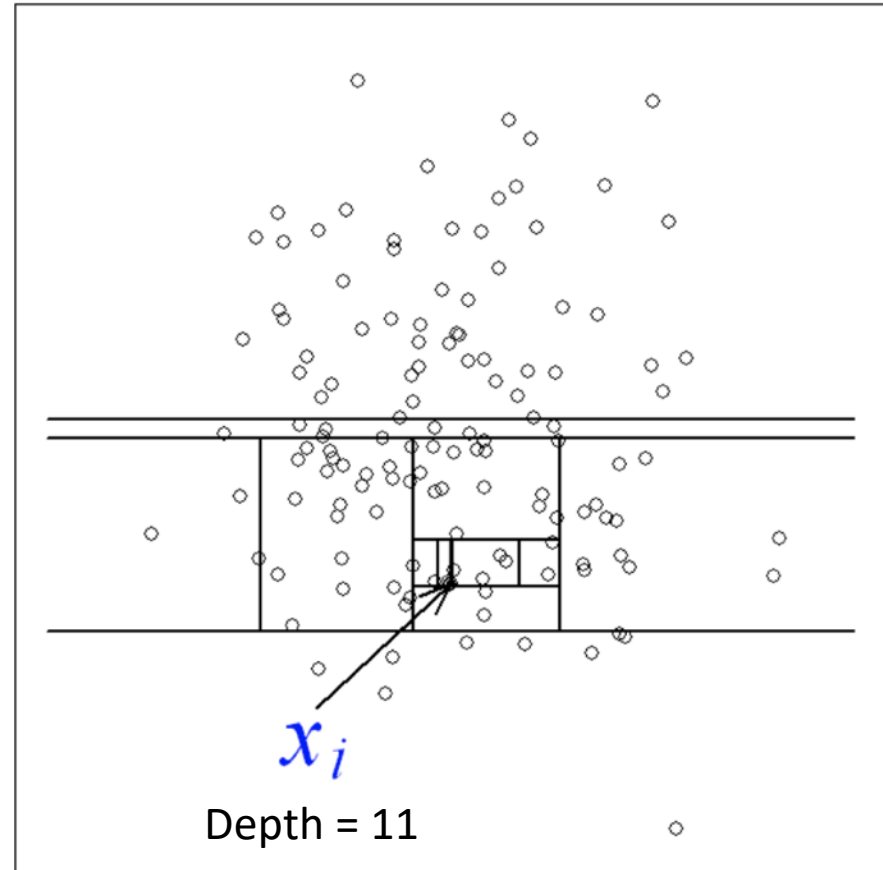
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# Isolation Forest



# Isolation Forest

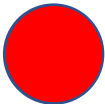
- Other items take more random splits to isolate
- Outliers: low average depth across all trees in the forest



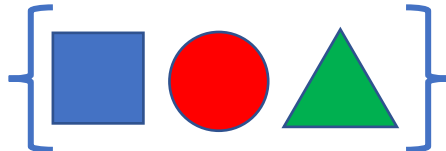
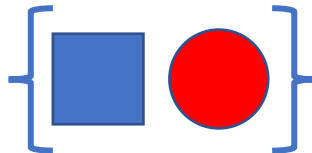
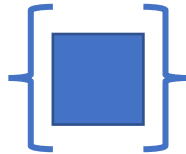
# DEMUD

- Incrementally growing model (Singular Value Decomposition) of what has been selected (learned) [Wagstaff et al., 2013]
- Select “most difficult to model” item at each step

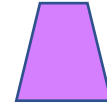
Selection



Learned



Model




$$D = U \Sigma V^T$$

# DES Outliers – What have we found?

- Data set: 12M objects observed by DES
  - R-band magnitude + 3 colors: (G-R, I-R, Z-R)
- Select top 1000 outliers with each algorithm
- Browse results using interactive web-based Outlier Explorer
- Classify outliers by category:
  - Detector error
  - Model-fitting error
  - Human-made transient
  - Astrophysical transient
  - Scientifically interesting – consider follow-up observations

