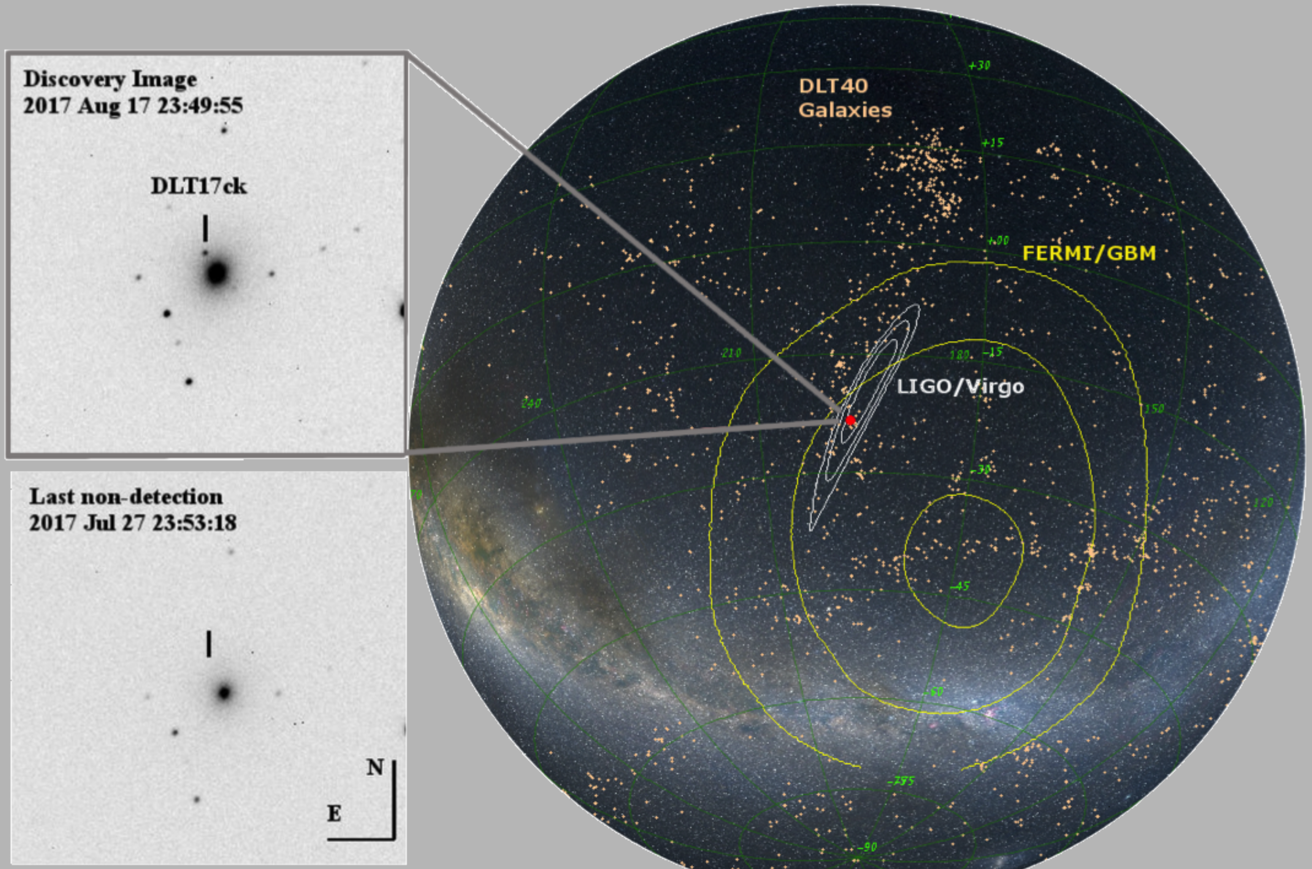
Gravitational wave electromagnetic counterpart searching

Sheng Yang on behalf of GRAWITA and DLT40

INAF-observatory of Padova
UNIPD-Department of Astronomy
UC Davis-Department of Physics

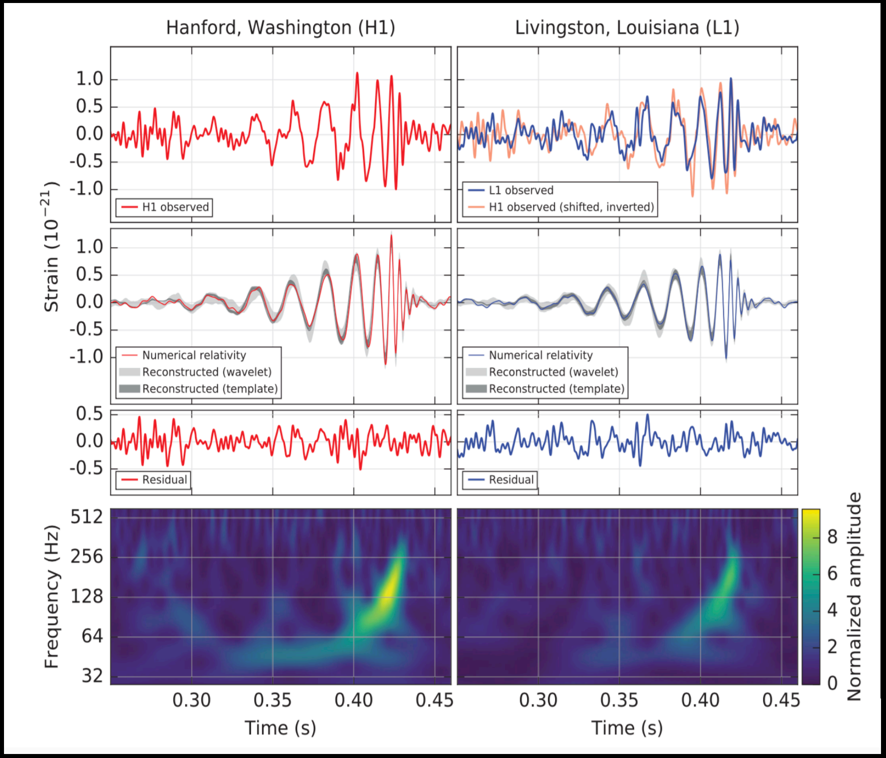


7/6/2018

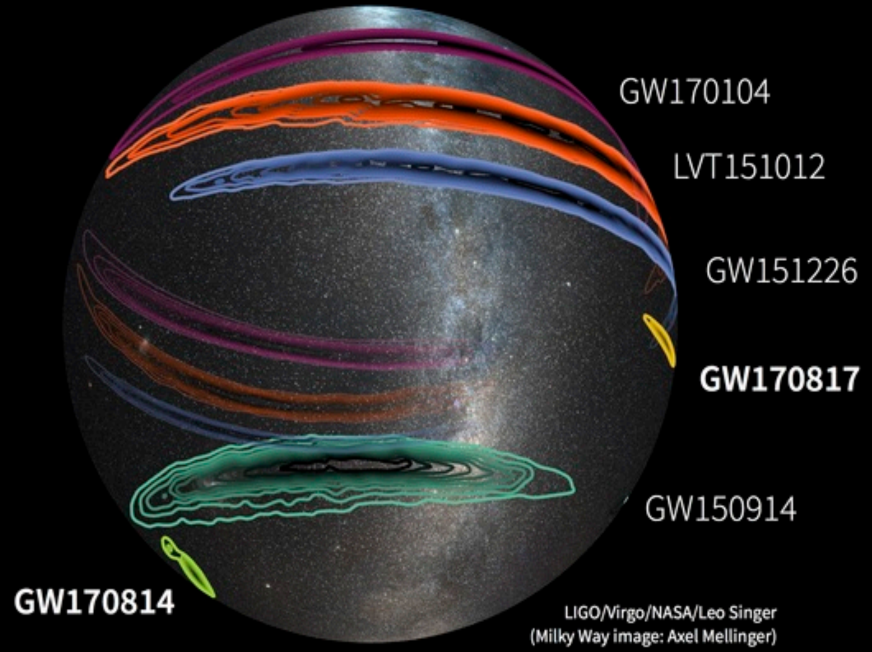
GEMMA
Gravitational-waves, ElectroMagnetic and dark-MAtter Physics Workshop

GW astronomy era

GW150914, PRL, 116, 061102

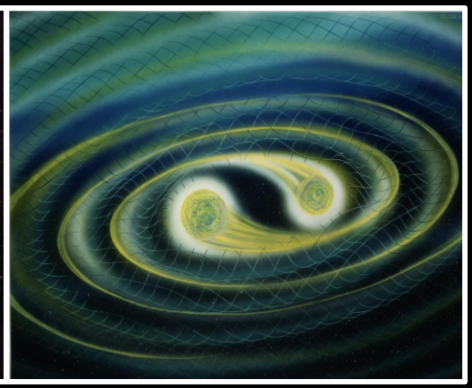


CBC: 5 BBH, 1 BNS in O1+O2



For terrestrial interferometers, 10-1000 Hz:

- CBC, the most promising GW source, considering waveform template, rate (tens per year), range (80 Mpc for BNS).
- CC SN (galactic, 2 per century)
- NS instabilty



Why EM counterparts are interesting?

