Looking Below the Noise - Asteroid Hunting With the LSST

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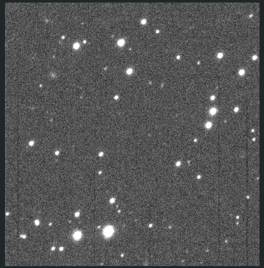

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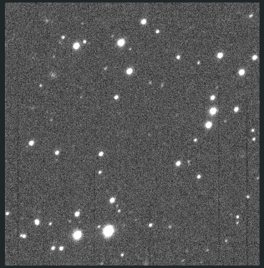

Choosing rose-tinted glasses

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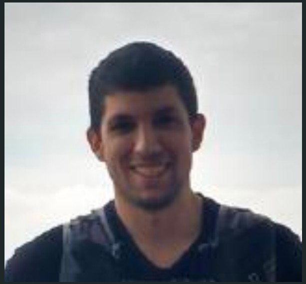
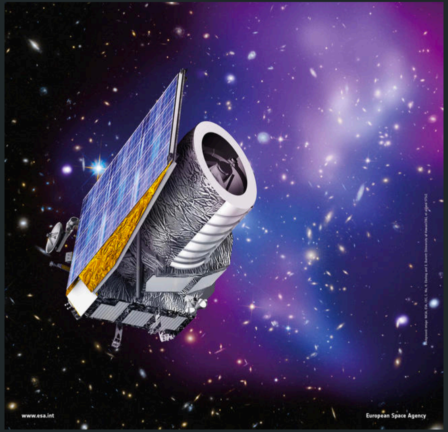
Choosing filters for large surveys

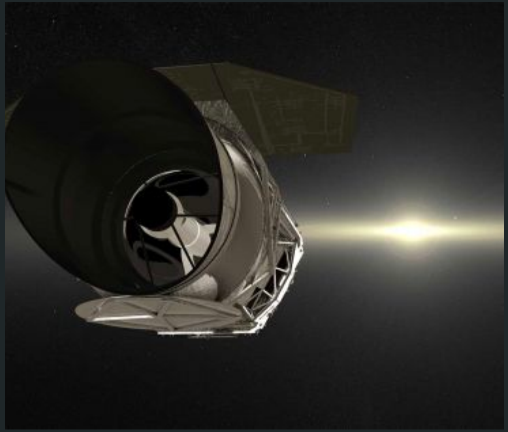


Bryce Kalmbach (University of Washington)

Jake Vanderplas (Google)

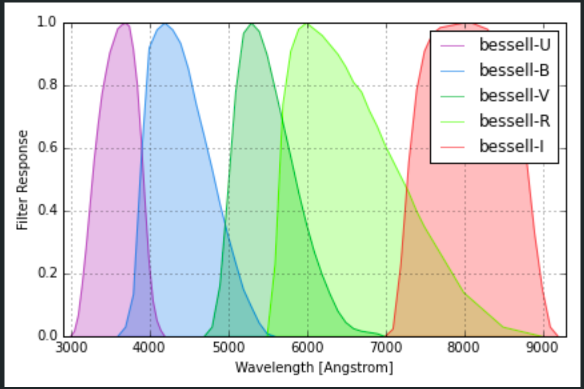
Why should I care ?



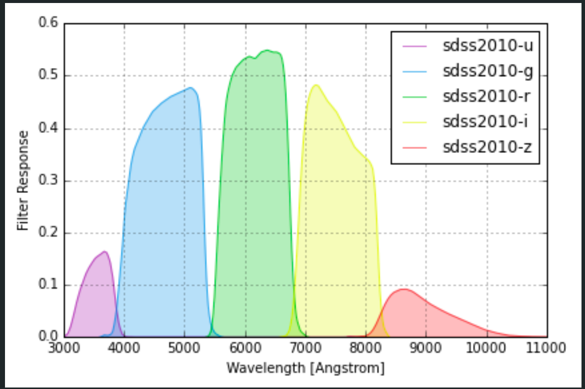


Finite observing time (and filter changes)
Wavelength dependent sensitivities (sensor and atmosphere)
Competing science objectives