# Outlier Explorer

Sky location and object id

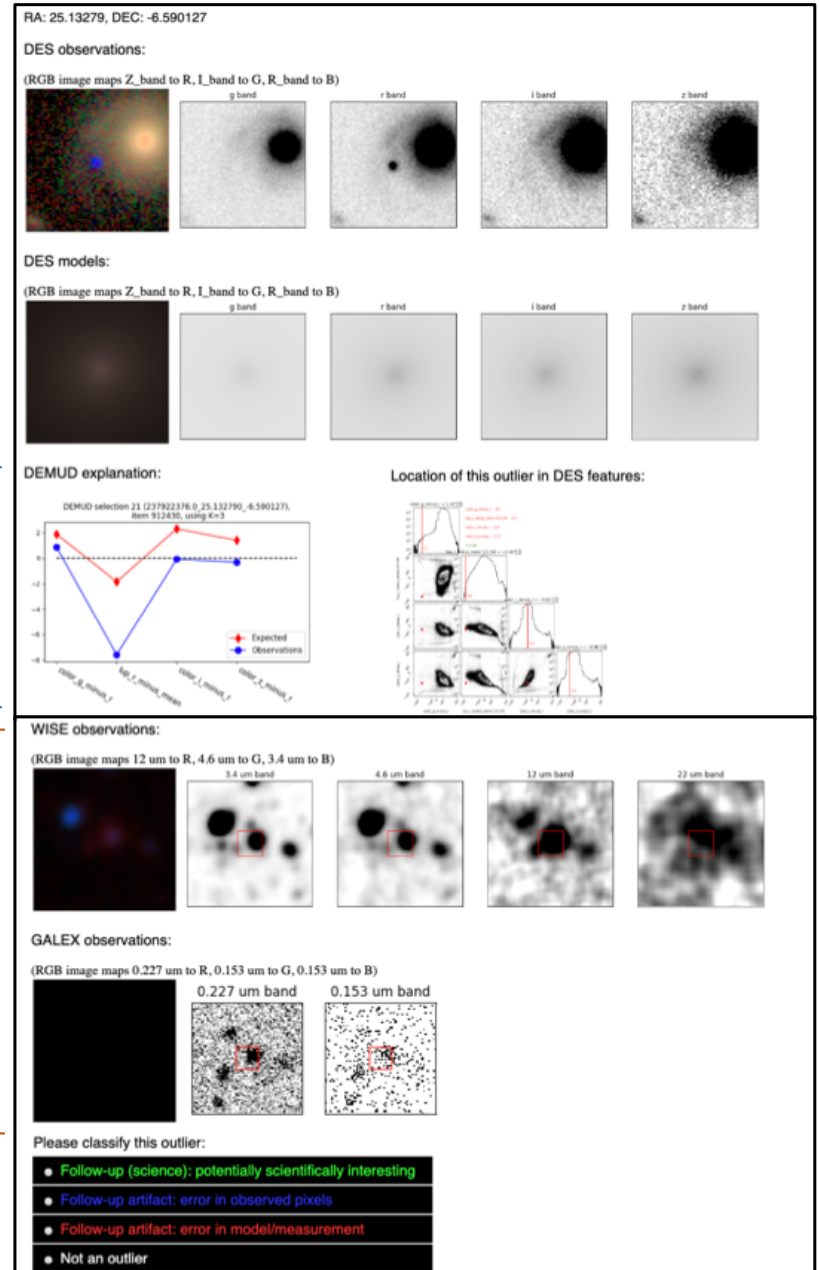
Observations

Model

Explanations

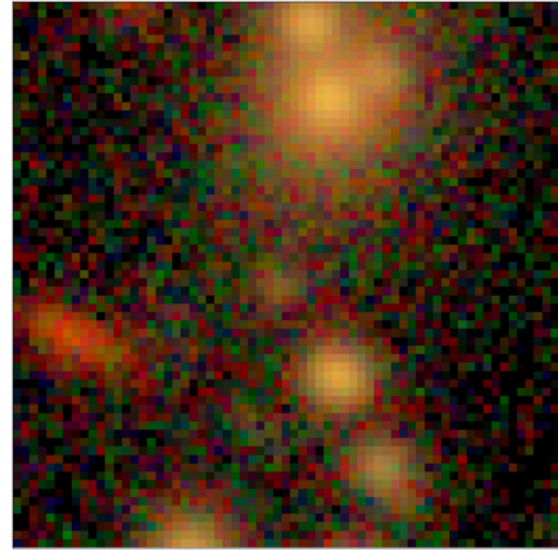
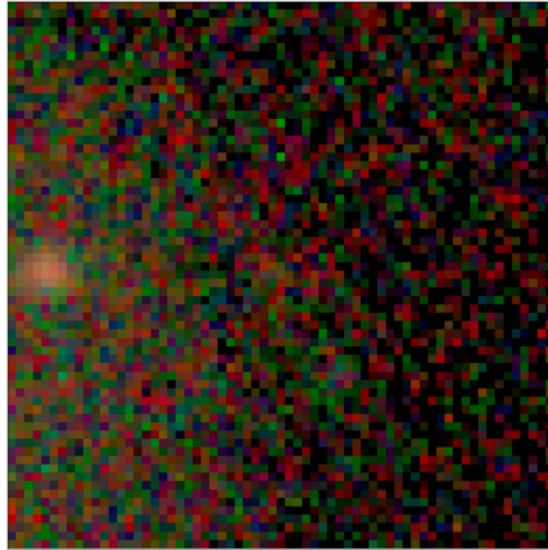
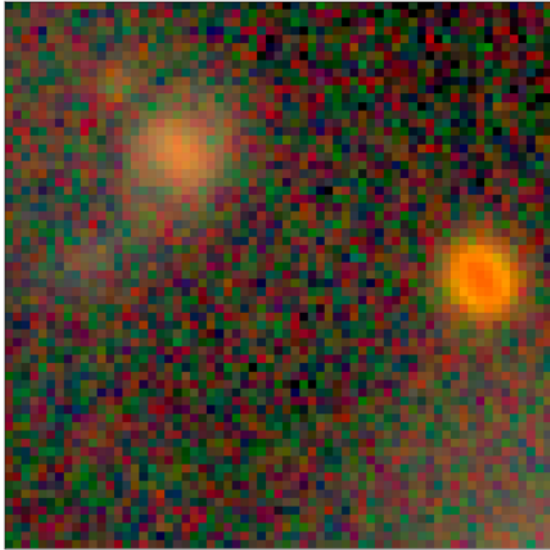
Coincident observations in other surveys