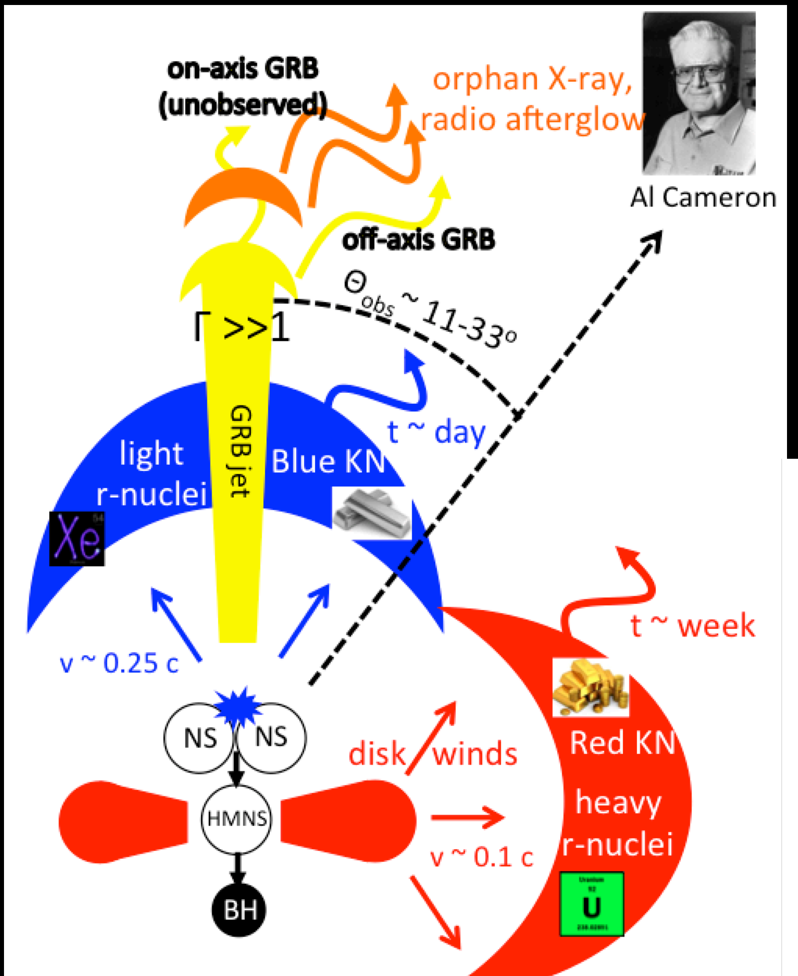
During GW inspiral phase:

- ❑ Distance
- ❑ Mass
- ❑ Position (deg)
- ❑ Spin

If EM available (one NS involved?):

- ❑ Precise (arcsec) sky localization
- ❑ Energetics
- ❑ Host galaxy – Redshift, Environment…
- ❑ Nucleosynthesis of elements
- ❑ Cosmology – Hubble constant
- ❑ Fundamental physics – e.g. speed of photons and GW
- ❑ Constraint models of GW+EM emitters

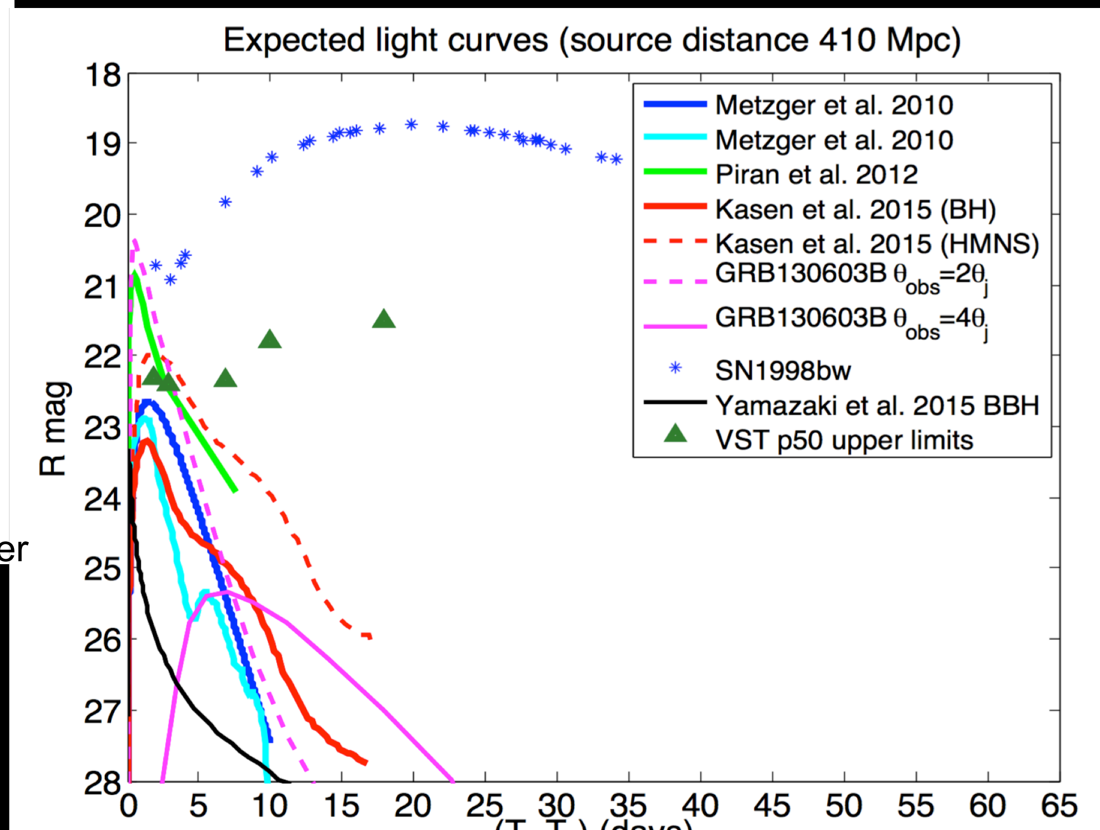
EM emission expected from BNS, NS-BH



Credit by B. Metzger

anisotropic
sGRB (gamma)
afterglow (X, optical)

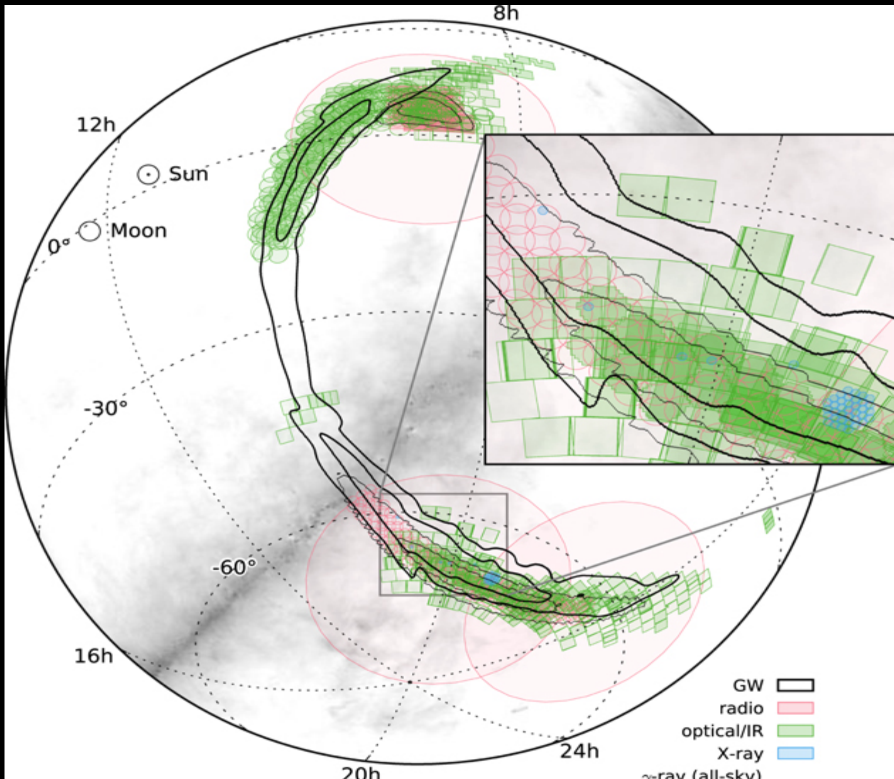
isotropic
afterglow (radio)
kilonova (optical,IR)



