# UKIRT Microlensing Survey as a Pathfinder for WFIRST

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## A Near-IR Survey with UKIRT

I-band microlensing surveys



OGLE



MOA



**KMTNet** 

#### near-IR microlensing surveys



#### UKIRT 3.8m NIR telescope @ Mauna Kea



WFIRST

## UKIRT 2015-2016 microlensing surveys

#### 2015 survey - Spitzer:

- Area: 3.4 deg<sup>2</sup>
- Duration: 39 nights
- Cadence: 5 epochs/night
- Total epochs per field: ~145
- Filter: H

#### 2016 survey - K2C9:

- Area: 6.0 deg<sup>2</sup>
- Duration: 91 nights
- Cadence: 2-3 epochs/night
- Total epochs per field: ~160
- Filter: H



Shvartzvald et al. 2017

## UKIRT 2017-2019 microlensing survey

#### 2017-2019 survey – WFIRST:

- Area: 10.5 deg<sup>2</sup>
- ~20 million lightcurves
- Duration: ~4 months / season
- Cadence: 1-3 epochs / night
- Filters: H & K



## UKIRT 2017-2019 microlensing survey

#### 2017-2019 survey – WFIRST:

- Area: 10.5 deg<sup>2</sup>
- ~20 million lightcurves
- Duration: ~4 months / season
- Cadence: 1-3 epochs / night



## **By-Eye Results**

Unfortunately we cannot completely escape from by-eye analysis. The computer has to learn from the labeled examples we provide.

- We start with an event finder similar to KMT (Kim et al. 2018), based on a 2-D (t<sub>0</sub>, t<sub>eff</sub>) grid search
- Manual UKIRT Lightcurve Evaluator (MULE) a python-based GUI to assist with the by-eye vetting of lightcurves

We look at everything with  $\Delta \chi^2 > 500$ .

- 2015: 23 events (out of 562)
- 2016: 65 events (out of 844)
- 2017: 177 events (out of 2852)
- 2018: 83 events (out of 843)



#### **UKIRT** microlensing events

2015: 23 events
2016: 65 events
2017: 177 events
2018: 83 events



## **Detection efficiency**

There is no way to calculate detection rates from a by-eye selection. Detection efficiency must be calculated based on some well-defined selection criteria – either machine learning or strict cuts.

Detection efficiency is calculated via simulated event injection/recovery.

- Inject events using PSF templates from PSFEx
- Run through full pipeline, including machine learning event detection
- Repeat for many stars, covering parameter space











## Machine Learning for Event Detection

Machine learning has the potential to improve

- efficiency in detecting events
- consistency in detecting events

This is particularly true for larger datasets (WFIRST). Meanwhile we are using UKIRT analysis as a pathfinder.

Goal 1: Save time in detecting microlensing events

Goal 2: Enable robust, efficient detection statistics

(cf. Wyrzykowski+ 2015: machine learning for OGLE data)

#### Machine-Learning Event Detection

How well do we do, compared to by-eye selection?

Only a modest increase in the number of events detected  $(177 \rightarrow 200)$ .

A handful of the original detections were missed by the machine learning scheme.

There were 26 false detections (variable stars that look similar to microlensing events).

(cf. OGLE; Wyrzykowski+ 2015)



## Machine-Learning Detection Efficiency

Injections of events into images are in progress. Meanwhile we are injecting events directly into light curves.



 $\rightarrow$  up to 60% detection efficiency

This is very high, particularly when considering the limitations of the UKIRT dataset (just 2 short seasons).

#### Near-IR event rate

#### Preliminary results:

- 1. High event rate in the central fields
- 2. No excess of events in the northern bulge



## **Additional Science**

#### <u>2015:</u>

• A massive remnant in wide binary:

OGLE-2015-1285 (Shvartzvald et al. 2015)

#### <u>2016:</u>

• Planets:

MOA-2016-227 (Koshimoto et al. 2017) OGLE-2016-0163 (Han et al. 2017) OGLE-2016-1190 (Ryu et al. submitted) OGLE-2016-0241 (Poleski et al. in prep.)

#### <u>2017:</u>

Planet:

OGLE-2017-0173 (Hwang et al. 2017)





#### UKIRT-2017-BLG-001b (Yos-1)



### **Differential Extinction**

Differential extinction reduces the accuracy of source star determination, e.g. UKIRT-2017-BLG-001Lb (Shvartzvald+ 2018), with clump color dispersion = 0.16 mag (cf. 0.04 mag intrinsic) and clump magnitude dispersion = 0.35 mag (cf. 0.17 mag intrinsic)





### Summary

The UKIRT microlensing survey is serving as a precursor for WFIRST by

- mapping the microlensing event rate
- identifying regions with high differential extinction
- developing analysis tools (e.g. machine learning)
- enabling hands-on experience for new microlensers (e.g. me)

Beyond microlensing, the survey data is available for

- variable stars
- outlier events
- extinction maps
- Galactic structure
- etc.