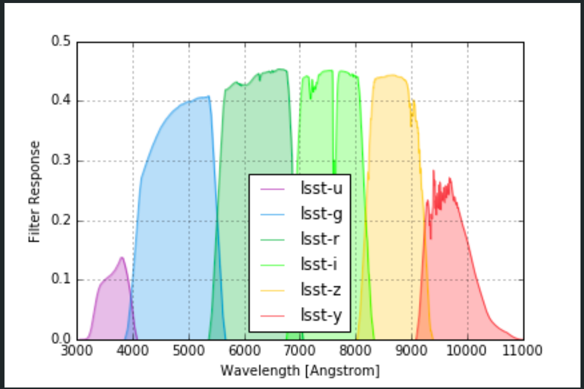
Broadband Filters



Johnson-Cousins



SDSS

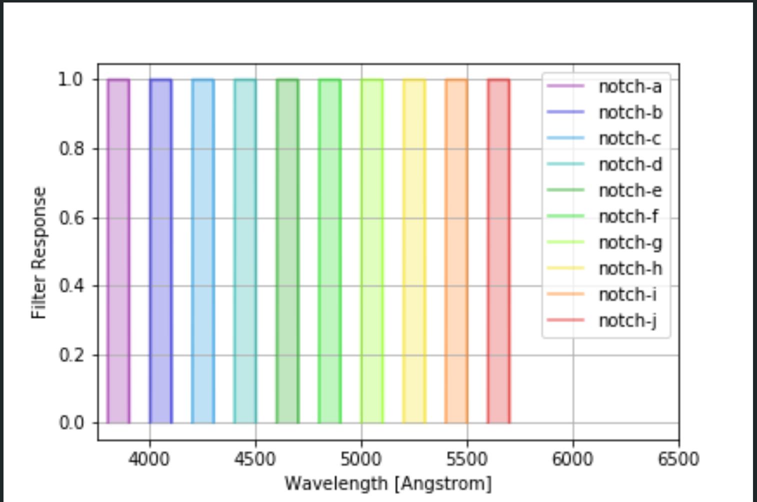


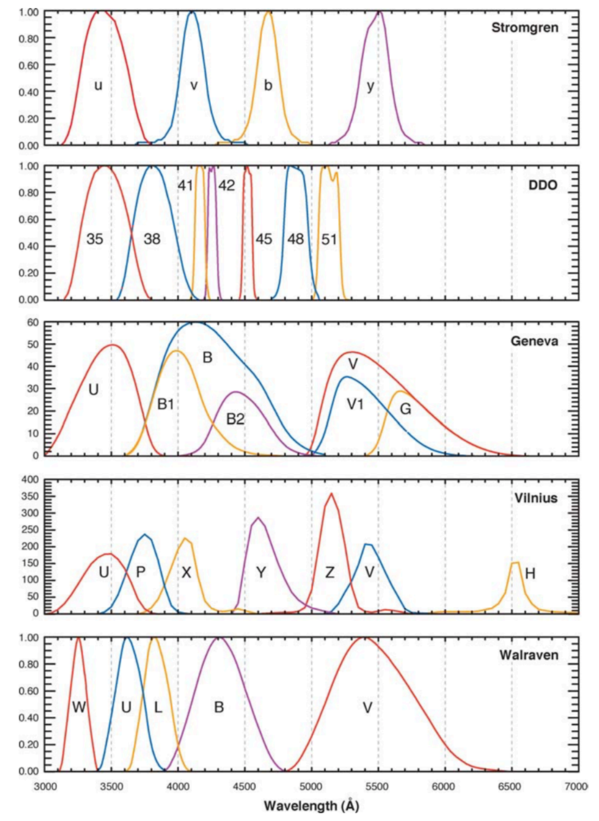
LSST

Choice of filters is somewhat adhoc

Intermediate Band Filters

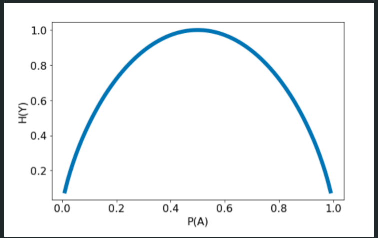
Broad set of filters available and development of interference filters we can define a range of complex filters (e.g. notch or comb filters)





Bessel 2005

Information Theory



- Entropy
  - A measure of uncertainty in an observed variable
  - Maximized when all outcomes are equally probable
  - Minimized when only one outcome is non-zero

$$H(y) = -\sum_i p(y_i) \log_2[p(y_i)]$$

50% 50%

Maximum Entropy 1 bit

90% 10%

Lower Entropy 0.46 bits

100% 0%

Zero Entropy

Information Theory

- Conditional Entropy
  - Amount of entropy in an observation of Y when X = x_j is known
  - How much uncertainty remains about a feature when I make a measurement of a related feature?
  - Example:
    - Y is the probability of illness
    - X is age

$$H(Y|X) \equiv \sum_{i,j} P(x_j) H(y_i|x_j)$$

32% chance of illness

80% < 52 yr.

20% chance of illness

20% >= 52 yr.

80% chance of illness

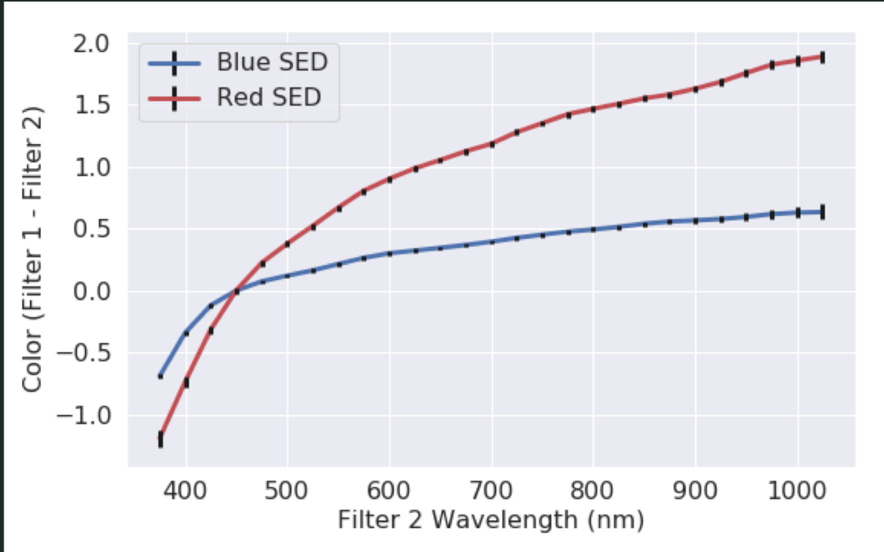
Information Theory

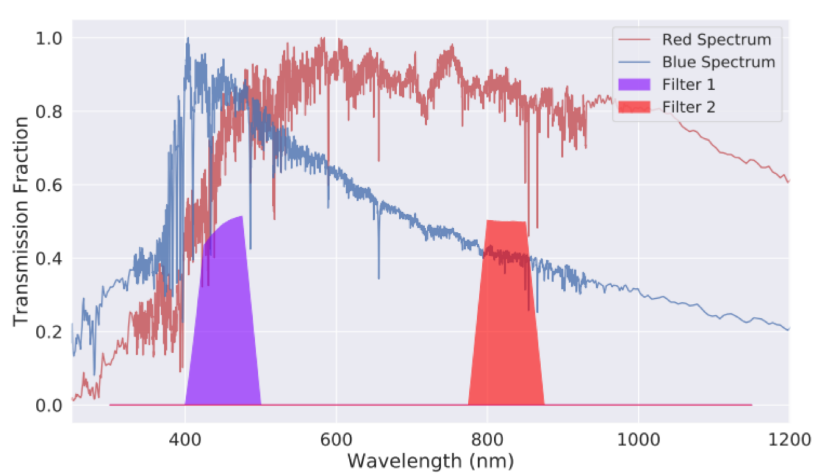
- Information Gain (IG)
  - Difference between total entropy and average conditional entropy
    - Average effectiveness of a measurement X in supplying information about a feature, Y
  - The more information gain we can derive from a measurement of X then the more this measurement reduces our uncertainty in another property Y