Courtesy of G. Stratta

Fast transient:
- Challenge for follow-up and identification
- TDA needed

EM follow-up: ‘Seek needle in a haystack’

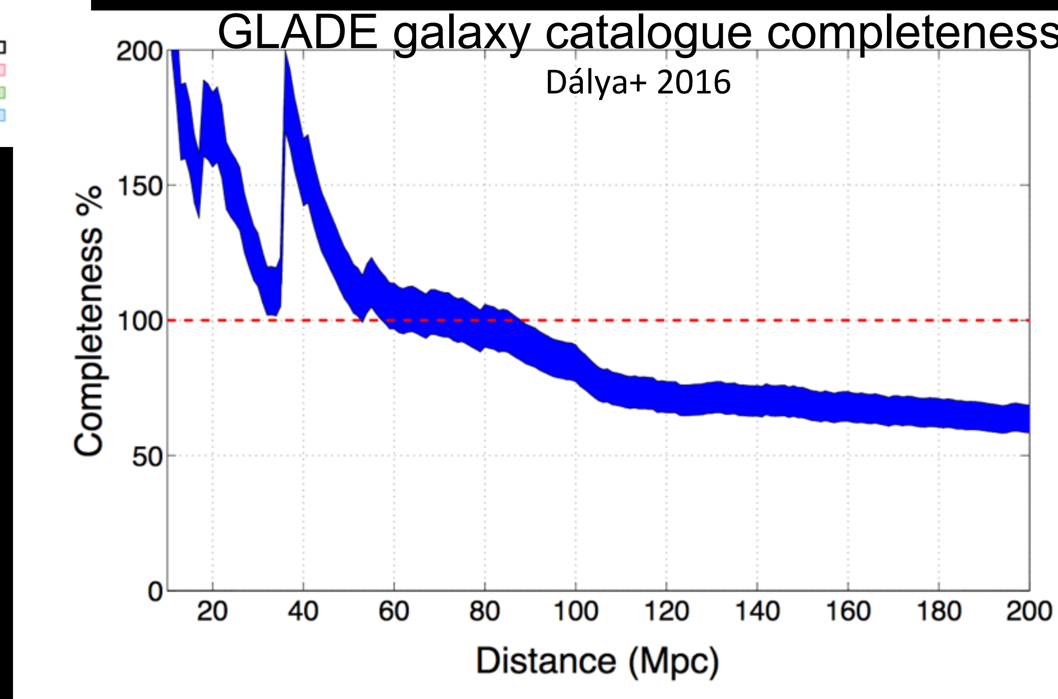


EM follow-up for GW150914
Abbott B.P., et al. 2016

Optical GW follow-up: fast, wide, deep.

1. ‘blind search strategy’: wide-field tilling search on high probability GW region
   e.g. **GRAWITA**

2. ‘targeting search strategy’: pointed search of selected galaxies in high probability GW region
   e.g. **DLT40**



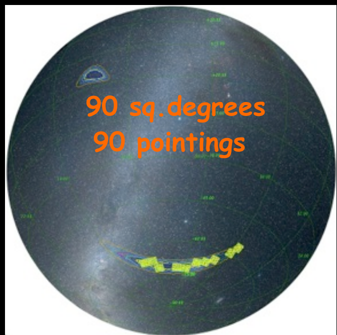
Triangle localization:

~100-1000 square degrees(H+L)

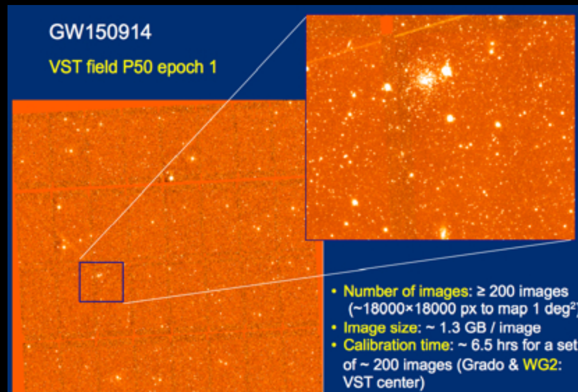
~10 square degrees(H+L+V)

