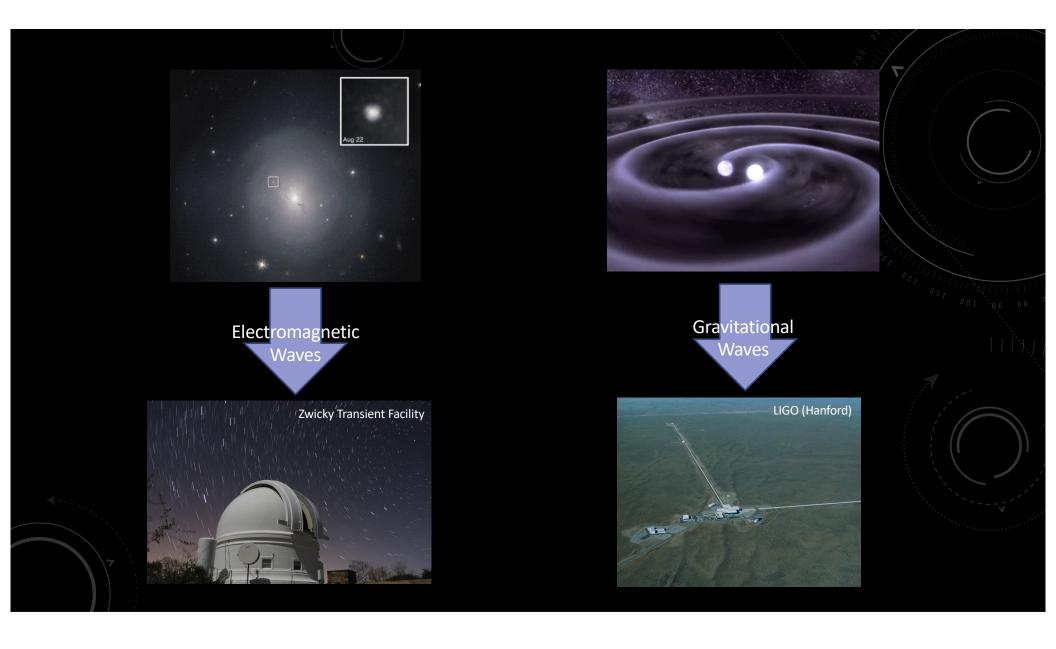
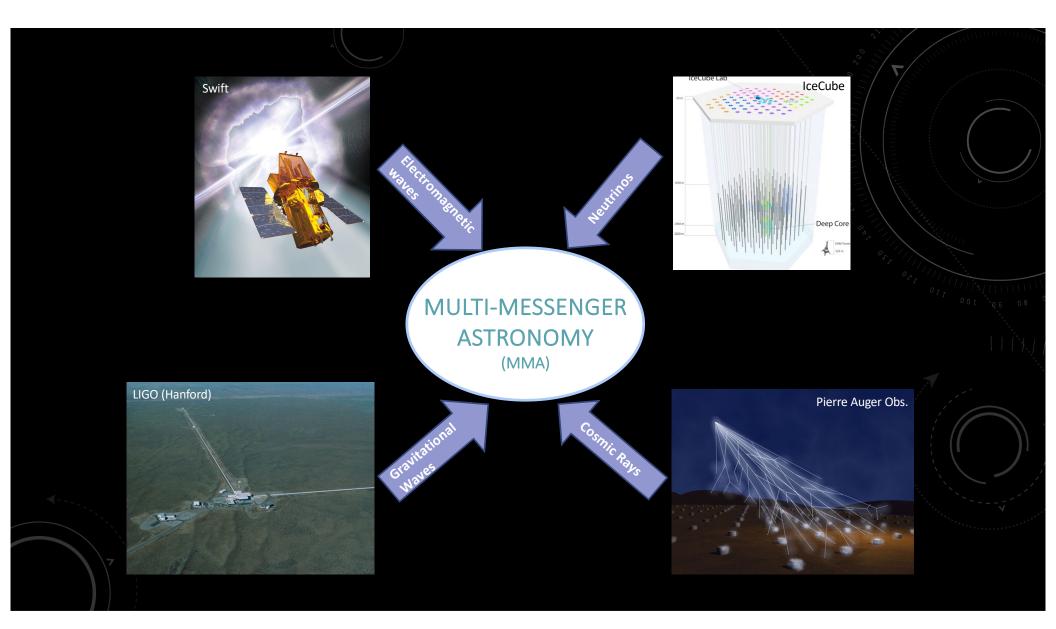
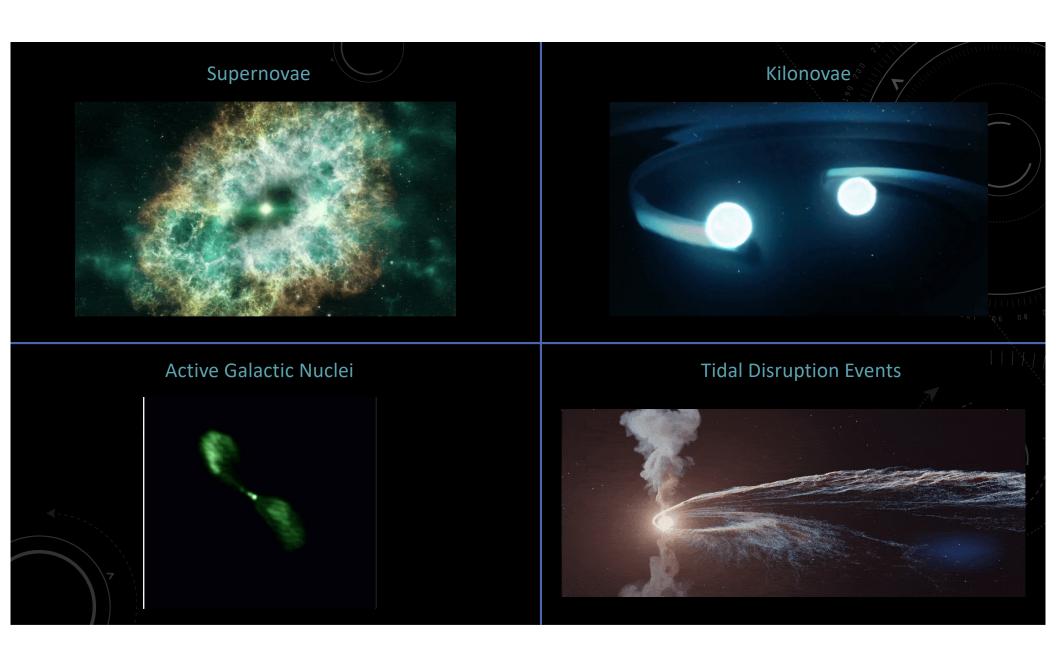
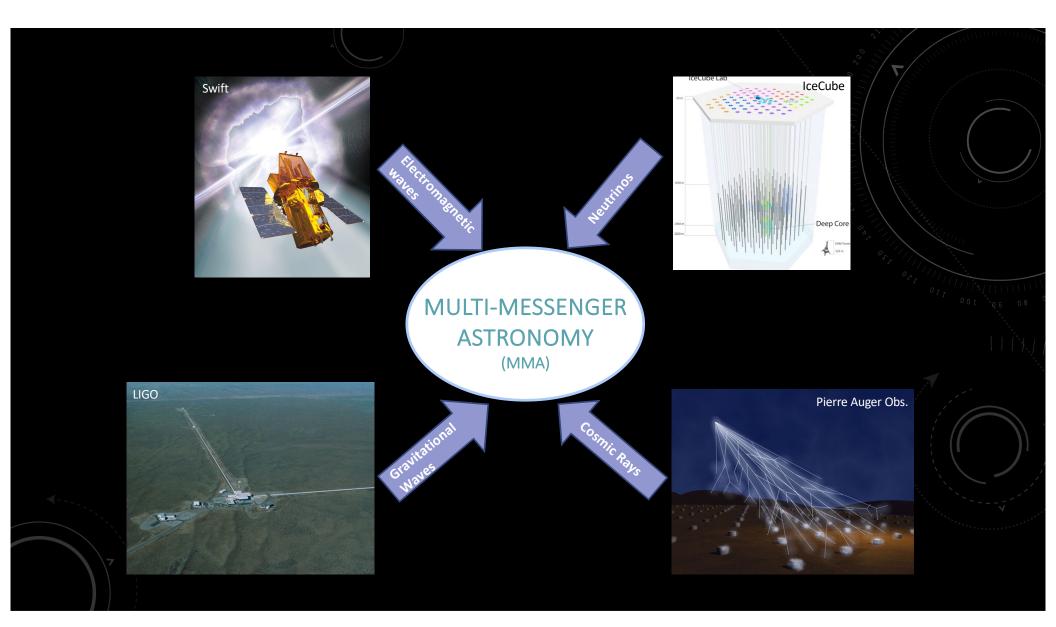
AUTONOMOUS REAL-TIME DECISION-MAKING IN THE ERA OF MULTI-MESSENGER ASTRONOMY