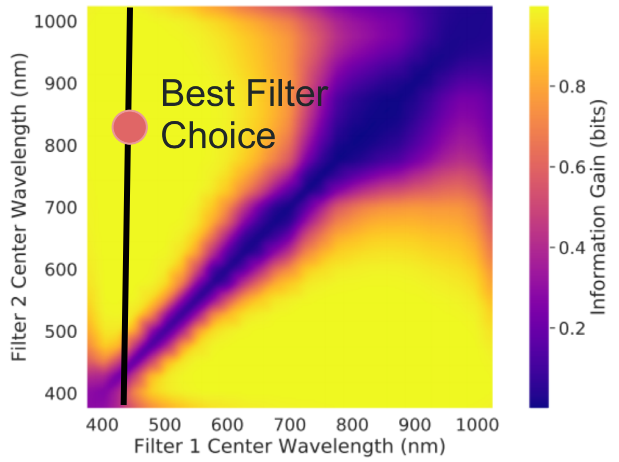
$$IG(Y|X) = H(Y) - H(Y|X)$$

Modeling type given color

- Example 1:
  - Measure colors to distinguish between two types of galaxy spectra







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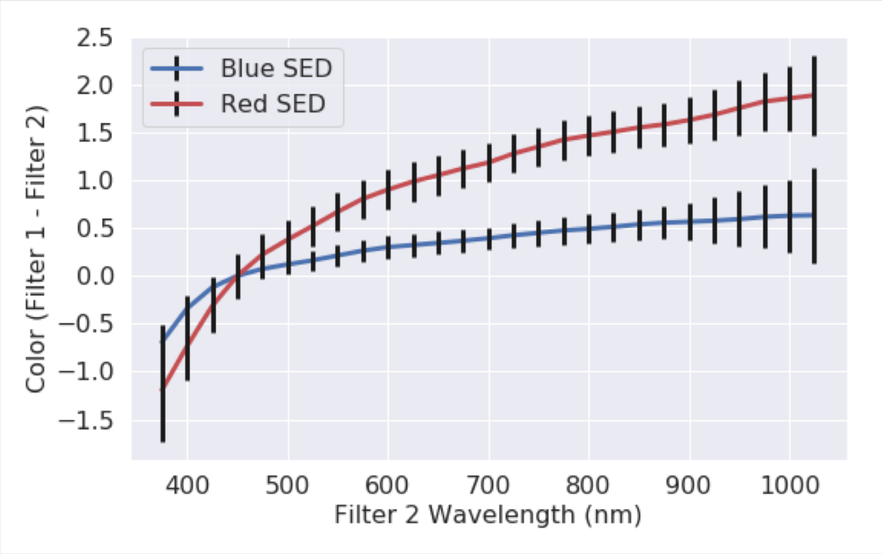
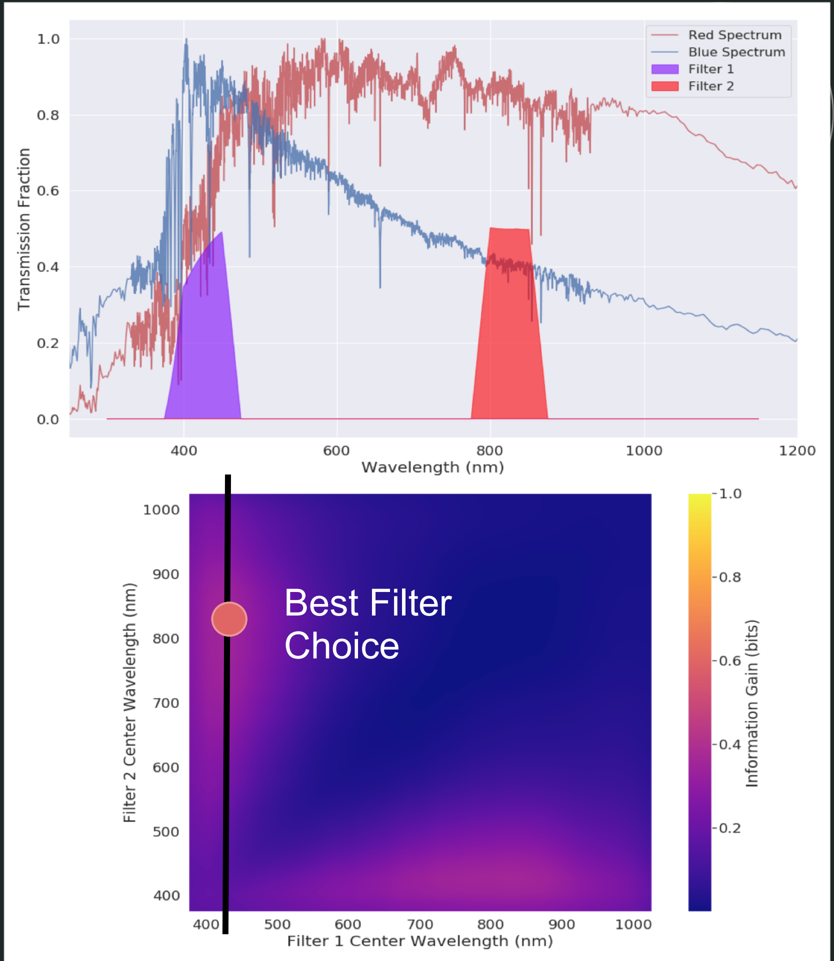
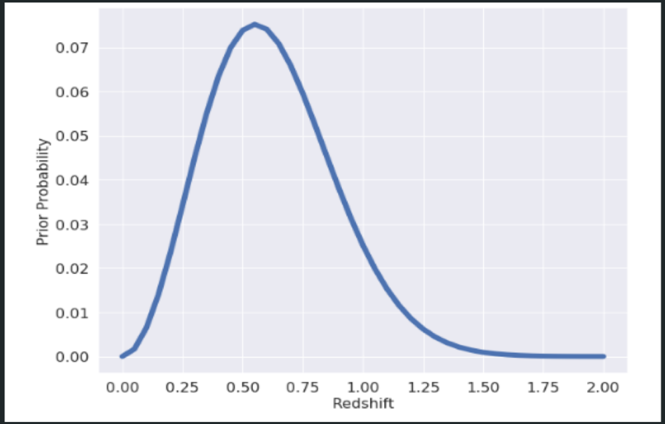
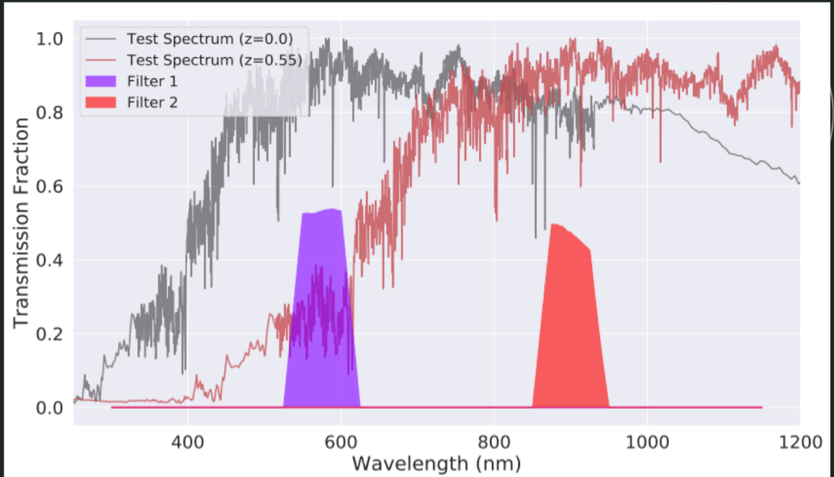