EXAMPLE OF GRAWITA RESPONSE

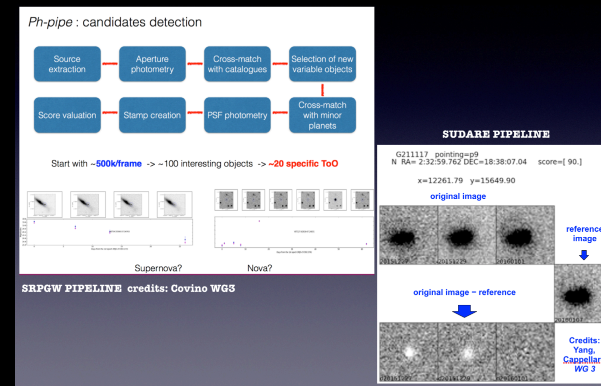
1. Tiling



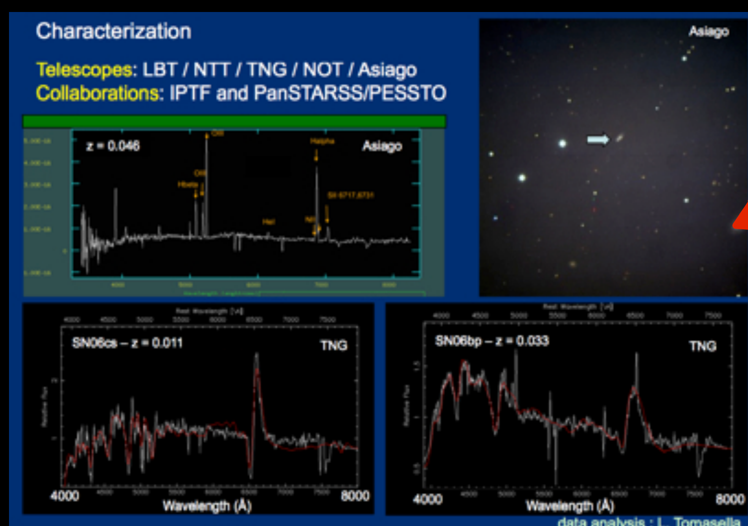
2. Observations



3. Search



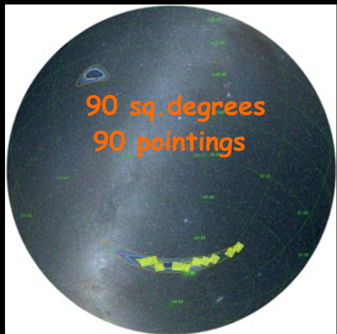
4. Characterization and follow-up



Courtesy of E. Brocato

EXAMPLE OF GRAWITA RESPONSE

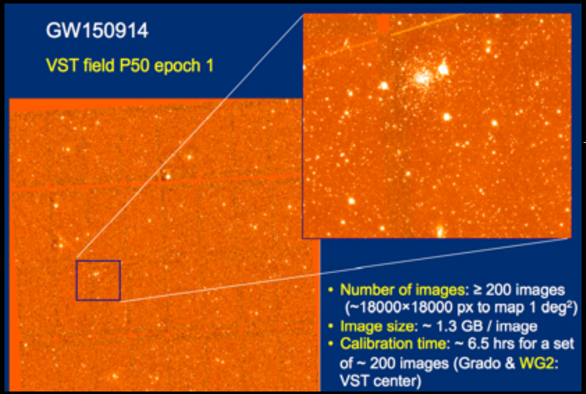
1. Tiling



GWsky

~30mins,
GraceDB

2. Observations

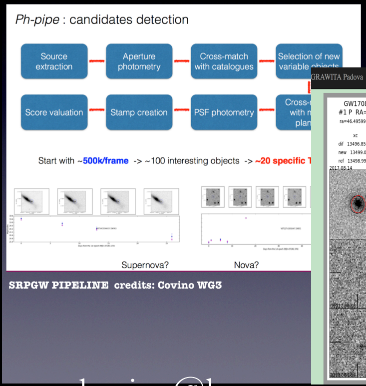


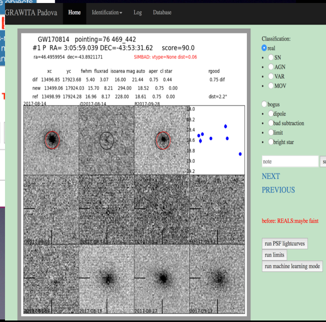
VST@Chile
VSTtube@Naples

2*45s per pointing
1 deg^2, ~21 mag

Archive

3. Search





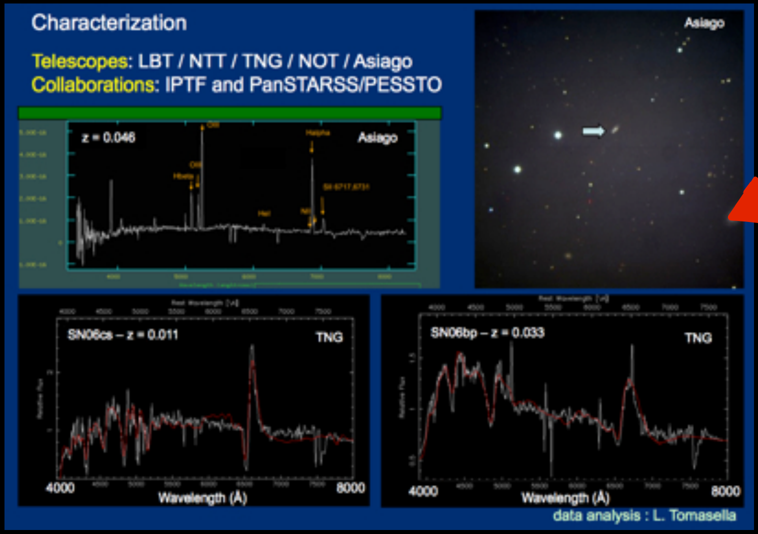
ph-pipe@brera
~hours

diff-pipe@padova
~1 day
with 10 cores

Before visual inspection, TDA:
- TR: 100-1000 candidates per pointing for diff-pipe
- ML?

~hours - weeks

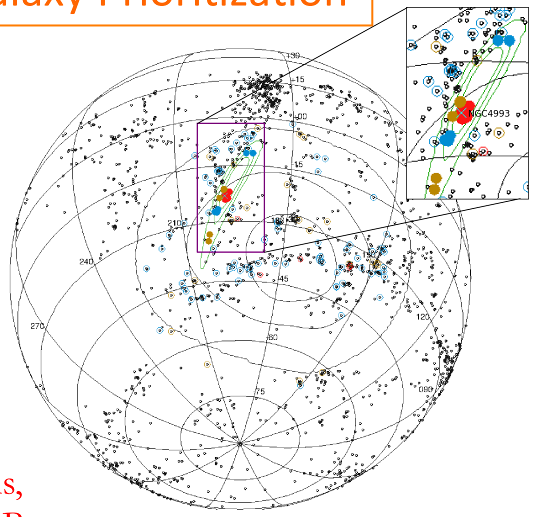
4. Characterization and follow-up



EXAMPLE OF GRAWITA RESPONSE

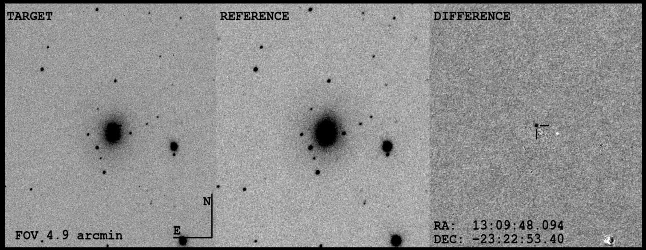
Example of DLT40 response

1. Galaxy Prioritization



~30mins,
GraceDB

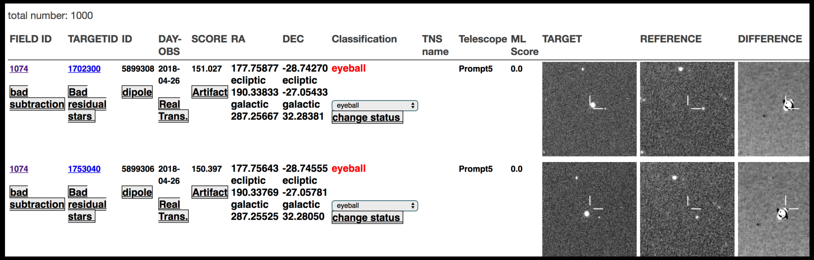
2. Observation



Prompt@Chile
dlt40pipe@Davis

45s per pointing
10*10 arcmin^2, ~19 mag

3. Search


total number: 1000

FIELD ID	TARGETID	ID	DAY-OBS	SCORE	RA	DEC	Classification	TNS name	Telescope	ML Score	TARGET	REFERENCE	DIFFERENCE
1074 bad subtraction	1702300 Bad residual stars	5899308 dipole	2018-04-26 Real Trans.	151.027 Artifact	177.75877 ecliptic 190.33833 galactic 287.25667	-28.74270 ecliptic -27.05433 galactic 32.28381	eyeball (eyeball) change status		Prompt5	0.0			
1074 bad subtraction	1753040 Bad residual stars	5899306 dipole	2018-04-26 Real Trans.	150.397 Artifact	177.75643 ecliptic 190.33769 galactic 287.25525	-28.74555 ecliptic -27.05781 galactic 32.28050	eyeball (eyeball) change status		Prompt5	0.0			