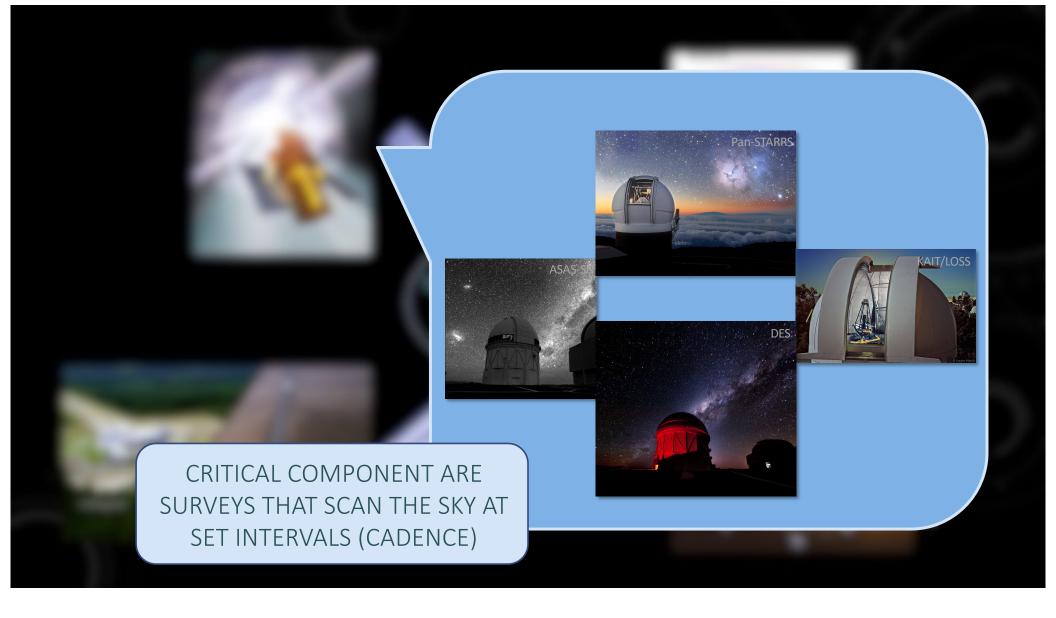
NIHARIKA "ARI" SRAVAN DREXEL UNIVERSITY





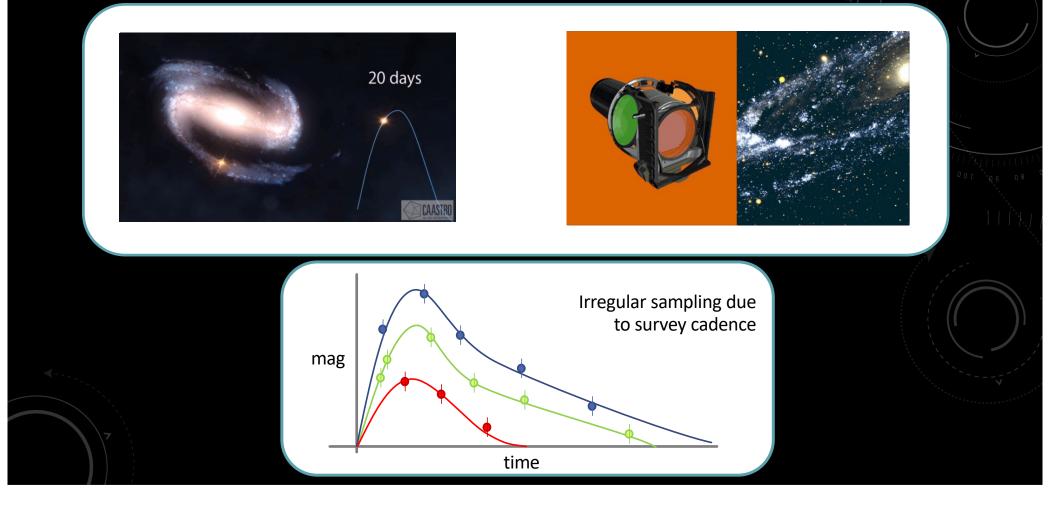






MULTI-COLOR LIGHT CURVES

(MULTI-CHANNEL TIME SERIES)