Classify outlier

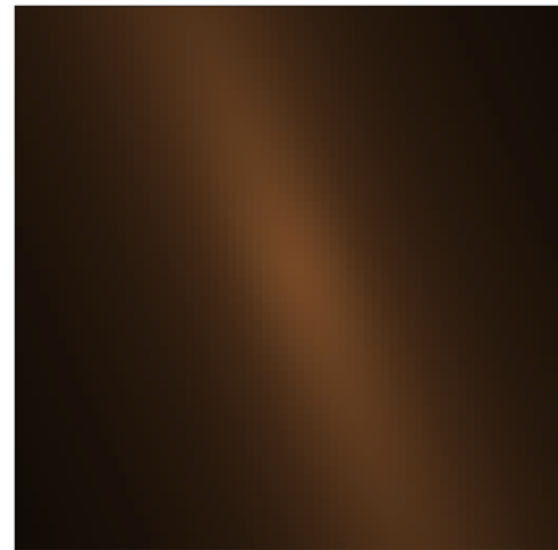
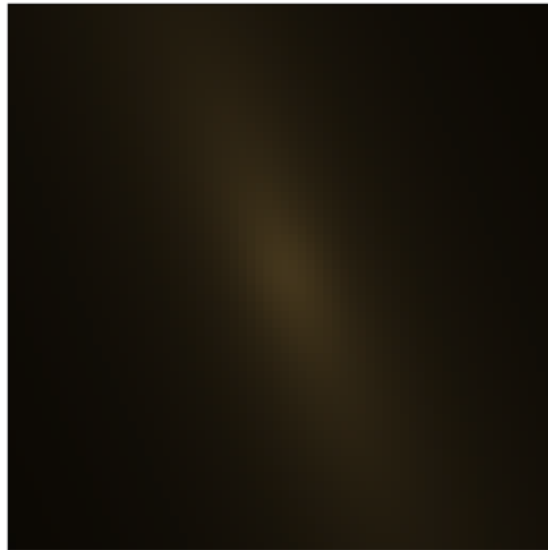
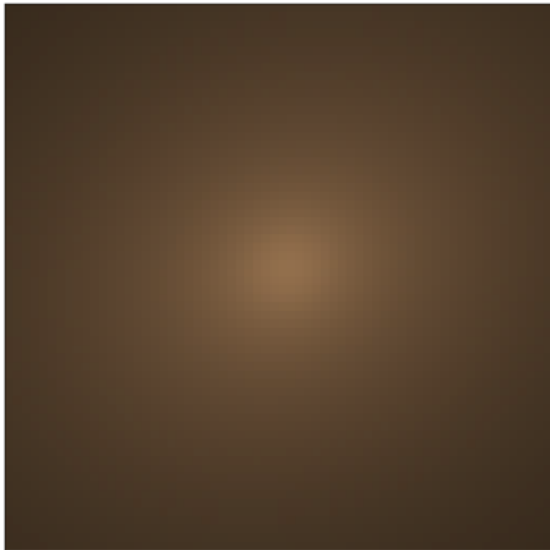