diff-pipe@Davis
~seconds

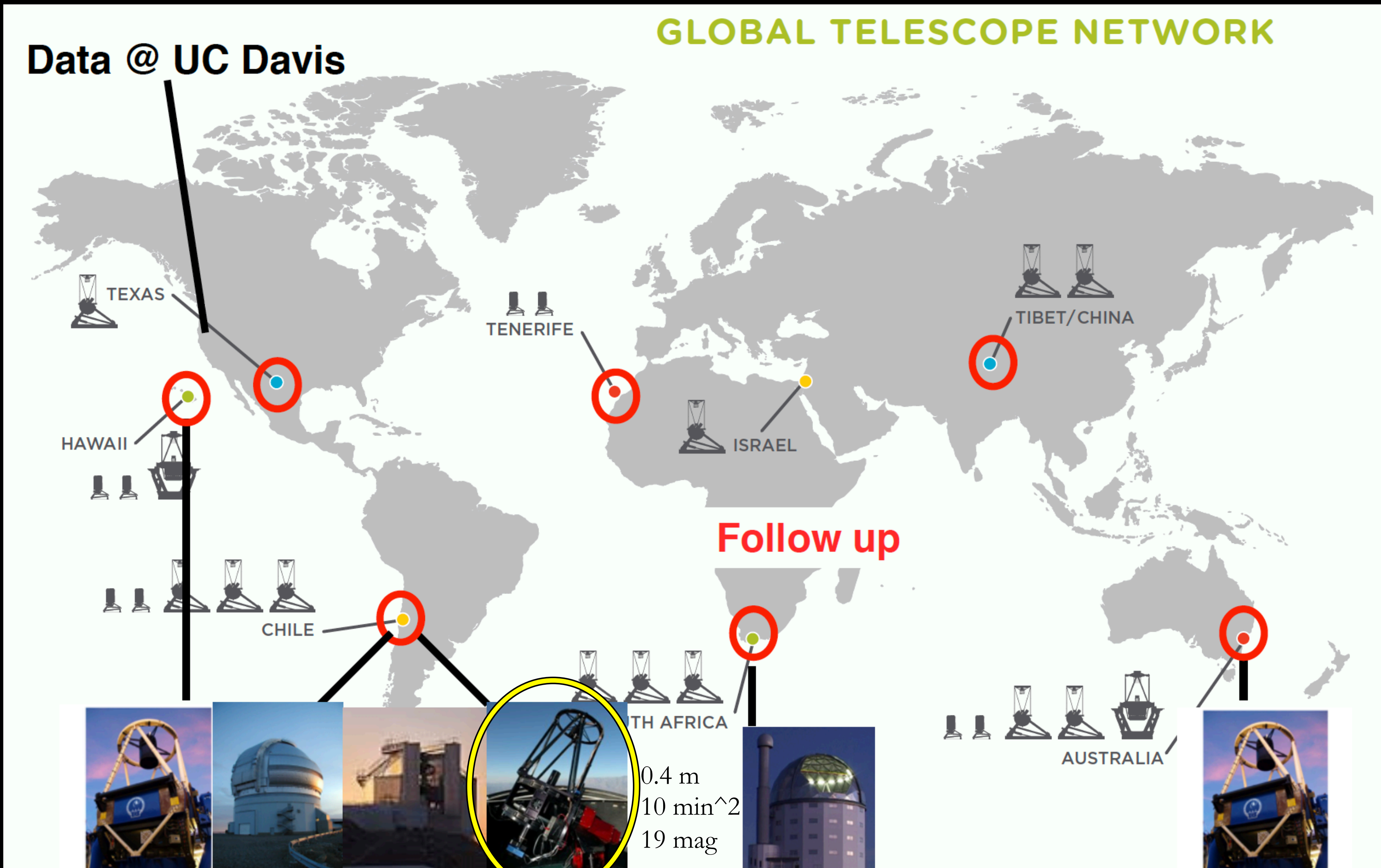
4. Characterizaion and follow-up

LCOGT/FLOYDS/Pessto…

- TR: ~1000 candidates per night
- ML: 50-100 per night

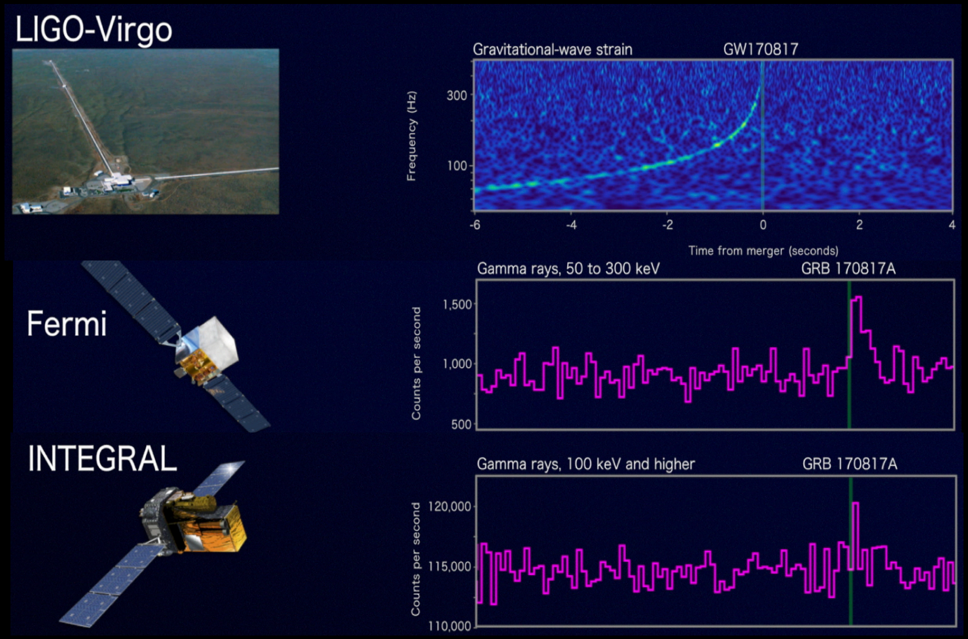
~minutes - hours

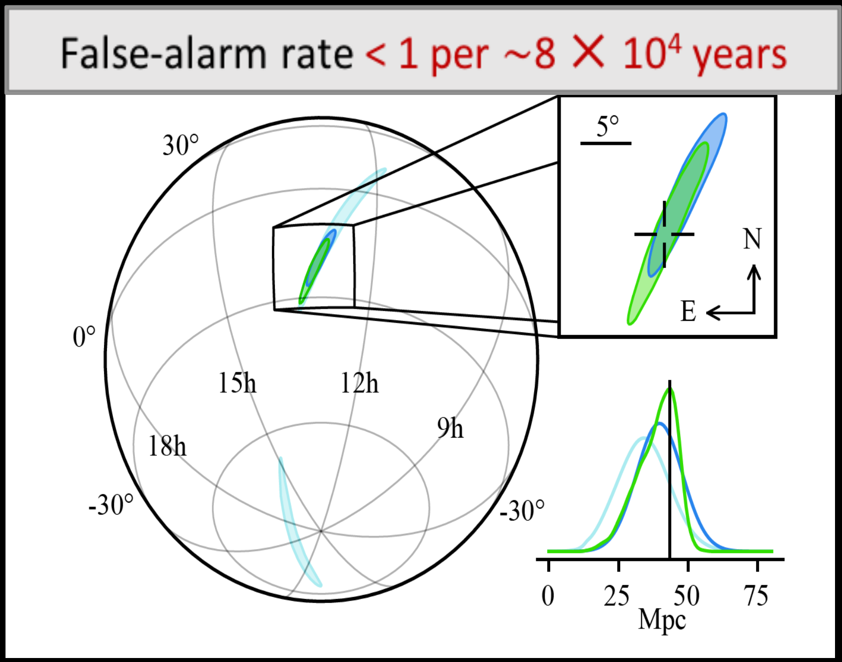
Example of DLT40 response

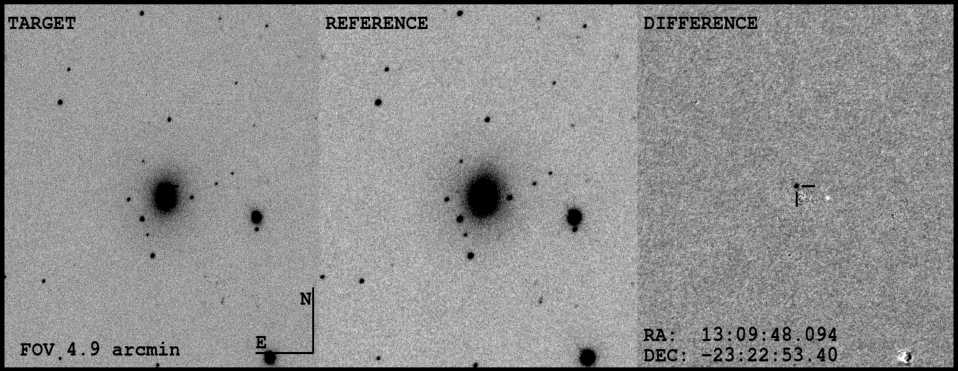


Courtesy of S. Valenti

LIGO O2, BNS @ 40Mpc



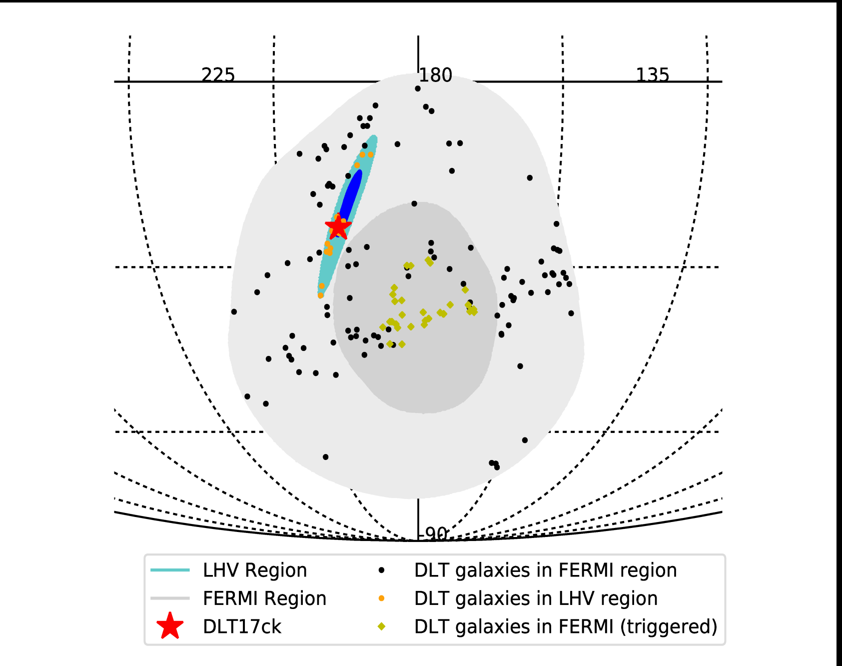




