Application of Compressive Sensing to Gravitational Microlensing Data
- and -
Implications for Miniaturized Space Observatories

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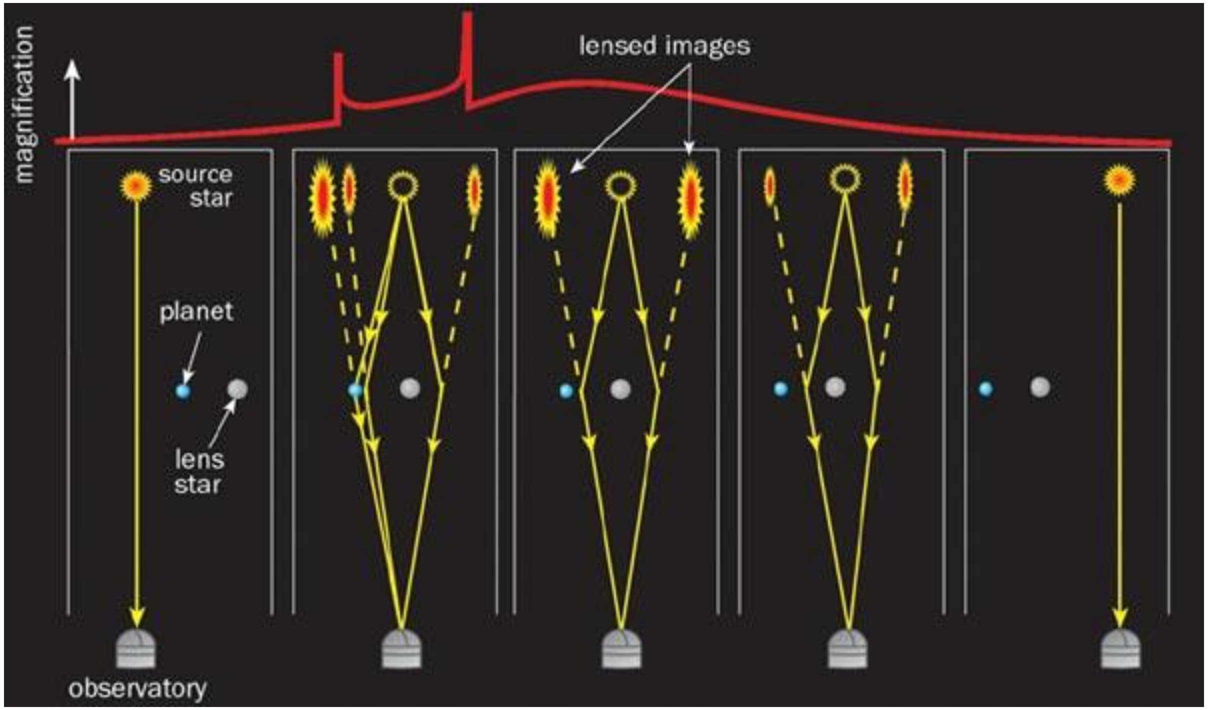
Outline

- Gravitational Microlensing
- Compressive Sensing (CS) Motivation
- Compressive Sensing (CS) Theory
- Single Lens Microlensing Events
- Simulation Results
- Conclusion and Future work