# DES Outliers: Model Errors

Data

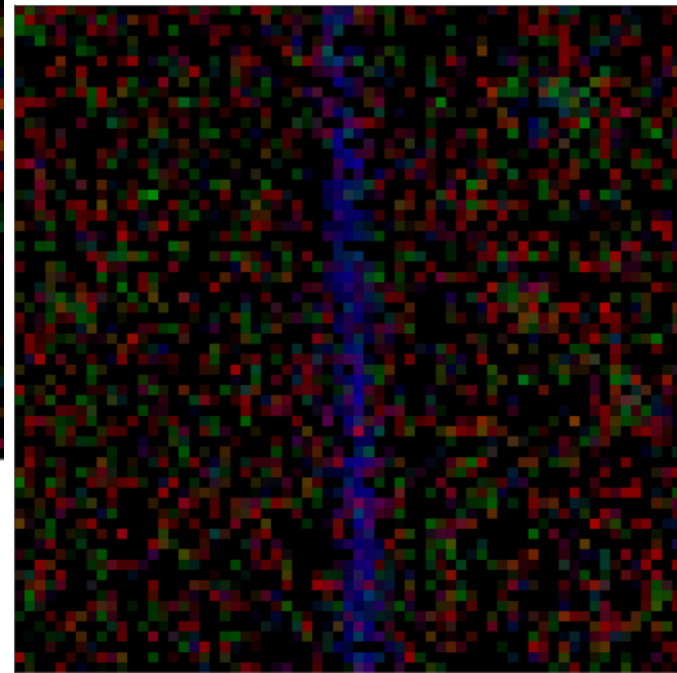
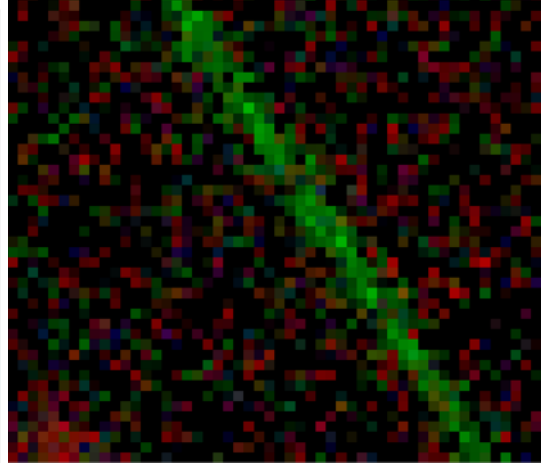
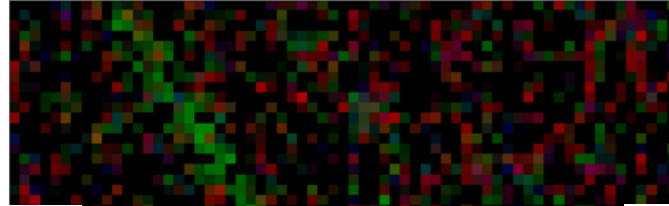


Model

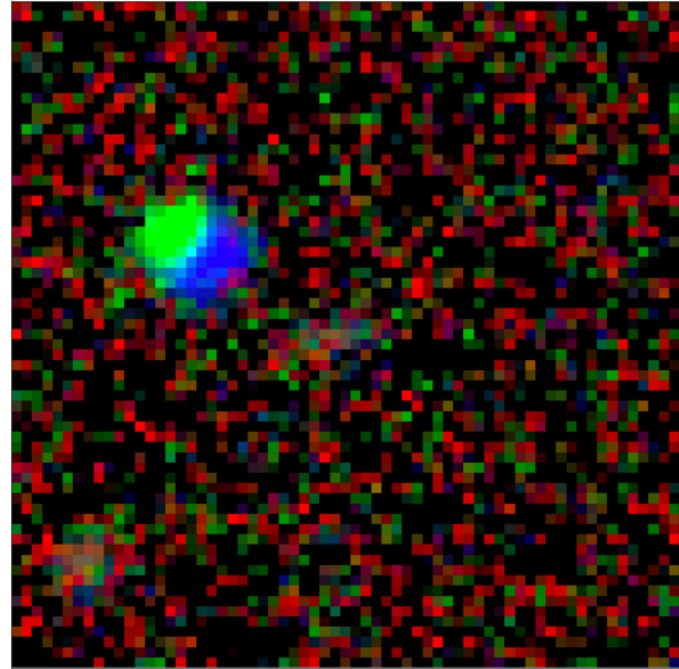
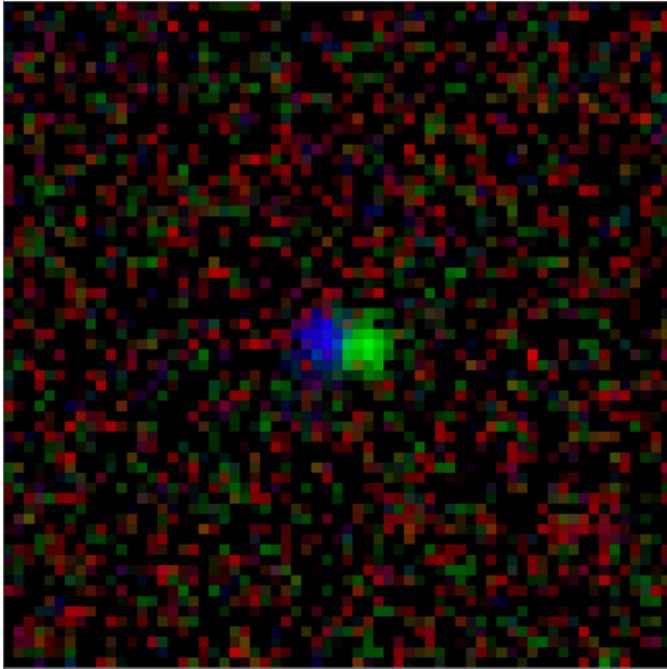