GW: On 2017 August 17.528 UT

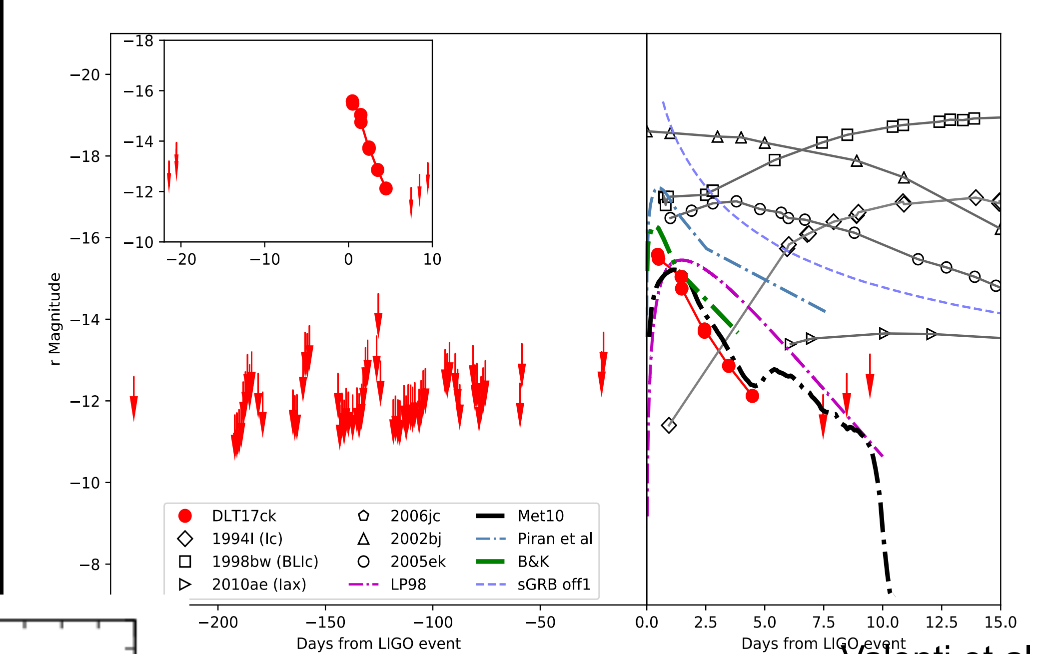
GRB: ~1.7s later

KN: sss17a, 10.86 h later; DLT17ck,11.09 h later

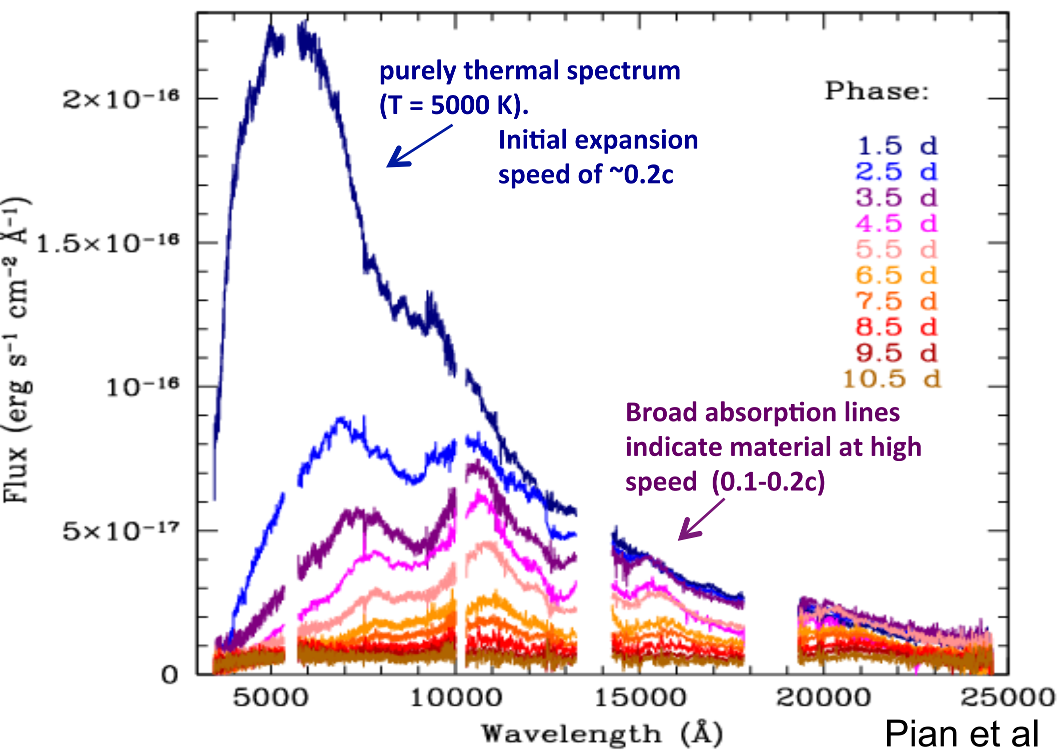


Kilonova AT 17fgo

DLT17ck Light curve
Very fast compare to standard SN
Close to KN model of Metzger 10



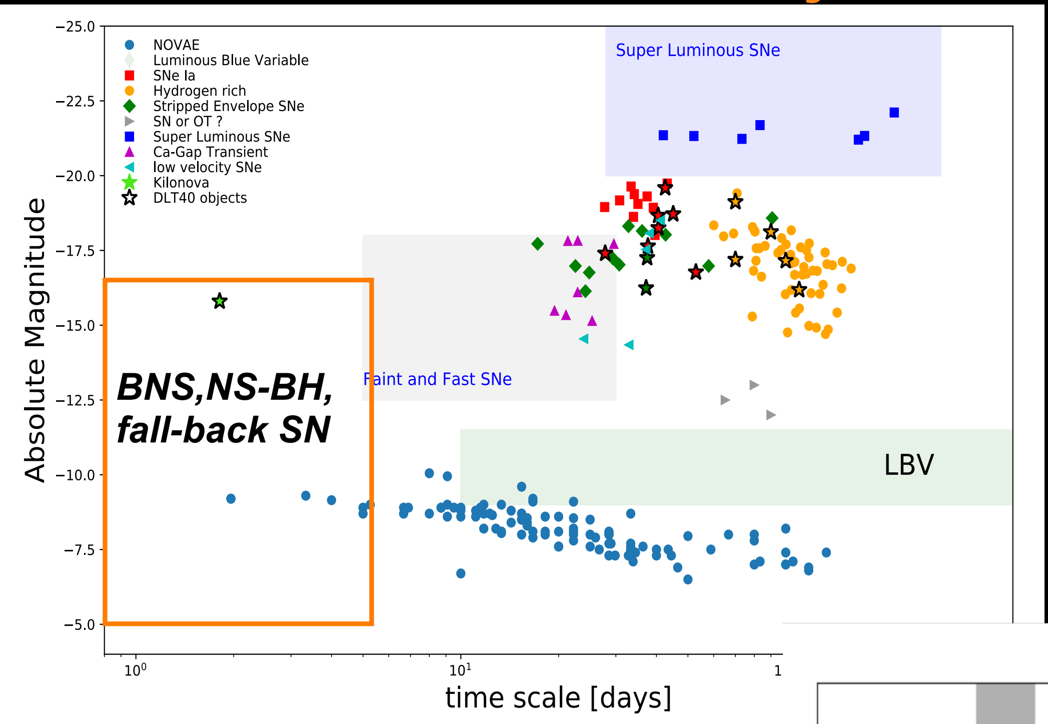
Valenti et al



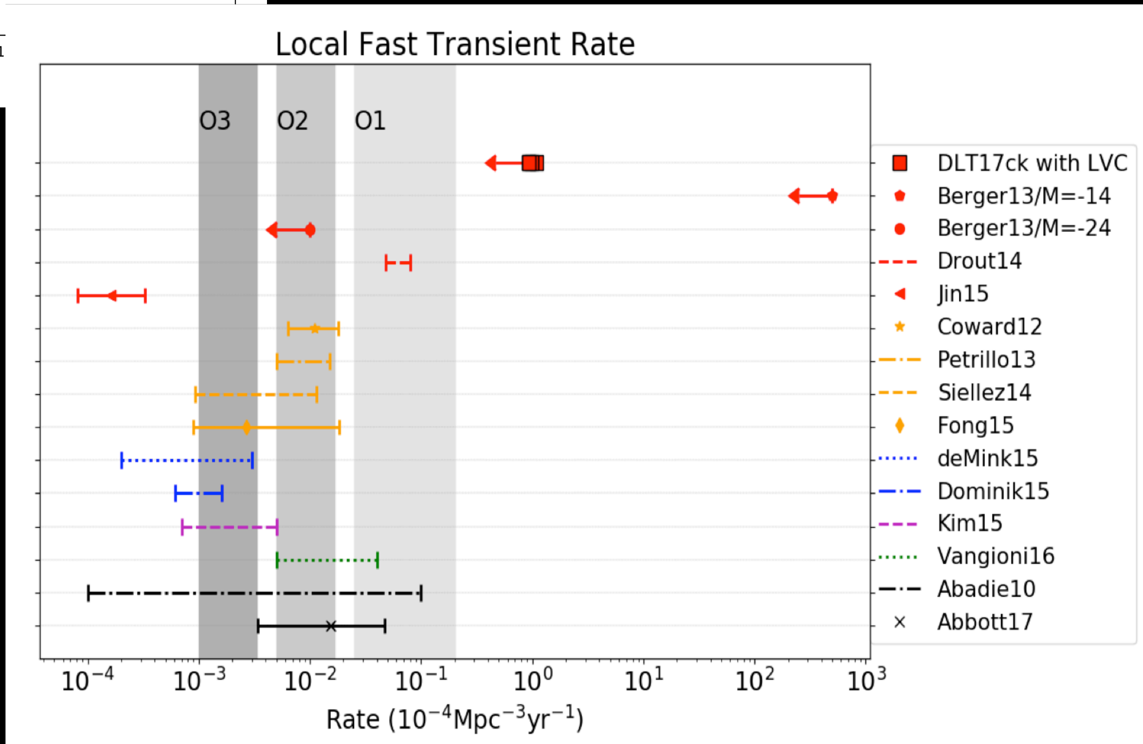
Pian et al

GRAWITA VLT spectrum

Why MMA?