RUBIN OBSERVATORY



- #1 flagship of US community, recommended by National Research Council since 2010, jointly funded by NSF and DOE
- Ten year survey (LSST) starting 2026
- ~ 10 million alerts/night or 20TB per night
- Broadcast worldwide within 60s
- 37 billion light curves
 - 6 filters (u,g,r,i,z,y or 320–1050 nm, 3 day cadence)





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ZWICKY TRANSIENT FACILITY

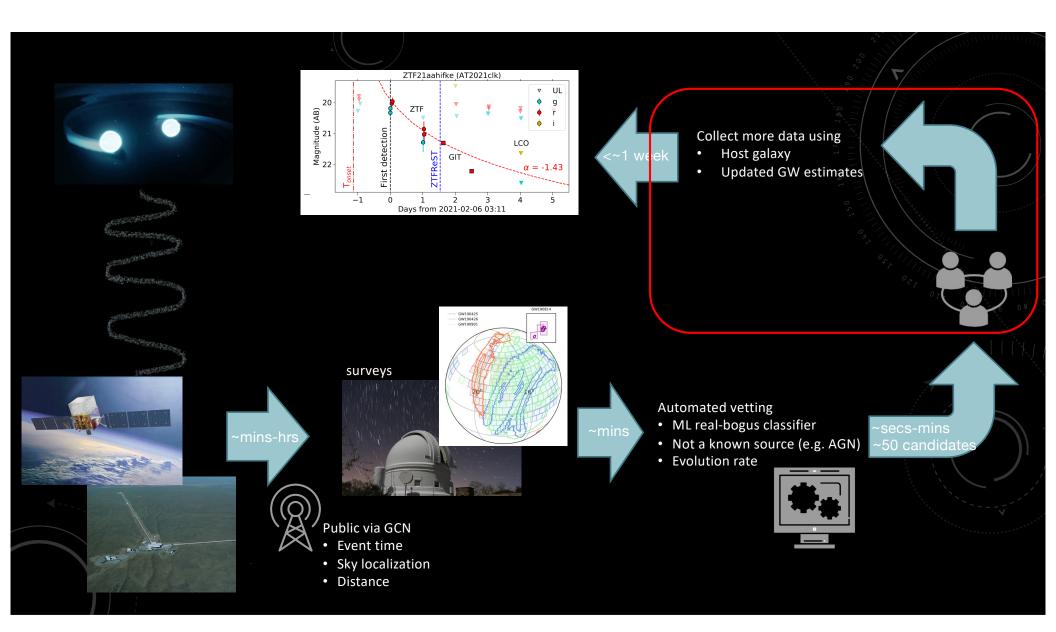


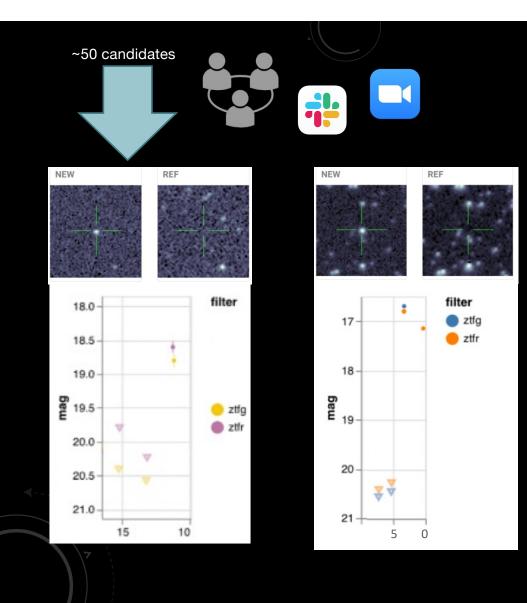
- Pathfinder to Rubin especially for transients
 - Operating at 10% Rubin scale
- Alerts broadcast within ~20 mins
 - Only survey with public real-time alerts
- 2 billion light curves and counting...
 - public survey in 2 filters (g,r, 2 day cadence)

private-partnership in i (+ other programs)

MULTI-MESSENGER SCIENCE

CURRENT PROTOCOLS AND LIMITATIONS





- Use limited resources to acquire more information to:
 - Identify the event
 - True event prob < 0.05
 - Maximize constraints on interesting light curve physics
- Additional follow-up is critical!
- Classifiers don't answer what to do next and how to adapt

Process needs to be:

- ✓ Free from fatigue/bias
- ✓ Low-latency
- ✓ Scalable

BY MID 2023

LVK will operate at twice the sensitivity

- 50-250 detections a year compared to 20 last time
- Localizations will not improve by much

BY LATE 2025

Rubin will come online and produce 10x as many candidates for human experts to analyze