# DES Outliers: Fast-moving aircraft

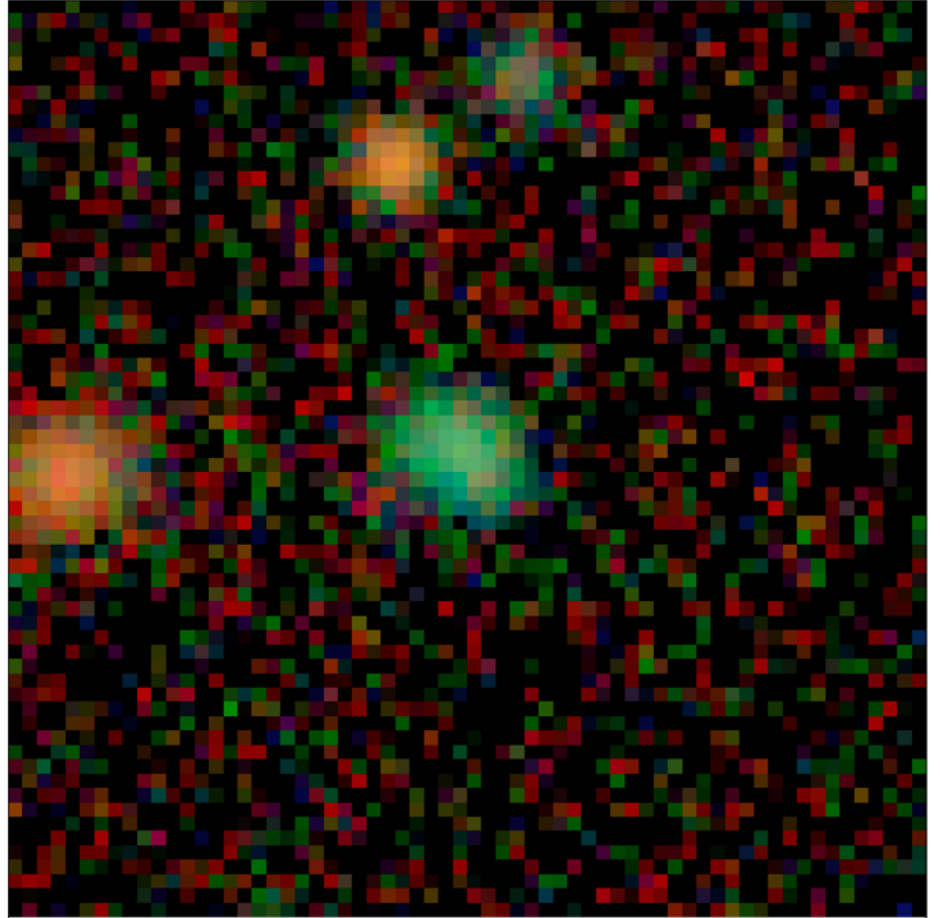


# DES Outliers: Asteroids?

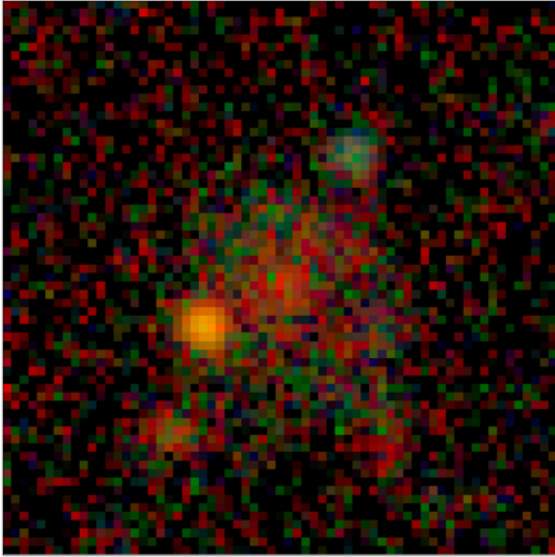


# DES Outliers: “Green Pea” Galaxy

- Discovered by SDSS citizen scientists in 2007
- Very low mass with high star-formation rate
- Common in the early universe, but rare today