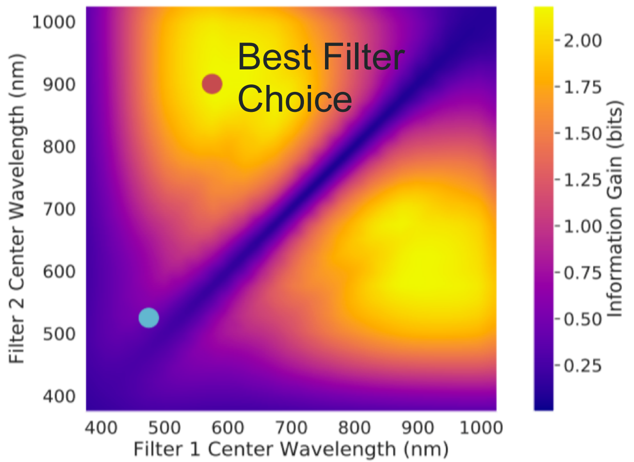


Designing filters for photo-z

- Example 2:
  - Measure IG(Y|X)
    - X is color, Y is redshift
  - Use a realistic galaxy spectrum and prior that peaks at z=0.55

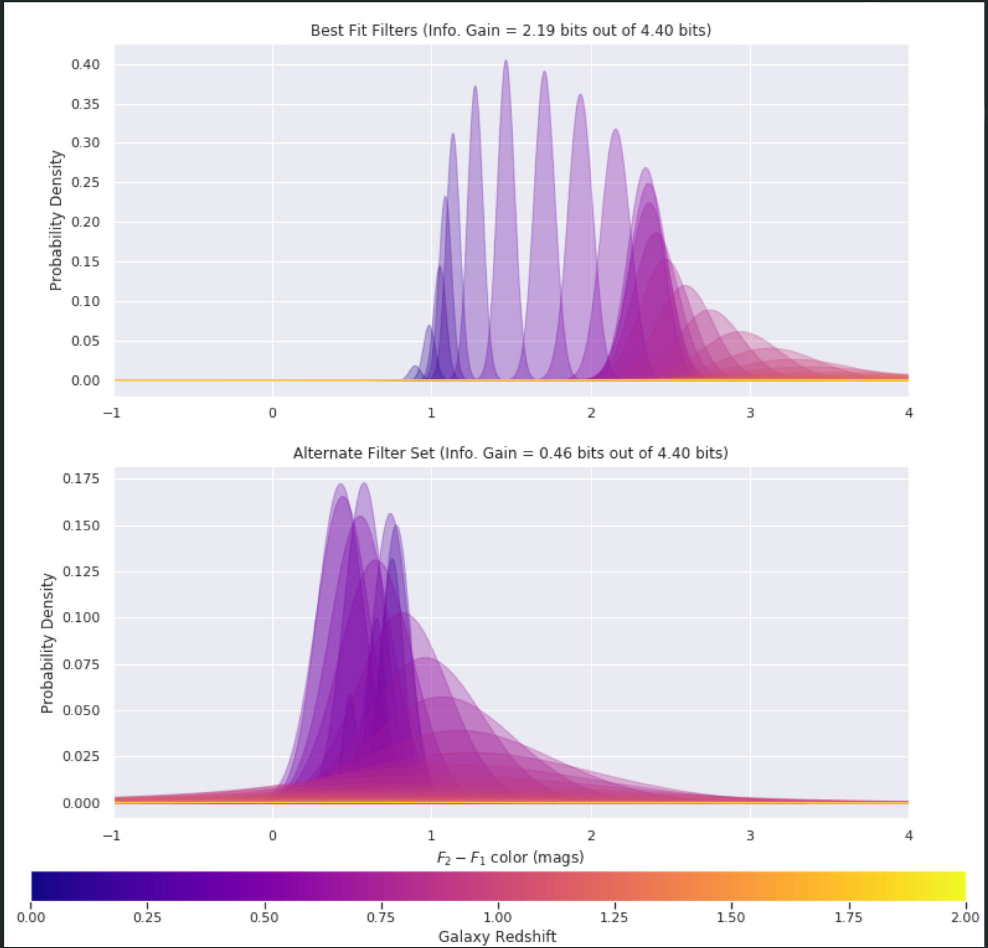






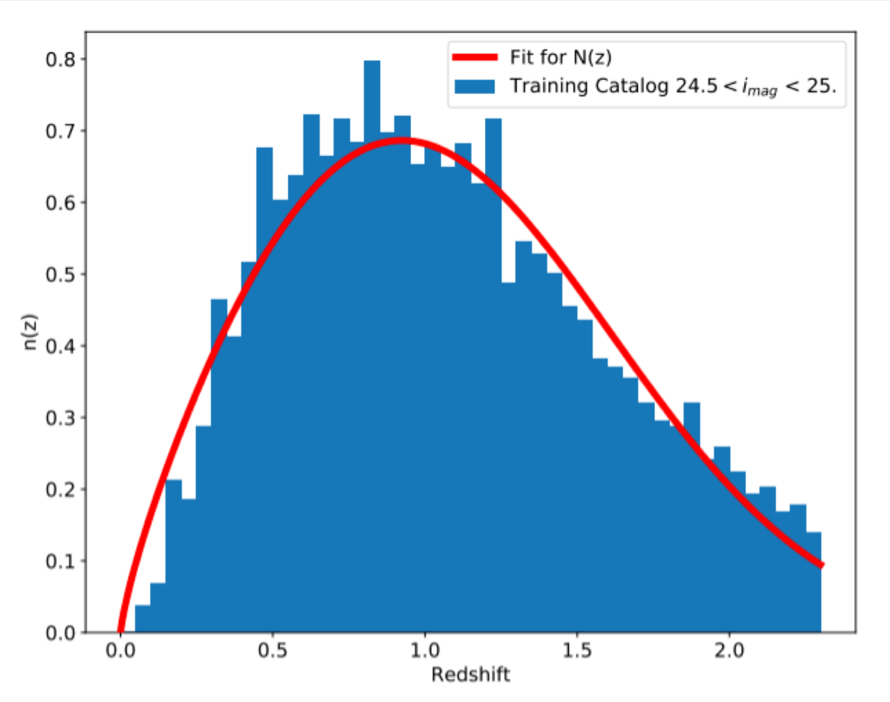
Colors and redshift

- The color distribution is approximated by a Gaussian affected by the signal to noise of the galaxy