## **Public Lightcurves**

2015-2018 lightcurves are available online (78M independent lightcurves for ~35M sources)

Standard NExScI archive tools for selection, sorting, visualization, etc.

Flagging of known events; cross-matching with OGLE/MOA microlensing surveys.



https://exoplanetarchive.ipac.caltech.edu/docs/UKIRTMission.html

https://exoplanetarchive.ipac.caltech.edu/cgi-bin/TblSearch/nph-tblSearchInit?app=ExoTbls&config=ukirttimeseries



# Scientific goals of UKIRT survey

#### NIR event rate as a function of (*I*,*b*):

- Crucial for WFIRST field optimization
- Combined with dust models  $\rightarrow$  Galactic structure

#### Event timescale as a function of (*l,b*):

• Bulge-bulge events are expected to be shorter (Gould 1995)

#### NIR coverage of events:

- Source color for Einstein radius (with finite source effects)
- NIR source flux for future AO lens flux measurements

#### New science:

• High cadence (daily) observations of unexplored regions (Galactic center).

#### **Target Field Selection?**

- 1. data reduction
- 2. microlensing event identification
- 3. completeness correction
- 4. updated galactic model / incorporation into mission yield simulations
  5. WFIRST target field selection
  - event rate map
  - differential extinction
  - overlap with ground-based surveys / potential ground-based follow-up

## Extinction

- Median H-K reddening within 20-arcsec pixels.
- High extinction is a problem for visible-light observations.



### **Differential Extinction**

 Based on CMD within 3-arcmin pixels, using David Nataf's code to find spread of the red clump.



#### **Application to Binaries**

The machine learning classifier has been optimized to identify single-lens-single-source events. *What about binaries?* 

Detection efficiency decreases for highly anomalous light curves, but not by much -~10% reduction for q=0.1

Most importantly, this selection effect can be quantified and corrected.



## Step 3: Pick a Classifier

A complicated N-dimensional space has to somehow be divided into different categories (microlensing, variable, artifact, etc). There's lots of options here:

nearest neighbor, support vector machine, gaussian process, decision tree, random forest, neural net, AdaBoost, naive Bayes,... We find that **random forest** is fast and accurate within our training set.



microlensing fit

blue=microlensing events; red=other variables

## **Step 2: Feature Selection**

#### Class: Movies you like

Movie features:

- length of movie name
- director
- genre

**Class: Microlensing event** 

Light curve features:

- flux, dispersion
- # of obs., # of successful obs.
- $\chi^2$  for microlens curve, flat line, sloped line, sinusoid, drop 1 or 2 pts.
- $\Delta \chi^2$  between those fits
- fit parameters and error bars for each fit
- time of event relative to observing window
- random numbers (for testing purposes)
- $\rightarrow$  The classifier will tell you the ranked importance of each.

### Goal 1: Efficiently Detect Events

How well do we do, compared to by-eye selection?

The random-forest classifier provides a microlensing probability for each lightcurve. These probabilities are not well calibrated, but they are meaningful relative to each other.

Normally we count an event as microlensing if the probability is >50%.

By varying this threshold, we can make a more conservative or more liberal selection.



## Machine learning vs traditional selection

# machine learning can give40-60% detection efficiency

an example of deterministic cuts with 10-20% detection efficiency



It is impossible to do a self-consistent comparison with OGLE/MOA. Instead, we are working on a UKIRT vs UKIRT comparison, machine learning vs deterministic cuts. (w/ advice from Przemek).

#### UKIRT-2017-BLG-001: Extinction



### UKIRT-2017-BLG-001: Extinction

#### Lessons for WFIRST

- Red clump color dispersion:  $\sigma_{(H-K_S)}=0.16$ 
  - Intrinsic = 0.04
  - Reddening = 0.15
- Dust scale height = 120pc (0.86°@8kpc)
- Red clump magnitude dispersion:  $\sigma_{K_S}$ =0.36
  - Intrinsic = 0.17
  - Extinction = 0.17
  - DM = 0.28!
- Thin disk scale height = 300pc (2.1°@8kpc)





## UKIRT-2017-BLG-001: Extinction

#### Lessons for WFIRST

- Limitations of one season
- Estimation of  $\theta_*$ 
  - ...and thus physical properties
- Far disk population
- Possible solutions:
  - Multi-band information
  - Avoid high spatial differential extinction fields
  - •>1° off the plane?