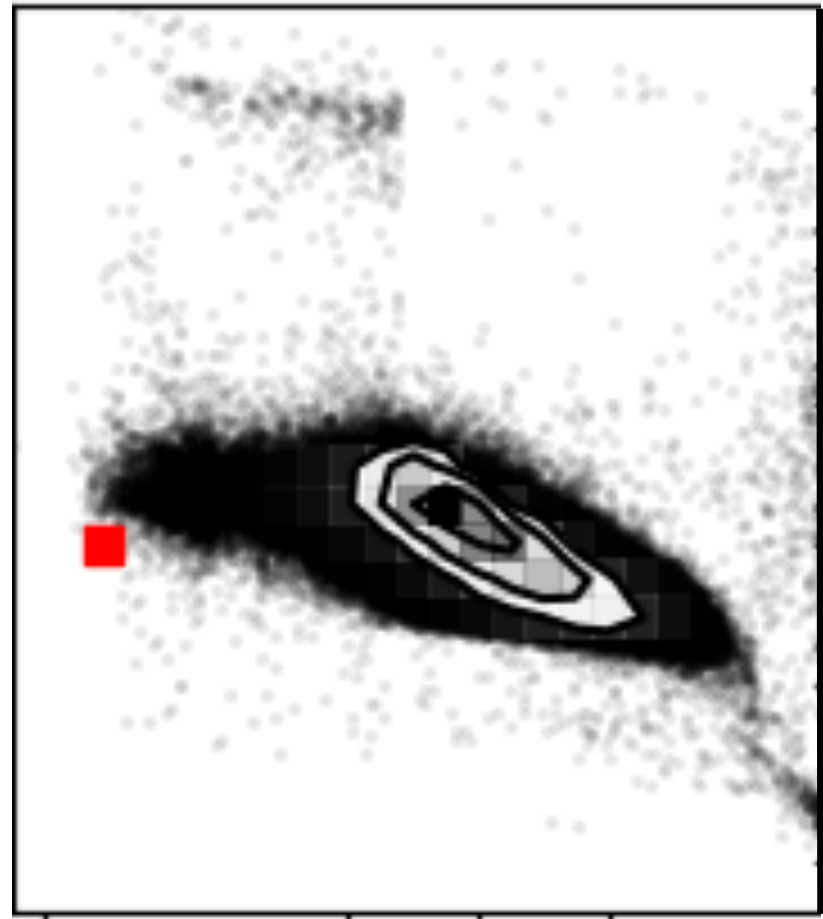


# Why is this object an outlier?