- Optimal filters maximize the chance that a galaxy observed with a given color is at a specific redshift
    - Especially for redshifts near the peak of the prior



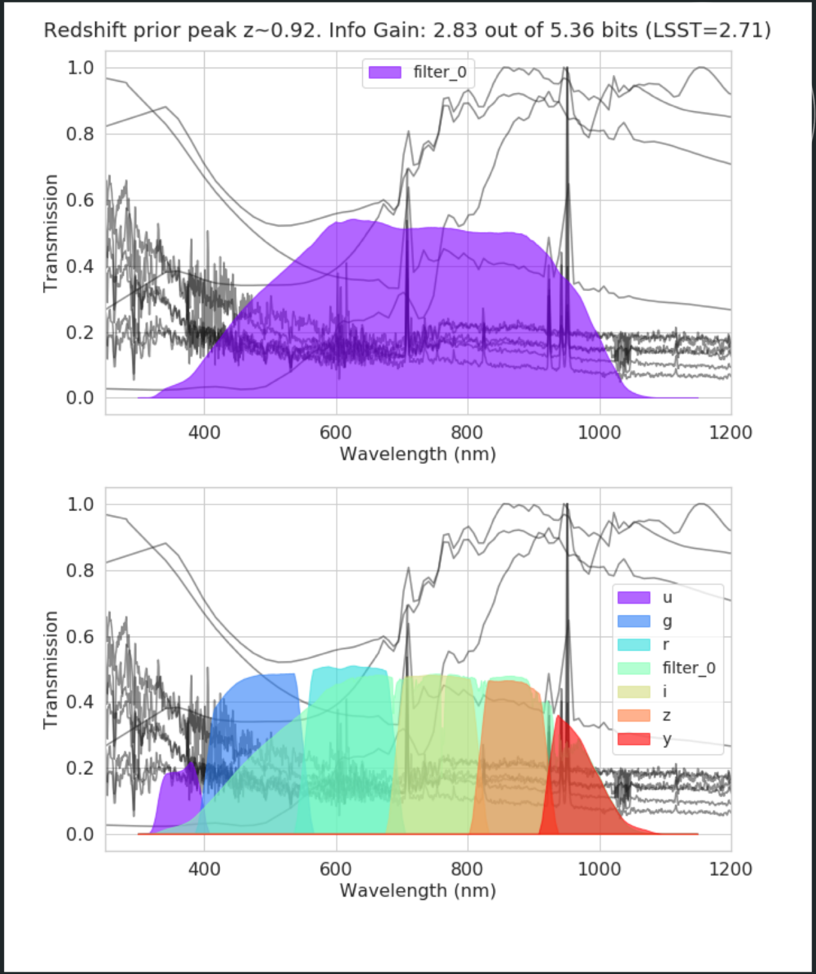
Realistic Experiments

- Calculated galaxy color distributions using 10 templates at 46 redshift bins from $0 < z \leq 2.3$
- Template magnitudes were normalized to $i = 25$
- Used prior appropriate for fainter galaxies