Gravitational Microlensing

- Technique to detect exoplanets and other astrophysical entities



Credit: Space Telescope Science Institute

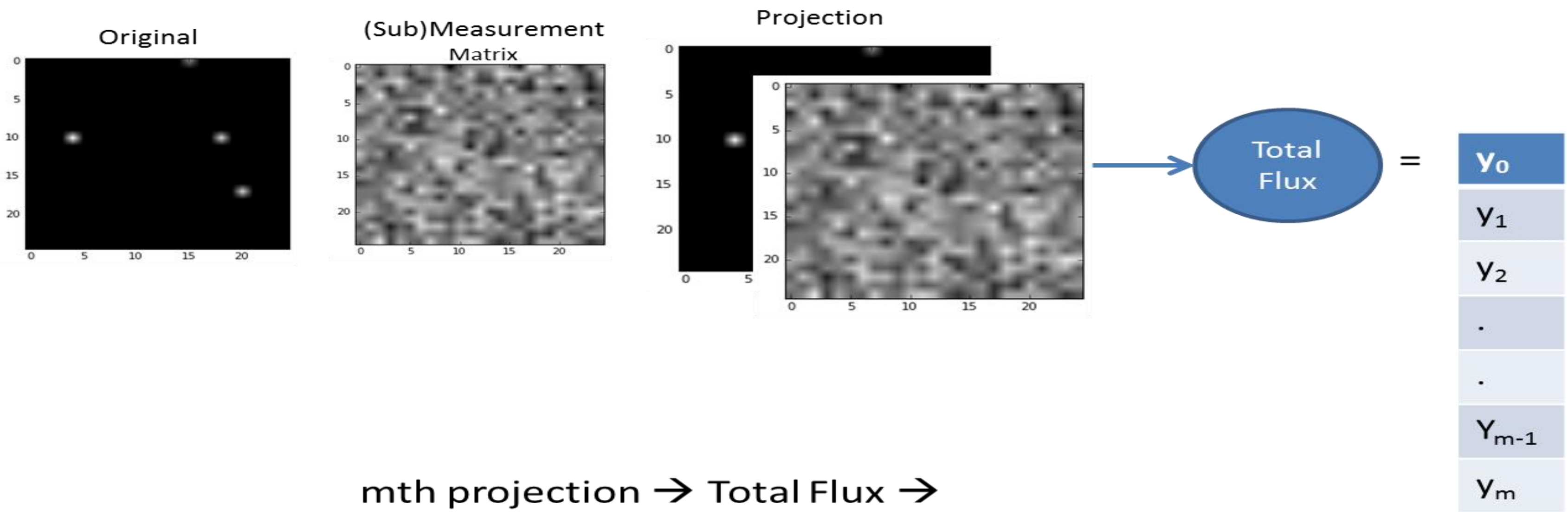
Current Techniques Limitations

- High rate sampling required to acquire the desired resolution
  - Miniaturized space observatories: Data bandwidth limitation
- Need high cadence for acquiring each image
  - If high cadence is not achieved, an exoplanet transition with a short period can be missed
- Miniaturized space observatories have power and on-board memory limitation
- **How do we achieve high resolution images at a high cadence by acquiring only a few samples?**

Compressive Sensing (CS) Motivation

- Acquiring each image pixel individually (sampling at the Nyquist rate) is wasteful when the information can be encoded in only a select few samples due to its sparse nature
- Exploit sparsity in images
- Microlensing Events are sparse in spatial domain when differenced
  - That is, at any given time only the stars exhibiting a microlensing event vary in flux
  - Only those stars are evident when differenced with a reference image

CS Theory



- Each sub measurement matrix gets transformed into a 1D signal representing a row in the measurement matrix.
  - M sub measurement matrices
- Reconstruct original image, given y vector and the associated (sub) measurement matrix for each element in y
  - $Y_{mx1} = \Phi_{mxn} x_{nx1}$
  - Optimization (L1 minimization) and greedy algorithms
- A unique solution is obtained only if the original image is sparse in some domain

Single Lens Microlensing Events

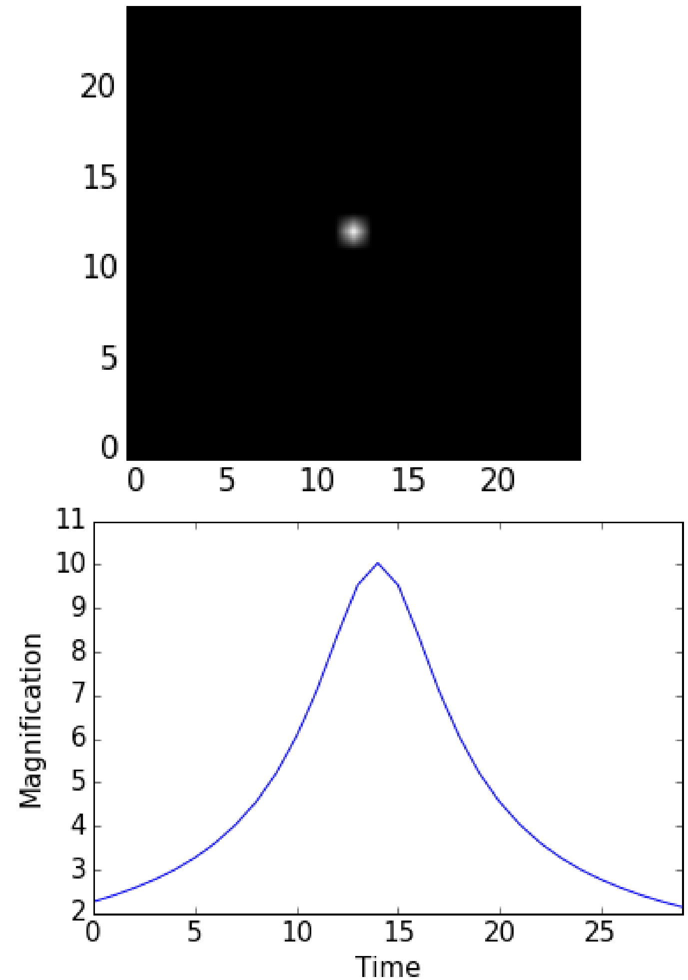
-Source star magnification only due to lensing star

-Magnification at each time is dependent on:

u_0: lens-source separation in terms of Einstein's ring radius

t_0: peak magnification time

t_e: Einstein's ring radius crossing time



Top: Original spatial domain image at time, t = 0
Bottom: Original time domain image with magnification at center pixel plus a 3 pixel radius