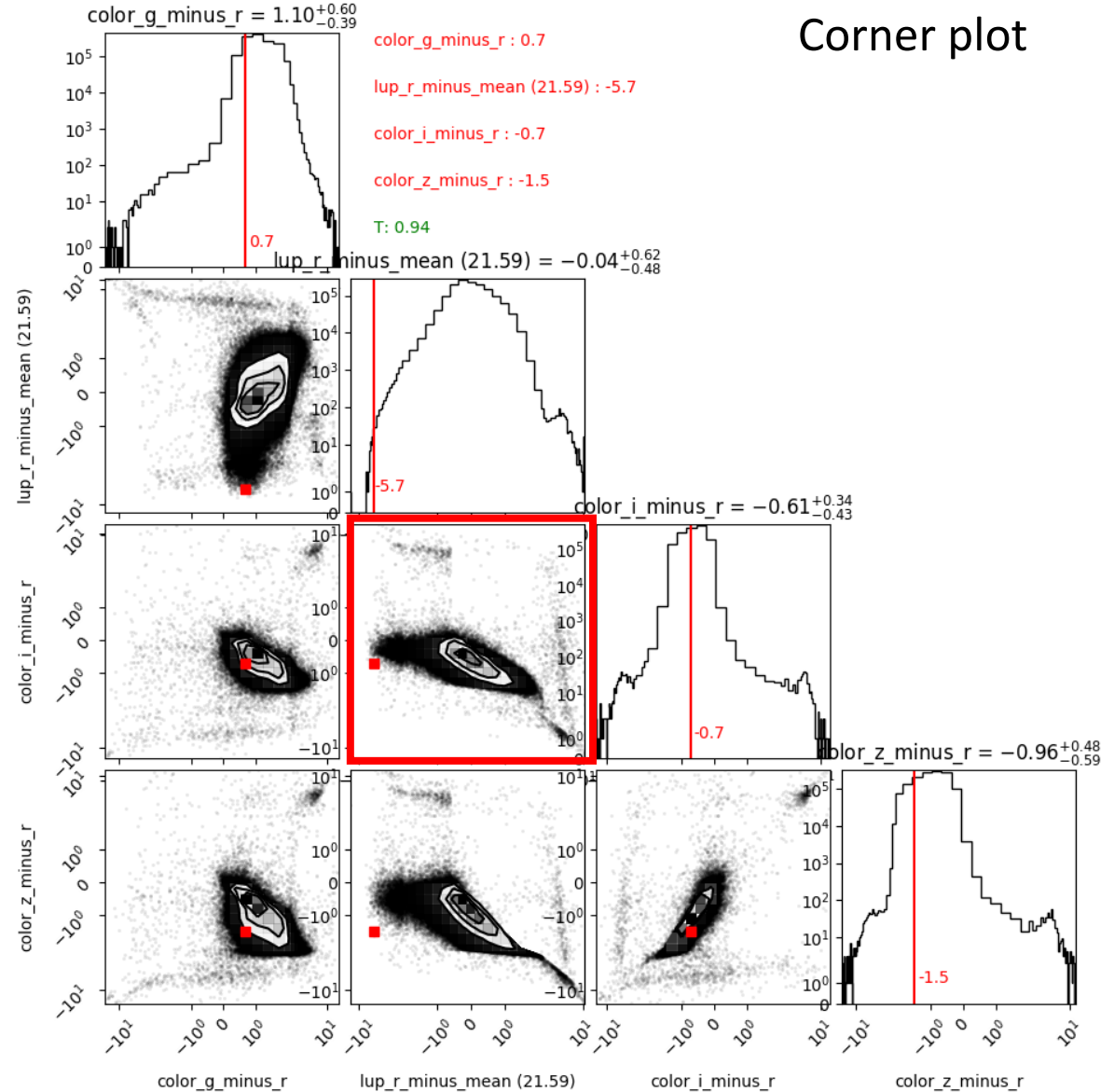
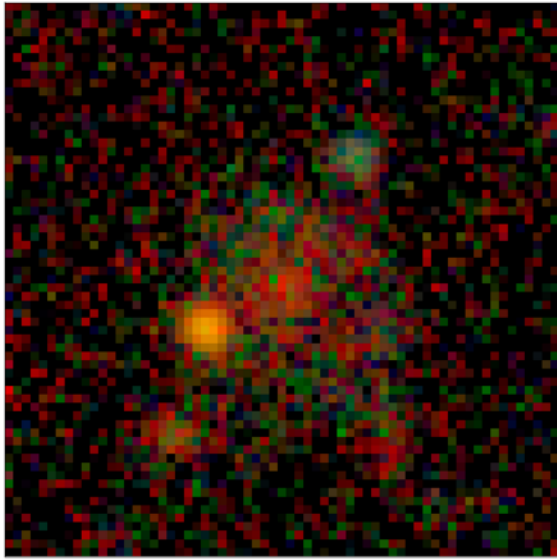
Data distribution plot