Follow-up resources will not increase at nearly the same rate

Current protocol not sustainable or suitable to get at statistics

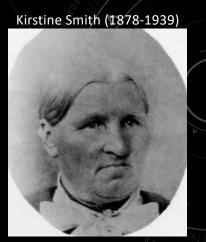


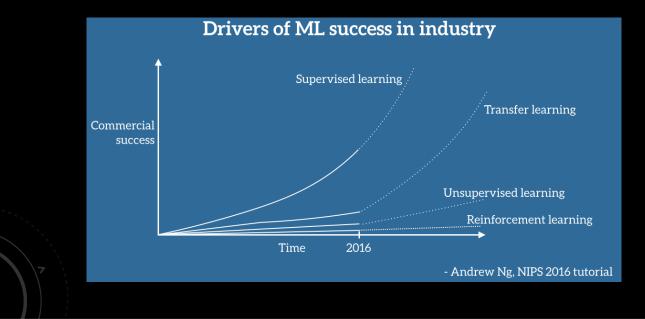


AUTONOMOUS REAL-TIME DECISION-MAKING

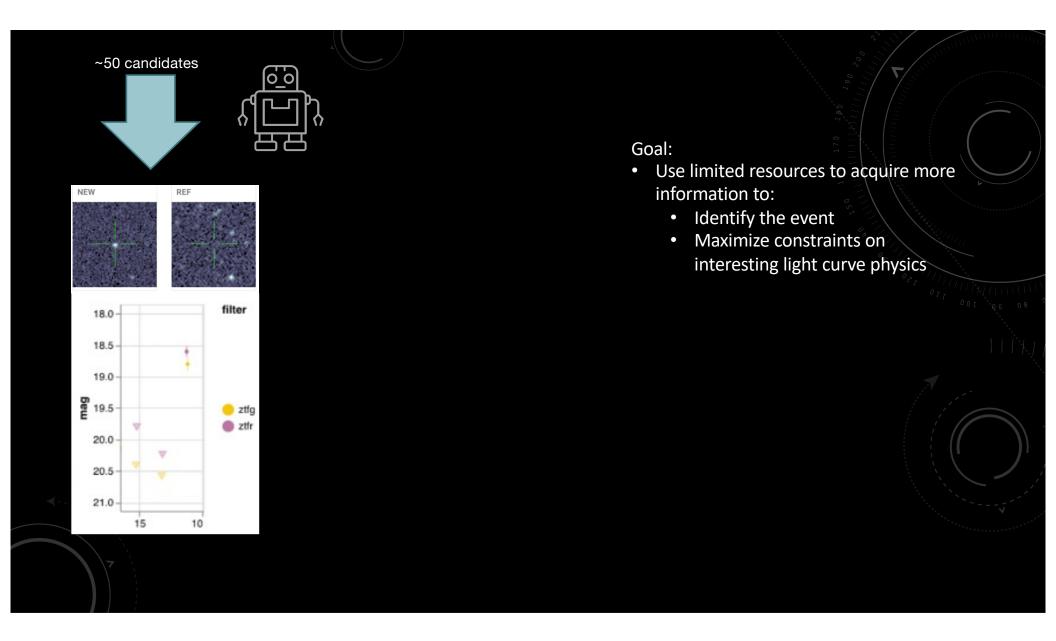
DECISION MAKING UNDER UNCERTAINTY

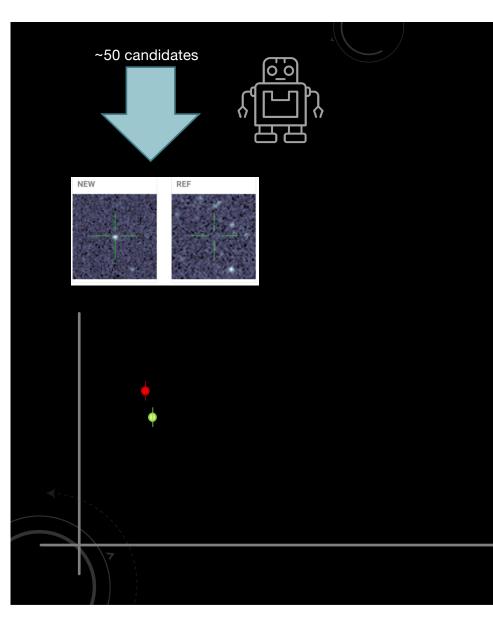
- Classically: Optimal experiment design
- Contemporary ML: Reinforcement learning, optimal sensing









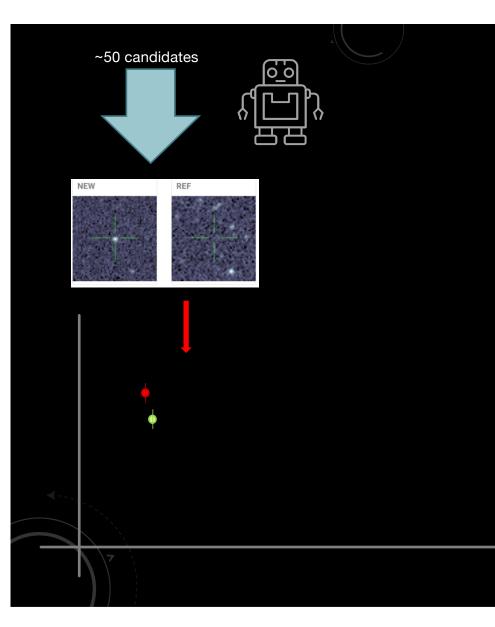


- Use limited resources to acquire more information to:
 - Identify the event
 - Maximize constraints on interesting light curve physics

Step 1:

Define *state* space

• e.g. observed multi-channel light curves



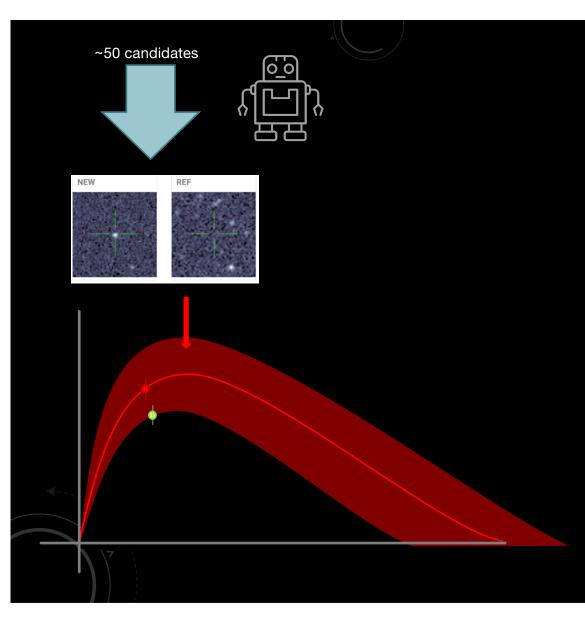
- Use limited resources to acquire more information to:
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Step 2:

Define action space

• e.g. add data in {g, r, g+r, do nothing}

In general, actions can be: Continuous Stochastic With variable cost and/or subject to budget

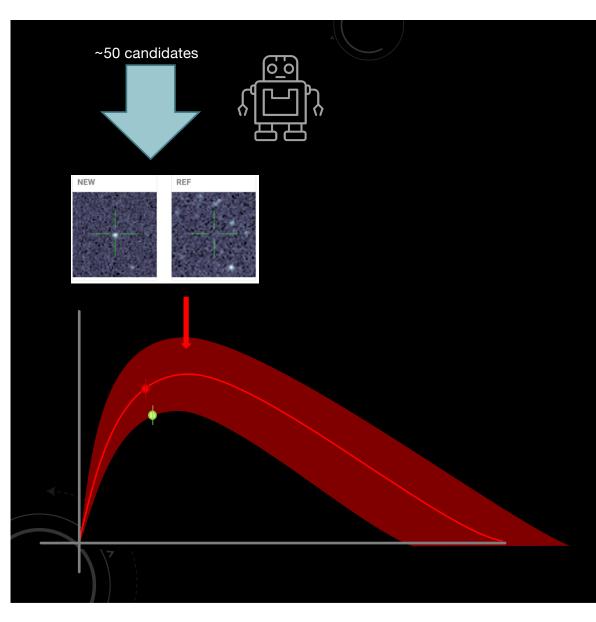


- Use limited resources to acquire more information to:
 - Identify the event
 - Maximize constraints on interesting light curve physics

Step 3:

Estimate outcome states given actions

Dynamics/transition: In general can be unknown and/or stochastic



- Use limited resources to acquire more information to:
 - Identify the event
 - Maximize constraints on interesting light curve physics

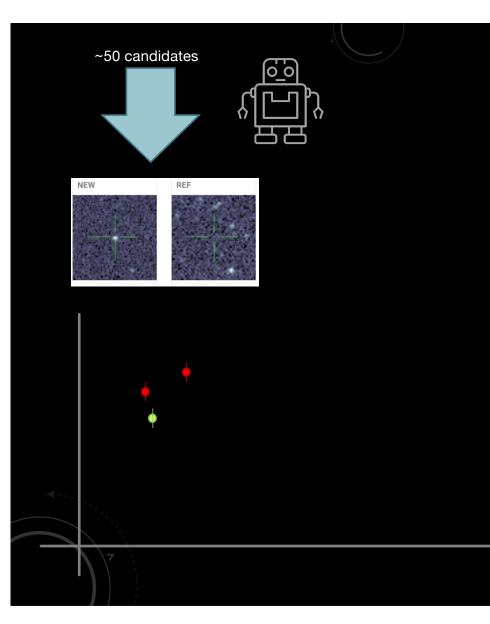
Step 4:

Estimate *utility* of outcome states:

- classification accuracy, TPR, F1-score, etc
- improvement in physics model parameters
- all of the above

In general can be stochastic

Your science!

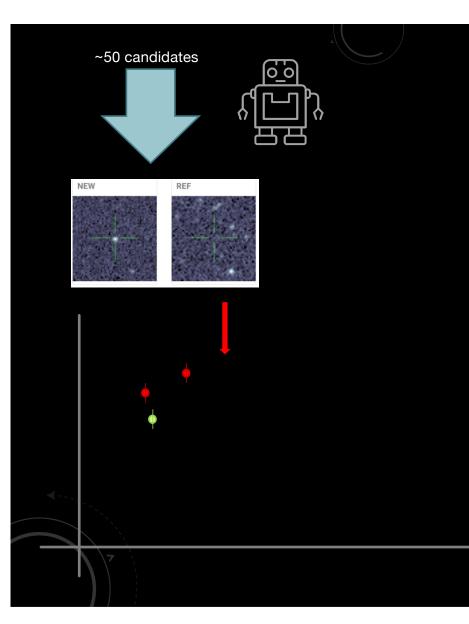


- Use limited resources to acquire more information to:
 - Identify the event
 - Maximize constraints on interesting light curve physics

Step 5:

Take action according to policy

- e.g. greedy policy: take action with maximum reward; does not guarantee optimal series of actions
- Commonly argmax a Q(s,a)



- Use limited resources to acquire more information to:
 - Identify the event
 - Maximize constraints on interesting light curve physics

Step 6:

Adapt to new information (inc. acquisition failure/latency, survey data)

Finish when episode ends or exhausted budget or repeat forever

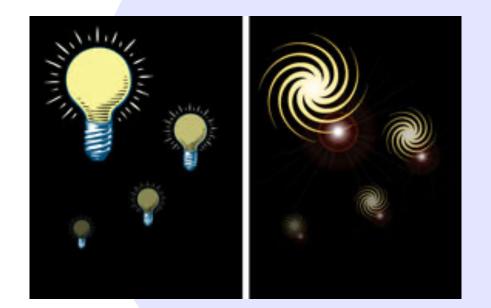
EXAMPLE 1:

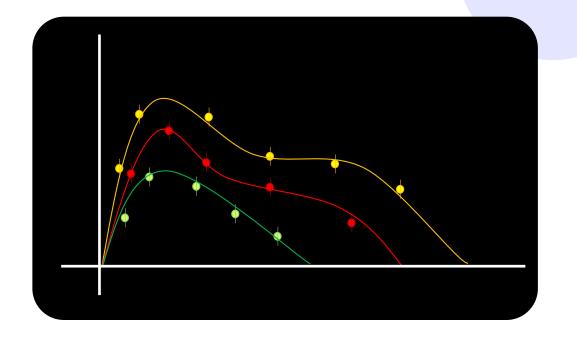
MEASURING EXPANSION OF THE UNIVERSE

Type la Supernovae

Constrain cosmological parameters: Hubble constant, Dark Energy equation of state, ...