Simulation Setup

All Simulations are performed in **Python**

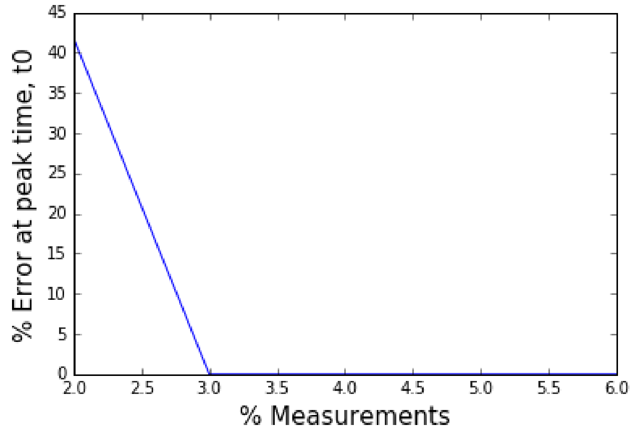
Gravitational Microlensing Parameters

- Single lens event
- $u_0 = 0.1$
- Total 30 time samples
  - Peak magnification at time value = 14
  - Einstein's ring crossing time at time value = 29

CS Parameters

- Image size = 25x25
  - N = 25x25 = 625 pixels
- Measurements, M, is varied from 2% of N to 6% of N
  - $\% \text{ Measurements} = \frac{M}{N} \times 100$
- Sparsity: number of non-zero (or significant value) pixels = 1
- Measurement matrix, : Bernoulli Random with 0's and 1's
  - 100 Monte Carlo simulations to vary measurement matrix each time

CS Reconstruction

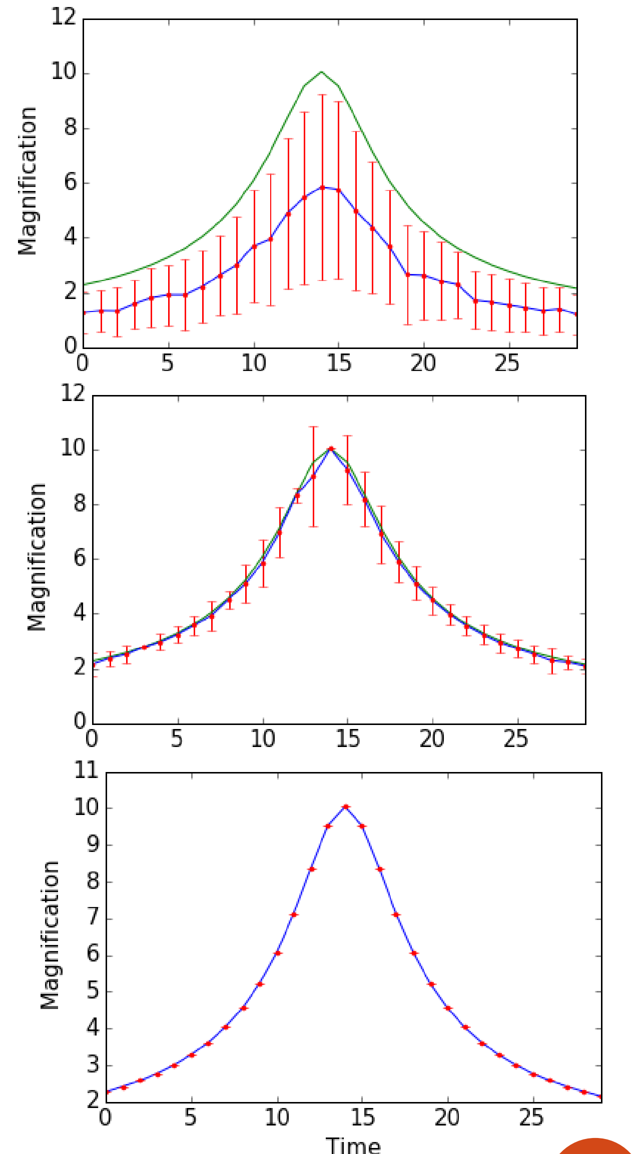


% Error at t0 over center pixel with 3 pixel radius

% Measurements = $\frac{\#\ of\ measurements}{\#\ of\ total\ pixels}$ x 100

Green: Original signal
Blue: Reconstructed signal
Red: Error bars

Top: 2% measurements
Middle: 3% measurements
Bottom: 4% measurements



Resolution Accuracy

% Measurements $\frac{M}{N}$ x 100	Error Difference in Reconstruction at t_0	Average Standard deviation over all t
2	4.19	1.6
3	0.00009	0.52
4	0.00013	0.00096
5	0.00013	0.00078
6	0.00016	0.00073

- Change in magnification at peak time, t_0, is 0.5 units of flux
  - **Resolution error << 0.5 to capture changes in microlensing curve**
- **4% of N measurements gives optimal error**, along with a low standard deviation, providing lower uncertainty

Conclusions and Future Work

- For a clean image, with very low sparsity, only 4% of Nyquist rate samples are required to reconstruct the image
  - **Significant reduction in data volume and power**
  - **Greatly benefit space flight observatories**
- Future work will include studying
  - Point spread functions and its implications for CS
  - Dense, crowded field images
  - Difference imaging for CS applications
  - Binary lens systems

Acknowledgement

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References

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- [3]S. Seager and R. Dotson, *Exoplanets*. Tucson: University of Arizona Press, 2010.