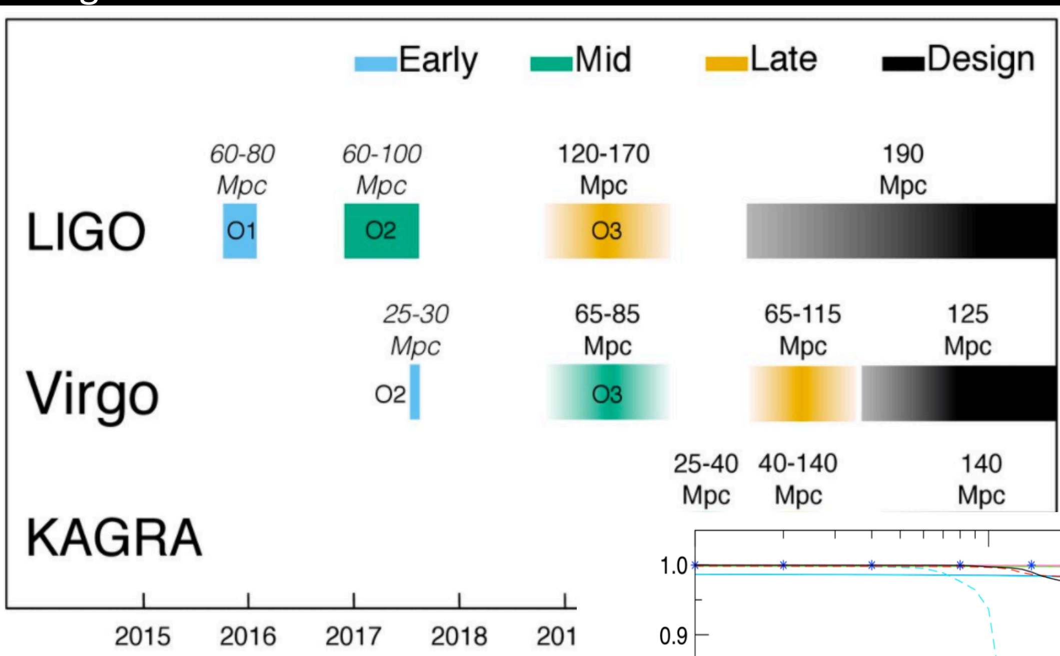
Very rare: cadence for classification & rate

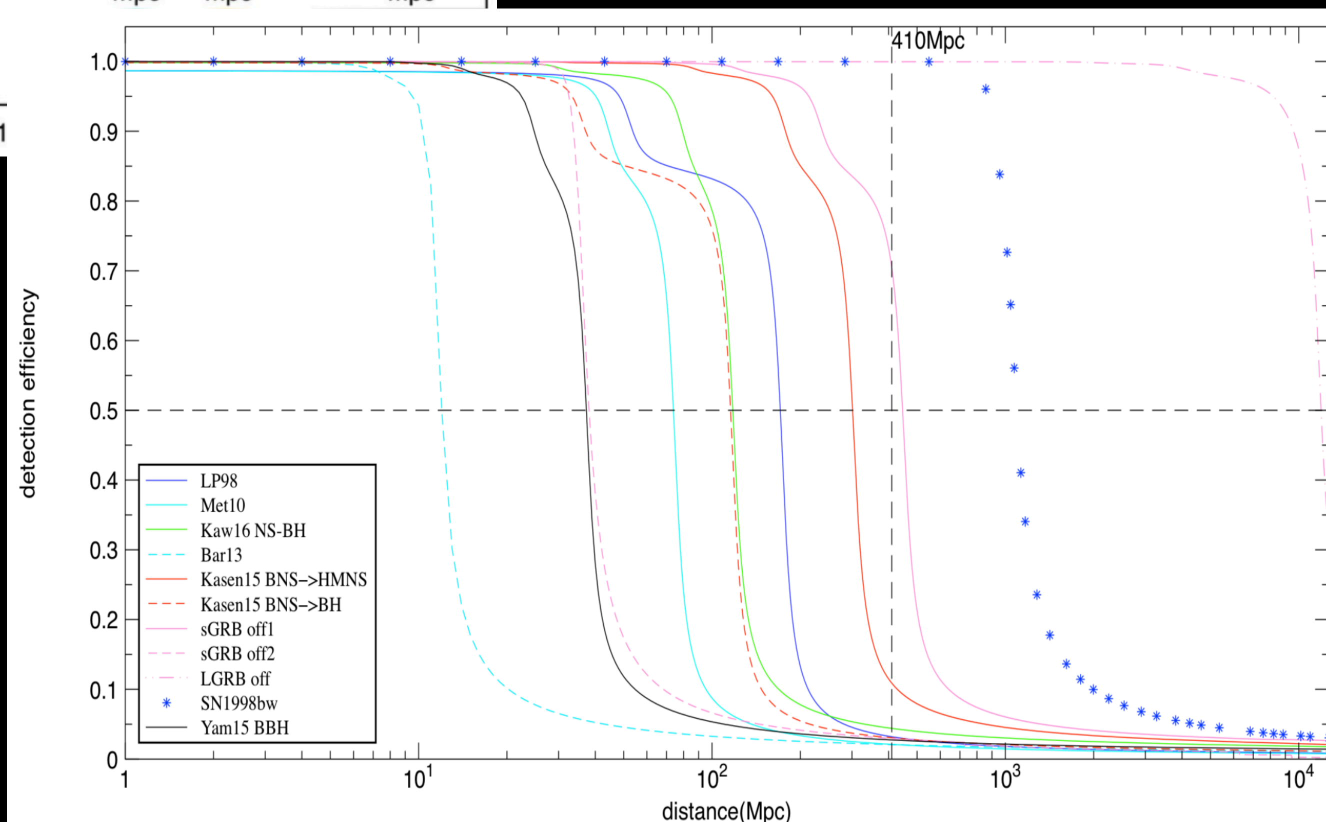


BNS rate estimation:
Detecting a kilonova with a survey like DLT40 (independently on the LIGO trigger) will take ~18.4 years!