Low redshift samples constrain local large-scale structure properties: growth rate, velocity flows



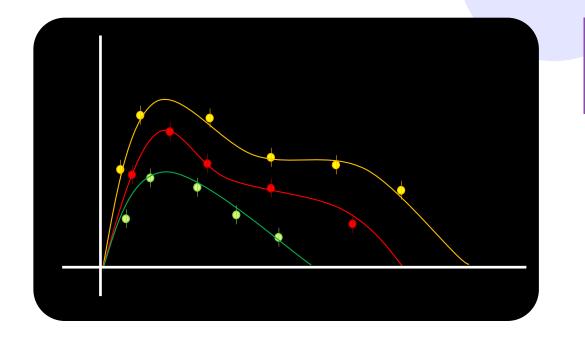


 x_0, x_1, c are light curve fit parameters (z is spectroscopic)



Cosmology is $f(x_0, x_1, c, z)$ for a sample of SNe

Real-time SN Ia LC augmentation to maximize cosmology



Minimize uncertainty on light curve fit parameters (in quadrature)

Minimize uncertainty on cosmology

Real-time SN Ia LC augmentation to maximize cosmology

Problem statement:

Augment photometry to branch-normal SN Ia light curves from ZTF-I public survey (g and r) in g,r, and i to minimize net uncertainty on SALT2 parameters

Problem statement:

Augment photometry to branch-normal SN Ia light curves from ZTF-I public survey (g and r) in g,r, and i to minimize net uncertainty on SALT2 parameters

i-band important for precisely estimating H_0 (Burns+ 2018)

Second peak could help probe SN la explosion mechanisms (Folatelli+ 2010)

Data in UV or IR can help better calibrate models (Milne+ 2015)

Algorithm

Non-stationary MDP with finite horizon (60 day episodes)

State space: Observed photometry and expected data from survey (stochastic, 10x monte carlo). Remaining budget allocated randomly* Action space: {no action, g, r, i, gr, ri, ig, gri} Deterministic reward model: SALT2 + photo z A-optimality**

Deterministic dynamics mode

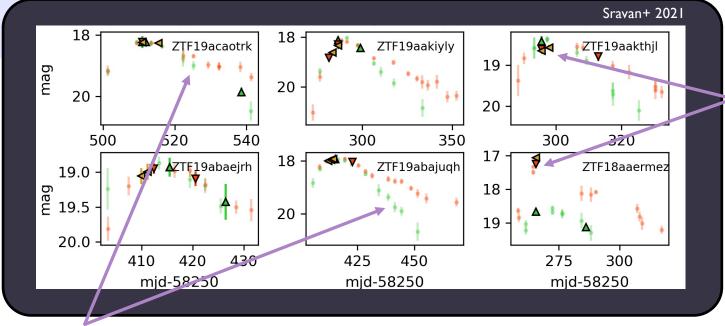
Upper limit using 2-D Gaussian Process regression over full LC For real time estimated with encoder-decoder LSTM trained on 10⁵ simulated ZTF SNe Ia (slightly lower performance) New state simulated using 2-D Gaussian Process fit to full LC and fed back the next day

Deterministic on-policy, fixed budget and unit cost

Take modal action with maximum reward and least cost across all rollouts. Threshold ϵ over no action (hyperparameter)

* substitutes expected **optimal** actions for expected **naïve** actions ** Distance error in quadrature. Note: min $\chi^2 \neq$ max liklihood Gap filling

Resolves phase with high variability (first and second peaks+valleys)



Augmented photometry to minimize uncertainty on cosmology

Survey light curve

Improvement in SALT2 parameters over naïve^{**} strategy

2-5% more improvement for faint SNe Ia (peak>18.5 mag) Due to gap filling, strong prospects for Rubin

Budget	Usage	$\delta(\sigma_{x0})$	$\delta(\sigma_{x1})$	$\boldsymbol{\delta}(\boldsymbol{\sigma}_{c})$	$oldsymbol{\delta}(\pmb{\sigma}_{z})$
3	2	2%	3%	5%	6%
6	5	3%	5%	4%	6%
9	7	5%	6%	5%	11%

Sravan+ 2021

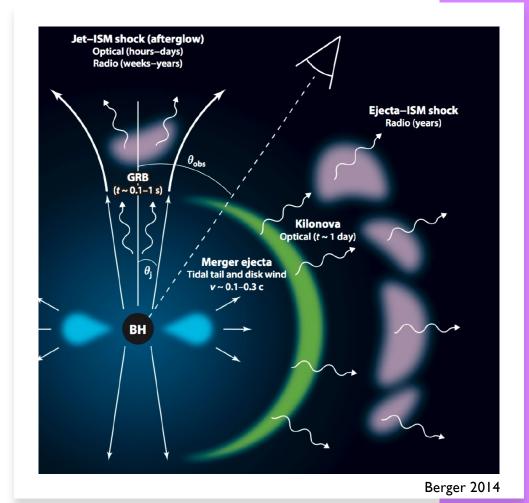
**Adding data itself can lead to improvement!

EXAMPLE 2:

IDENTIFYING GRAVITATIONAL WAVE ELECTROMAGNETIC COUNTERPARTS

Kilonovae

- UVOIR transients
- Probe nucleosynthesis in ejecta due to merger and associated power sources and the NS EoS
- Robust counterparts to most BNS and some NSBH mergers
- Short lived (<~I week) and faint



Pythia

Reinforcement learning agent that strategizes follow-up to identify kilonovae

- · Learns to evaluate the explore/exploit tradeoff
- Solves the credit assignment problem from any delayed consequences
- Adapts to new information, from its own actions or other sources

Toy sequential decision making under uncertainty problem:

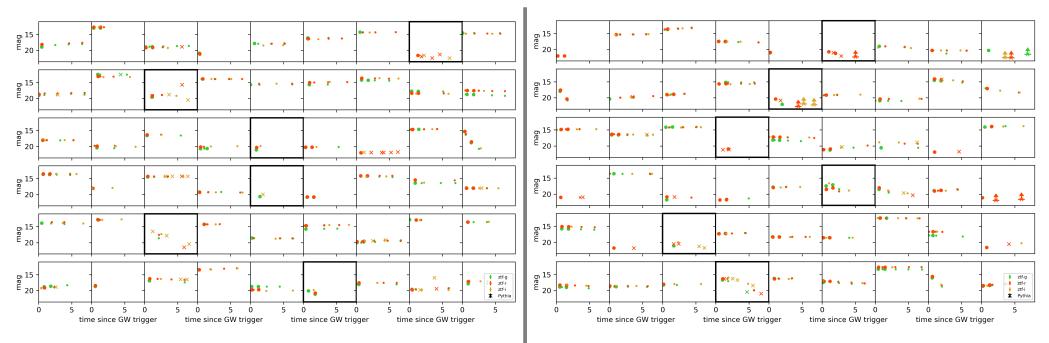
- 9 transients, one of which (always) is the true kilonovae (min photometry = 1)
 - Contaminants are SNe, unassociated GRB afterglows, shock breakout (do not include observational significance)
- Follow-up in ZTF g, r, or i (300s exposure) per day
 - Finite horizon 6 days (no action on day I)
- Reward I if agents adds data to the kilonova else 0
 - Maximize the number of follow-up to the true kilonova (non-model specific objective with the expectation that more data ~ better constraints)