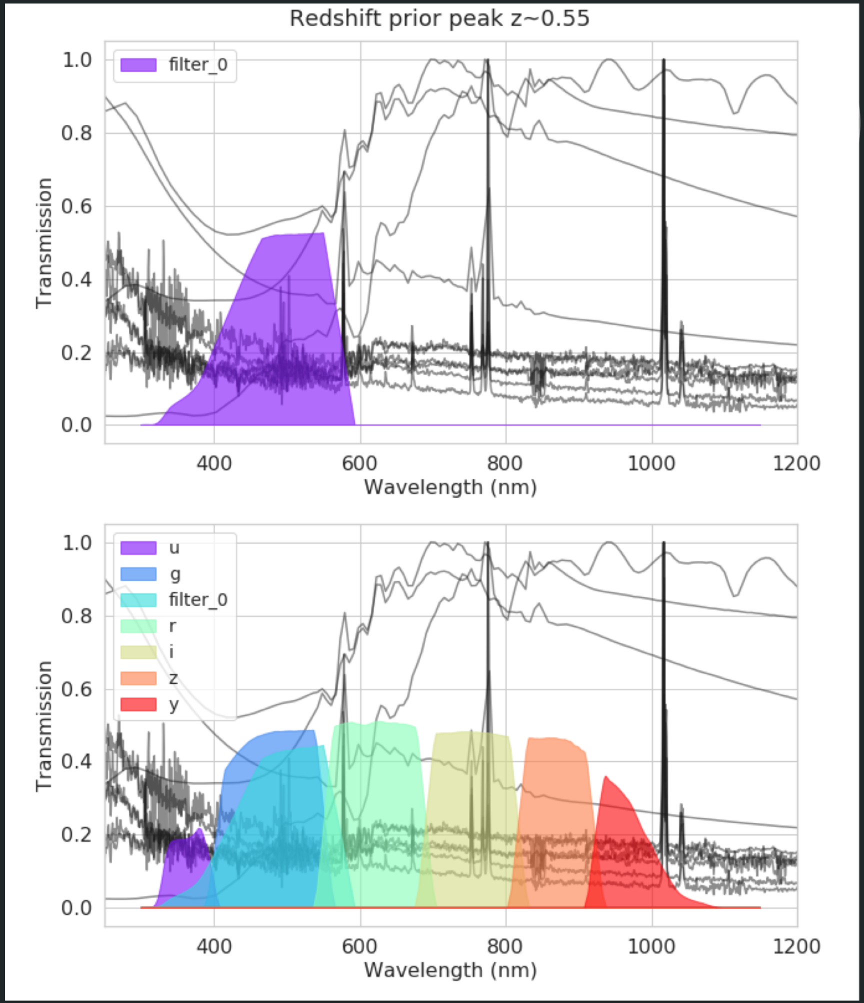
What would you observe after the LSST finished?

- First, looked at optimal 7th filter to add to LSST
- Optimal filter spans the Balmer break near the peak of the prior
- Improves information gain for LSST filters by 4%



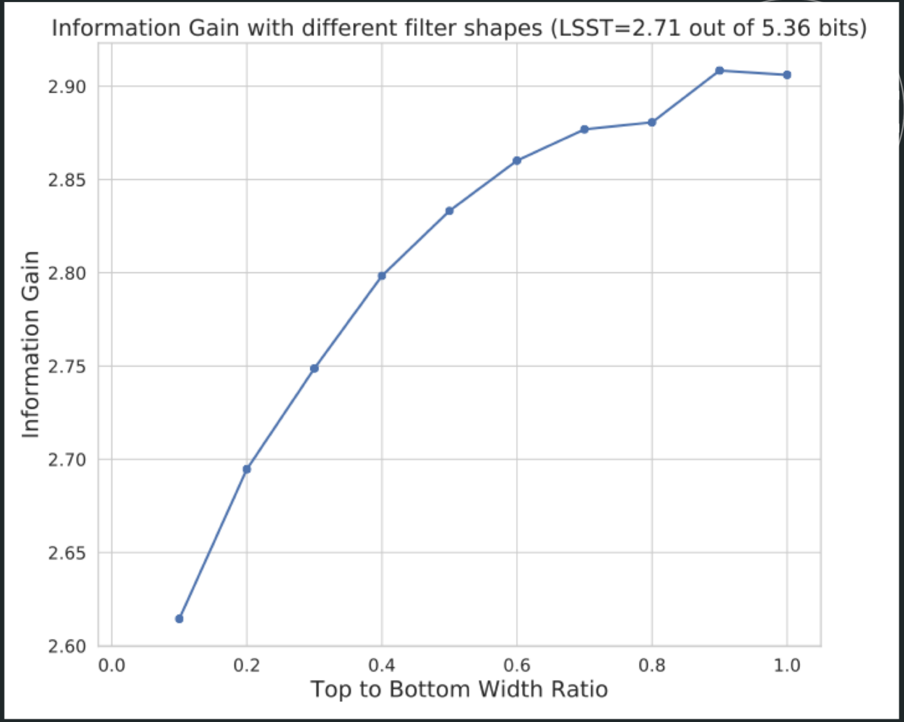
What would you observe after the LSST finished?

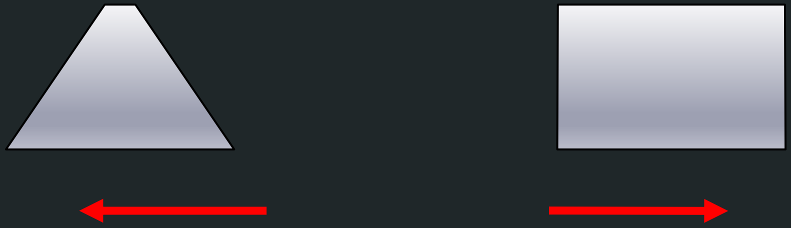
- Changing the prior leads to a change in the filter
  - Remains located near the Balmer break at the peak redshift