$I - R$  color

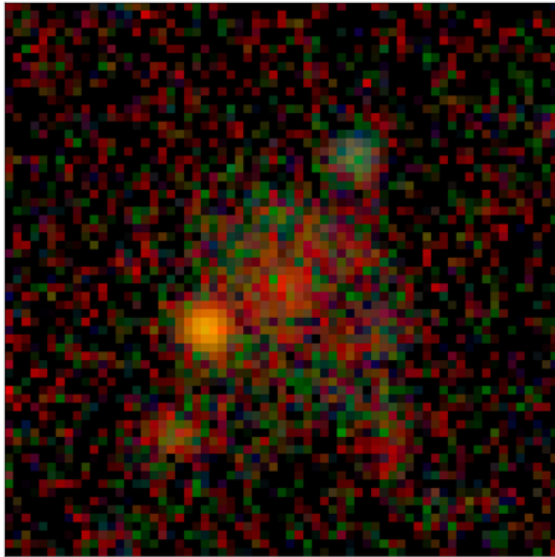


R-band luptitude

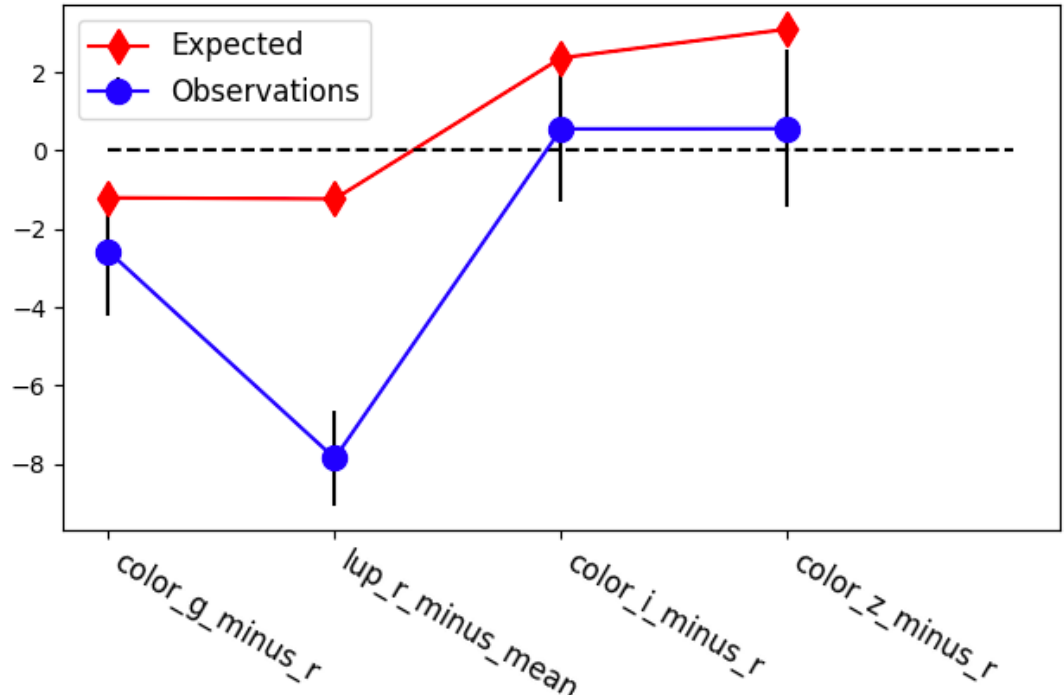
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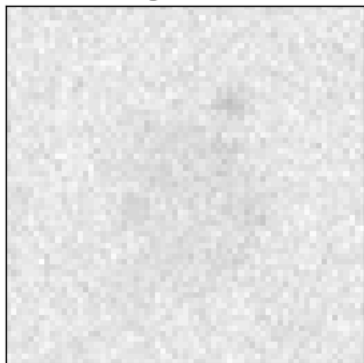
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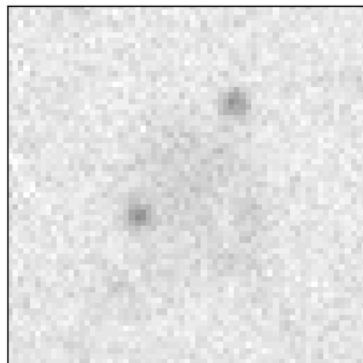
DEMUD Explanation



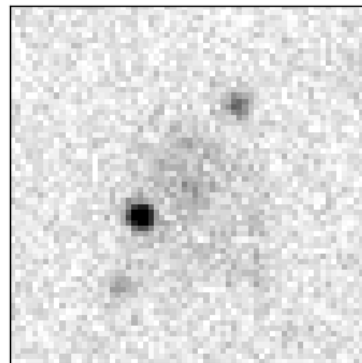
g band



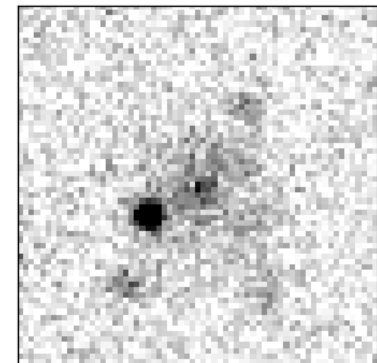
r band



i band



z band



# Takeaway Points

- Goal: Identify outliers in DES catalogs to
  1. Find, filter, and understand **artifacts**  
... to improve estimates of **dark energy** and **dark matter**
  2. Discover new kinds of objects
- Outlier detection methods
  - Isolation Forest
  - DEMUD: Discovery via Eigenbasis Modeling of Uninteresting Data
- Explanations aid in classifying and making use of outliers
- In progress: Review and publish DES outlier catalogs
- Same techniques will benefit future large surveys (e.g., LSST, WFIRST, SPHEREx)
  - We've also applied them to e.g., Kepler light curves, UKIRT catalogs

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