Pythia

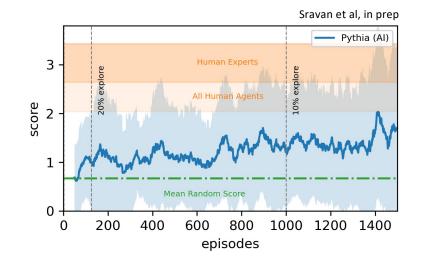
- Learns online (collecting new experiences) in simulated environment
- Linear VFA (state-action value $Q = x(s,a)^T \omega$
- x(s,a) is an CNN-autoencoder (for order invariance) representing the light curves with forecasted outcomes per action
- Learns ω via stochastic gradient decent and Adam optimizer

Algorithm SARSA and TD(0) target	
Initialize w to small random weights	
Set $\epsilon_0 = 1$	
for $k = 1$, M do	For each episode
$\epsilon \leftarrow \epsilon_0/k^n$	
Initialize s_1	
for $t = 1$, horizon do	
With probability ϵ select random action a_t	
otherwise select $a_t = \max_a \hat{Q}(s_t, a_t; \hat{w})$	
Execute action and observe reward r_t and next state s_{t+1} from each s_{t+1}	nvironment
With probability ϵ select random action a_{t+1}	
otherwise select $a_{t+1} = \max_a \hat{Q}(s_{t+1}, a_{t+1}; \hat{w})$	
$\textbf{Set} \ \Delta \hat{w} \leftarrow [r_t + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \hat{w}) - \hat{Q}(s_t, a_t; \hat{w})] \nabla_w \hat{Q}(s_t, a_t; \hat{w})$	
▷ : Loss is MSE between TD(0) target ³ substitute	ite for Q^*) and current Q
Update $\hat{w} \leftarrow \hat{w} + \alpha \Delta \hat{w}$	$\triangleright \alpha$ is using Adam
end for	
end for	

	agent	score	frac
	Pythia	1.84	0.81
	Non-expert 1	2.04	0.54
AI v humans	Non-expert 2	3.15	0.86
	Expert 1	2.64	0.76
	Expert 2	2.74	0.78
	Expert 3	2.94	0.72
	Expert 4	3.43	0.9



Sravan et al, in prep



PYTHIA

Linear VFA hypothesis class not sufficiently rich representation of true Q function

• Benefit is theoretical convergence guarantee. Demonstrates problem learnable!

Shifting to deep Q networks:

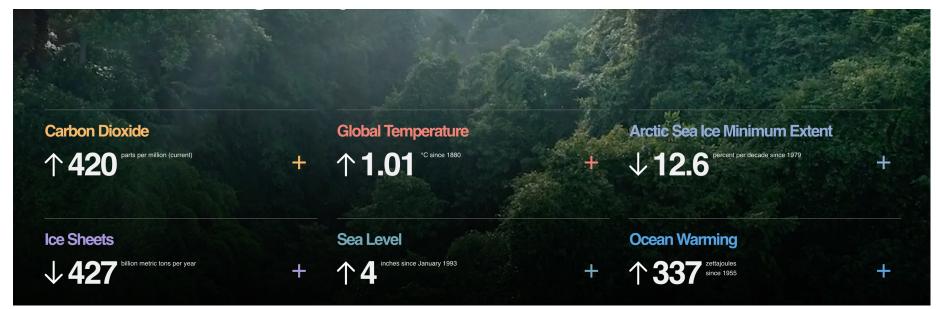
- Will remove two-step learning, one for x(s,a) in supervised/unsupervised learning and one for Q via Bellman updates in RL
- Efficient evaluation of realistic large action space, can have vector instead of scalar output

Carbon Footprint

Estimated emissions: 1210 kg of CO_2eq . assuming carbon efficiency of 0.432 kg CO_2eq/kWh

Approximately equal to:

- One round trip LAX-JFK (1180 Kg CO₂)
- 4900 km driven in an average combustion engine car



climate.nasa.gov

OUTLOOK

- Target maximizing constraints on the NS EoS and e.g. place constraints on maximum non-rotating NS mass
- Kilonova diversity with large samples
- Prepare for Rubin
 - Deeper and high SNR events
 - Motivates effective low-latency use of expensive space-based follow-up resources

Other messengers!