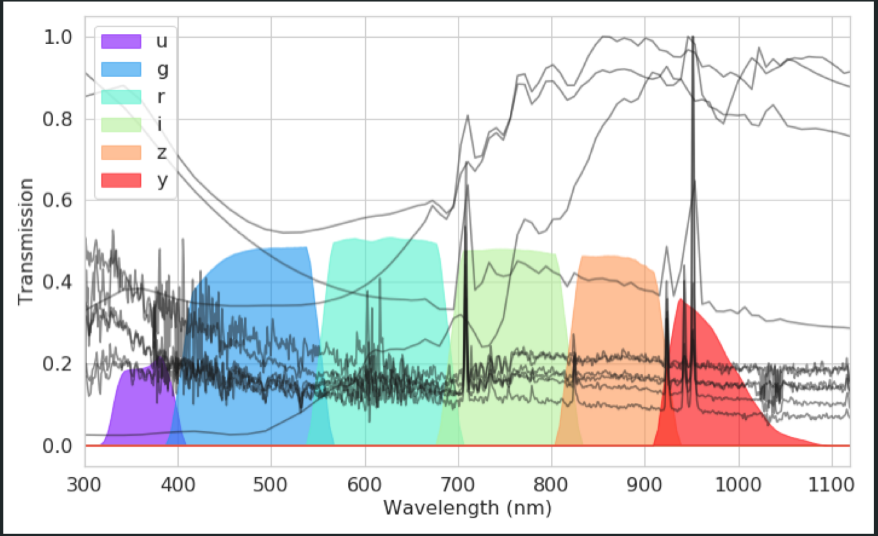
Optimal shape for a filter

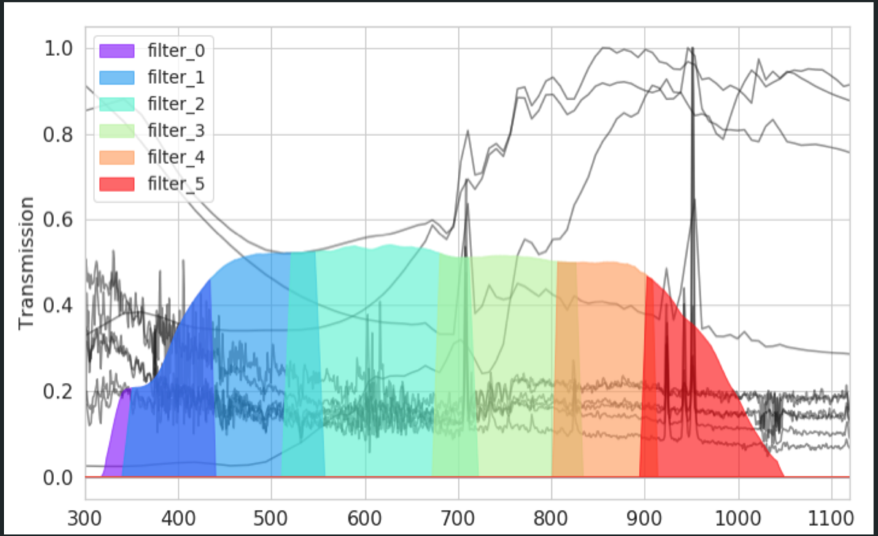
- What shape should a filter have
- Set a fixed ratio between top and bottom width of trapezoidal filters
- Found that more top-hat like filters are better for photo-z





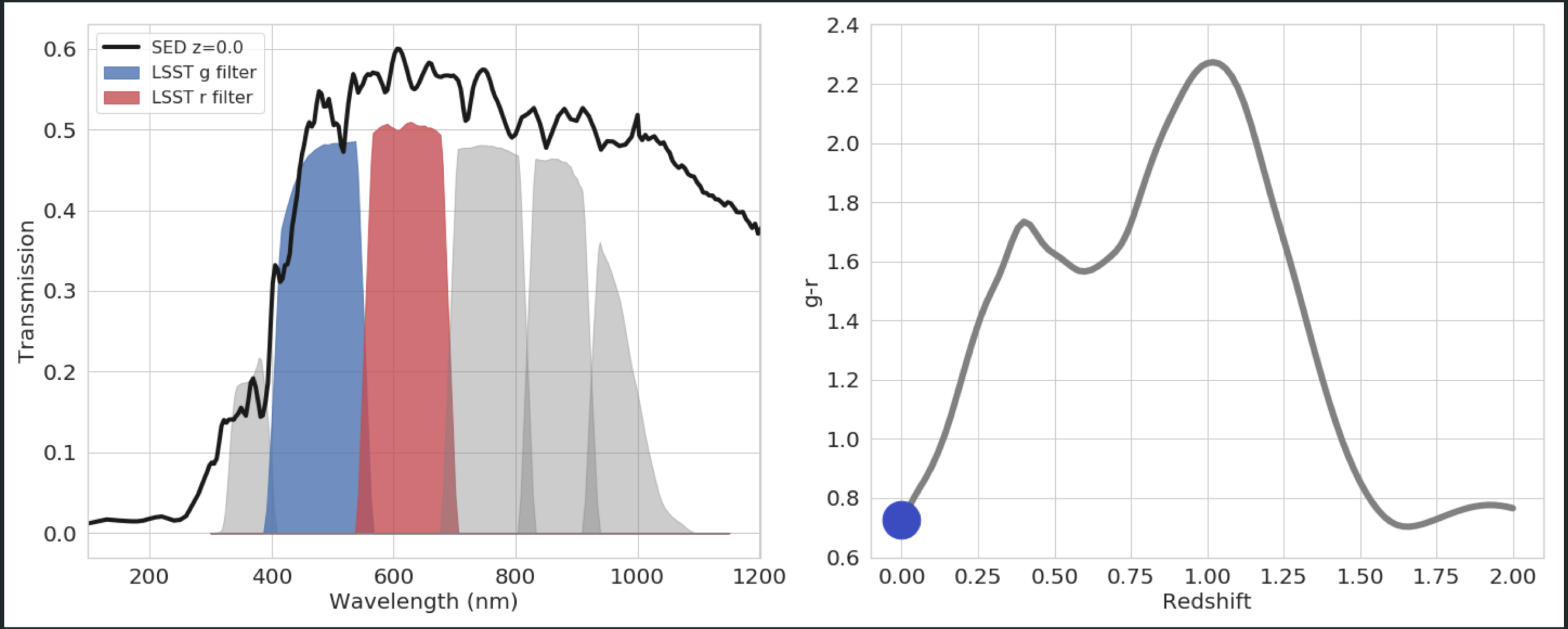
Improving on LSST





Photometric Redshifts (photo-z)

- Photo-Z relies upon features of spectral energy distribution (**SED**) moving through different photometric filters



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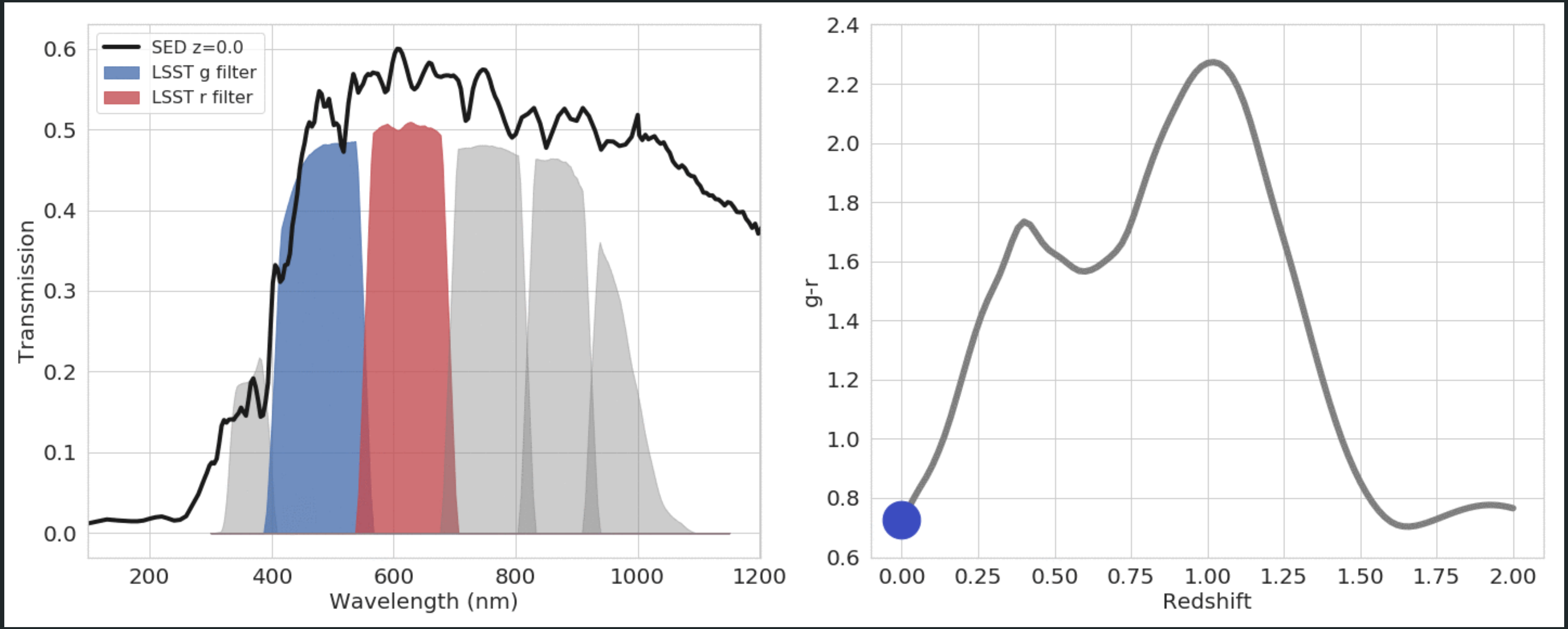
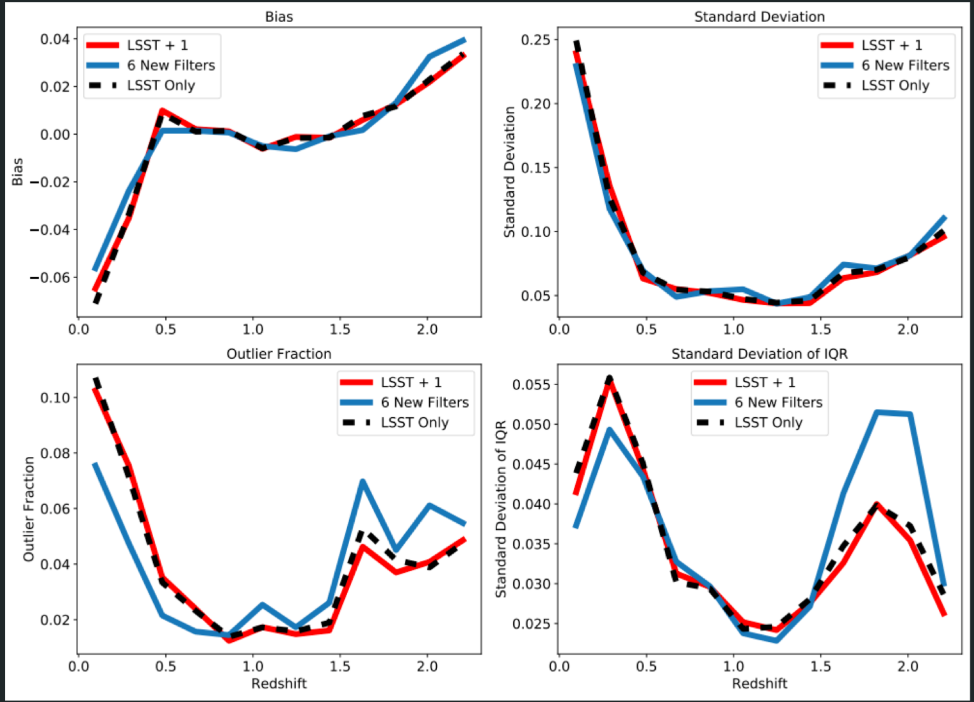


photo-z Testing

- Sample catalog of 245,106 training objects and 50,000 test objects
  - Redshifts: $0 < z \leq 2.3$
- Use Color Matched Nearest Neighbor (CMNN) method (Graham et al. (2018))
  - Returns nearest neighbor in color space measured with Mahalanobis distance
- Compared 4 metrics
  - Bias
  - Standard Deviation
  - Standard Deviation of Interquartile Range (IQR)
  - Outlier Fraction

Application to photo-z

- Used simulated catalogs of galaxy photometry with different filter selections



Where next?

- This can be applied to stellar colors or any distribution
- Build and optimize a series of comb filters (>dimensions)
- Integrate near-infrared filters with the LSST

- ...we also find asteroids