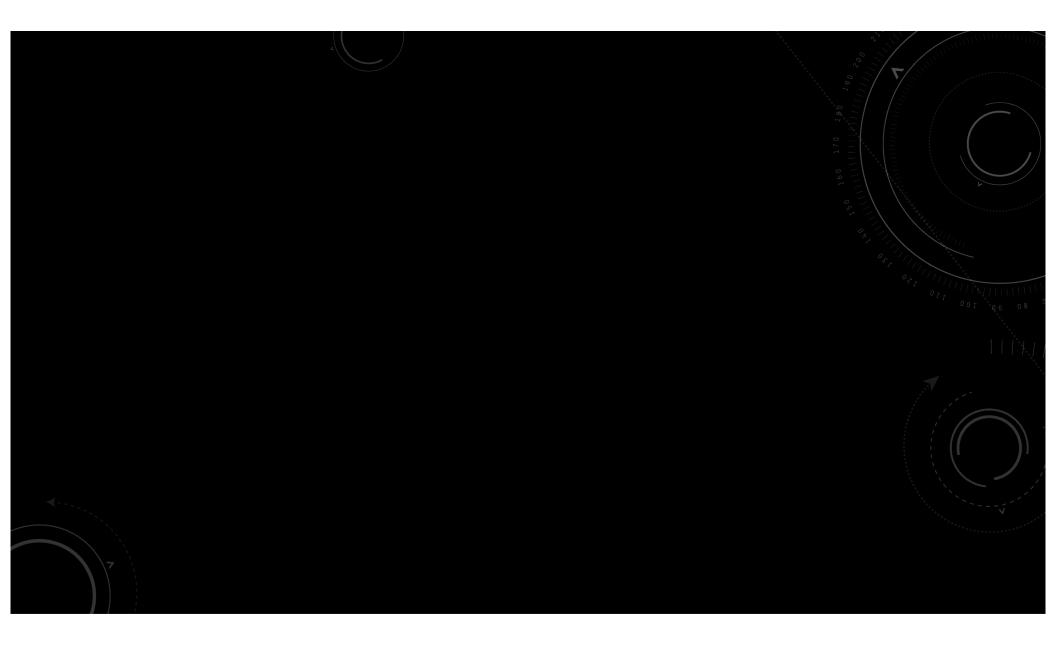
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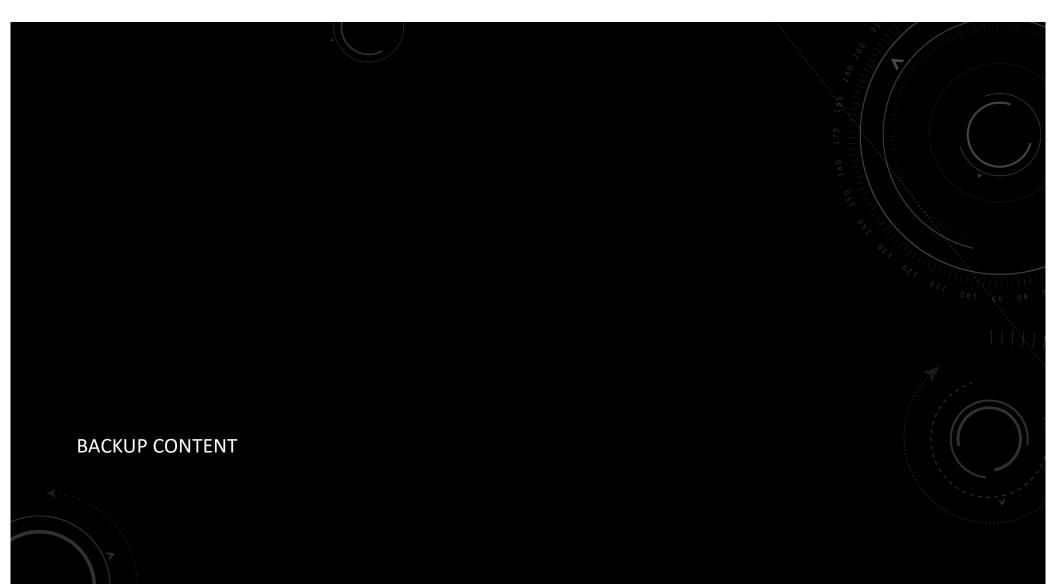


OUTLOOK

- Flexible to address any situation where real-time decisions need with resource limitations
- Approaches such as these are the ultimate human-machine symbiosis
 - Reduce burden of tedious work (especially for well-defined science cases)
 - Leave innovation and discovery to humans (?)





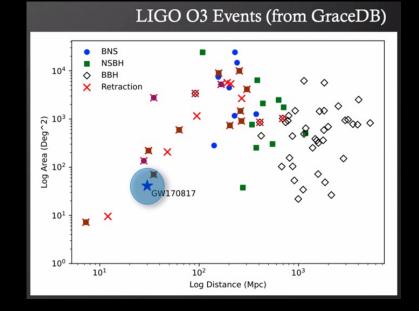


REFITT FOR ZTF

- Training dataset:
 - "Classical" SNe (Ia, II, IIn, IIb, Ib, Ic, Ic-BL) simulated from ZTF BTS, PS1, and all historic classified SNe with sdssg, sdssr photometry
 - 5k per type spanning flat z space 0-0.8 for SN Ia, 0-0.1 for CC SNe
- ML and forecasting:
 - Multi-D Gaussian Process LC fit
 - use k similar training LCs using Xception penultimate vector of modal training class (implemented as balltree)
 - align with cross-correlation
- Daily run at 0900PT (10 mins on 24 cores)
 - Ingested via Antares: within 60 d of trigger, <21 d since last photo, at least 3 photo with at least two in the same band >5 hours apart
- Recommendations for:
 - Photometry for events approaching peak and not in ZTF's observing plan
 - Classifications within |1wk| of forecasted peak
 - Anomalies (poor forecast)

WHY ONLY GW170817?

- For O3:
 - Median skymap size
 ~4000 sq deg
 - Median distance:
 - BNS ~ 240Mpc
 - NSBH ~ 320 Mpc



Run	BNS	NSBH	BBH
	Median 9	0% credible area	$(\deg^2)^a$
03	1672^{+94}_{-110}	1970^{+110}_{-110}	1069^{+43}_{-41}
O4	1820^{+190}_{-170}	1840^{+150}_{-150}	335^{+28}_{-17}
05	$1250\substack{+120 \\ -120}$	$1076\substack{+65\\-75}$	$230.3\substack{+7.8 \\ -6.4}$
	Median lu	minosity distanc	e (Mpc) <i>a</i>
O3	$176.1^{+6.2}_{-5.7}$	$337.6\substack{+10.9\\-9.6}$	871^{+31}_{-28}
04	$352.8^{+10.3}_{-9.8}$	621^{+16}_{-14}	$1493\substack{+25 \\ -33}$
05	620^{+10}_{-17}	1132^{+19}_{-23}	2748^{+30}_{-34}
	Annual	number of detect	tions cd
03	5^{+14}_{-5}	13^{+15}_{-9}	24^{+18}_{-12}
04	34^{+78}_{-25}	72_{-38}^{+75}	106_{-42}^{+65}
05	190^{+410}_{-130}	360^{+360}_{-180}	480^{+280}_{-180}

Petrov+ 2021 (adapted)