Future – O3

Range for BNS GW in O3



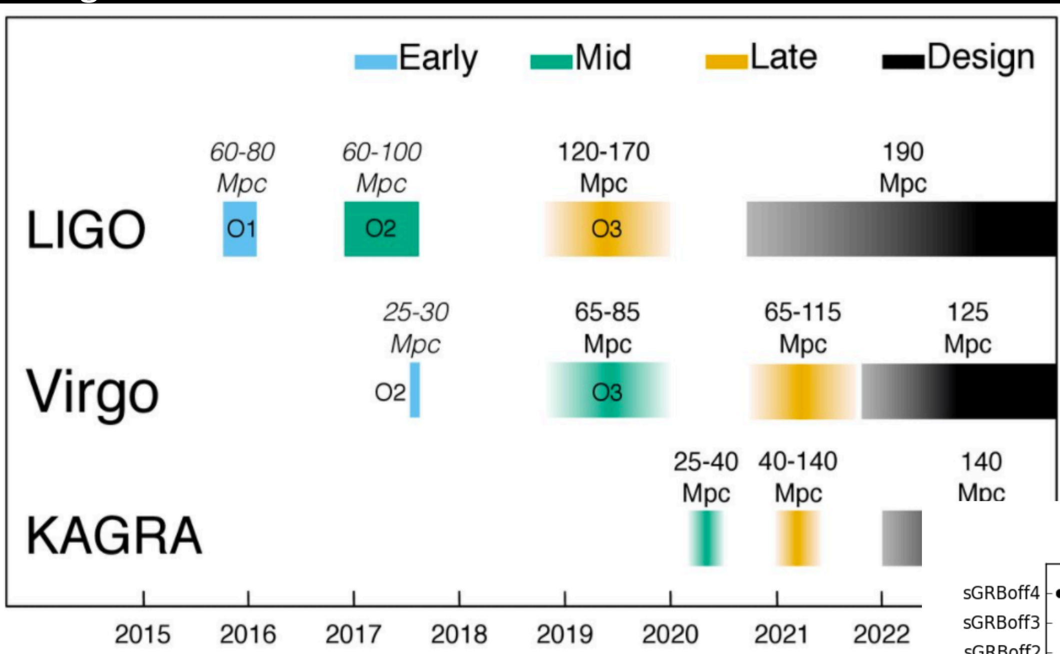


GRAWITA

Most of BNS models can reach up to 100 Mpc

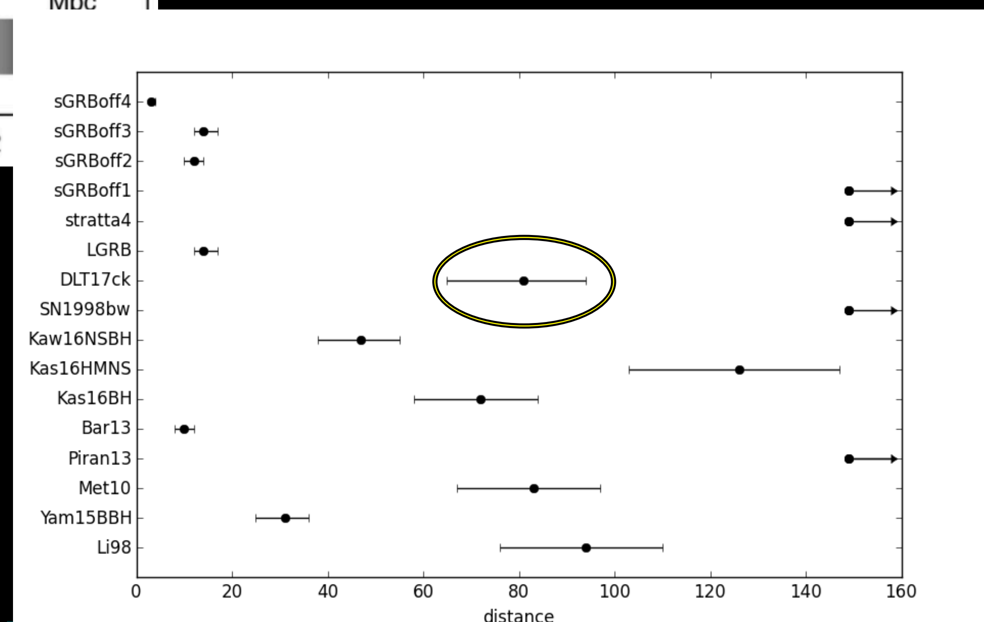
Future – O3

Range for BNS GW in O3

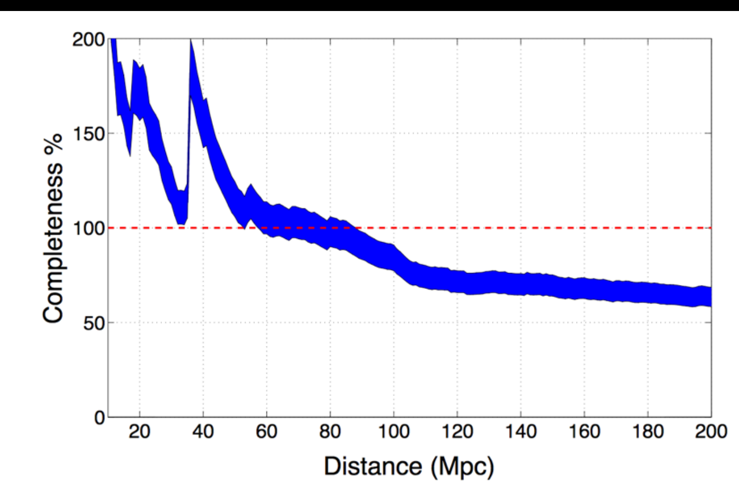


DLT40

More exposure per frame to reach deeper



DLT40	exptime	limit magnitude	Number of galaxies	Distance
O2	45s	19	400-600	70 Mpc
O3	100s	19.5	230	85 Mpc

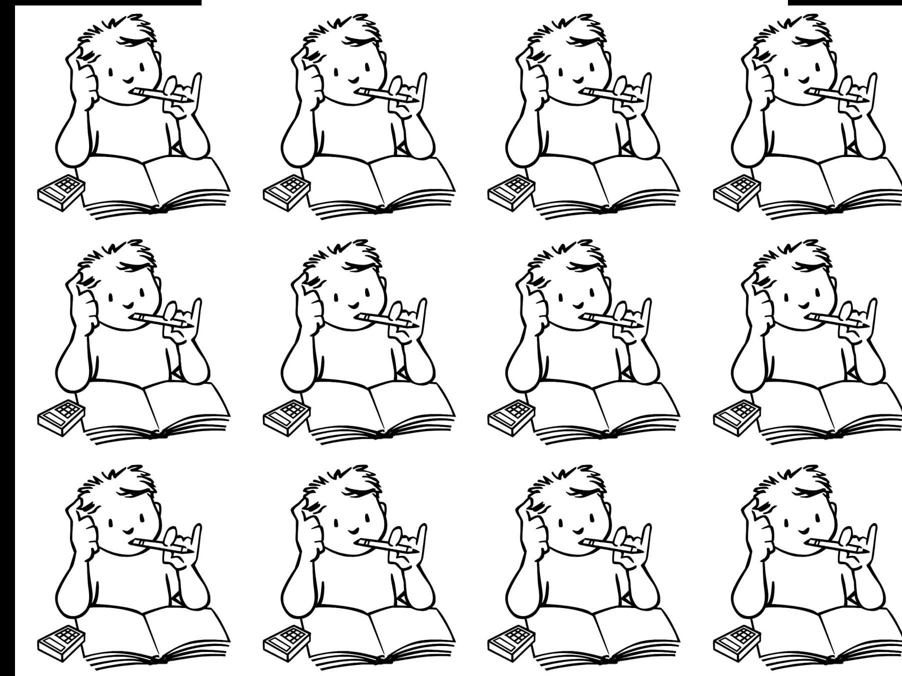


Galaxy incompleteness

Future - Machine learning

Human

Machine Learning



Philosophy:

- Human makes the rules and ML follows the rule
- Till now, ML can only do simple works

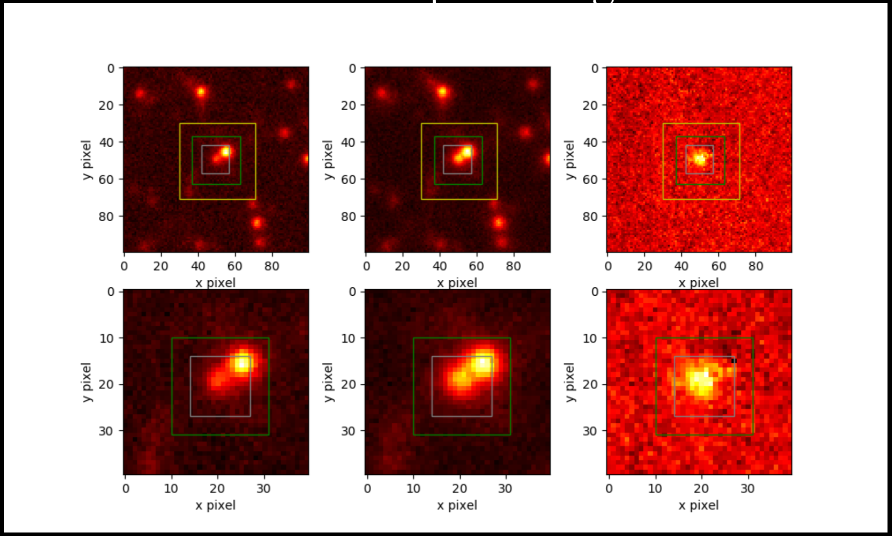
$$i\hbar \frac{\partial}{\partial t} \Psi(\mathrm{r},t) = \hat{H}\,\Psi(\mathrm{r},t)$$ ✗

$$1+1=3$$ ✓

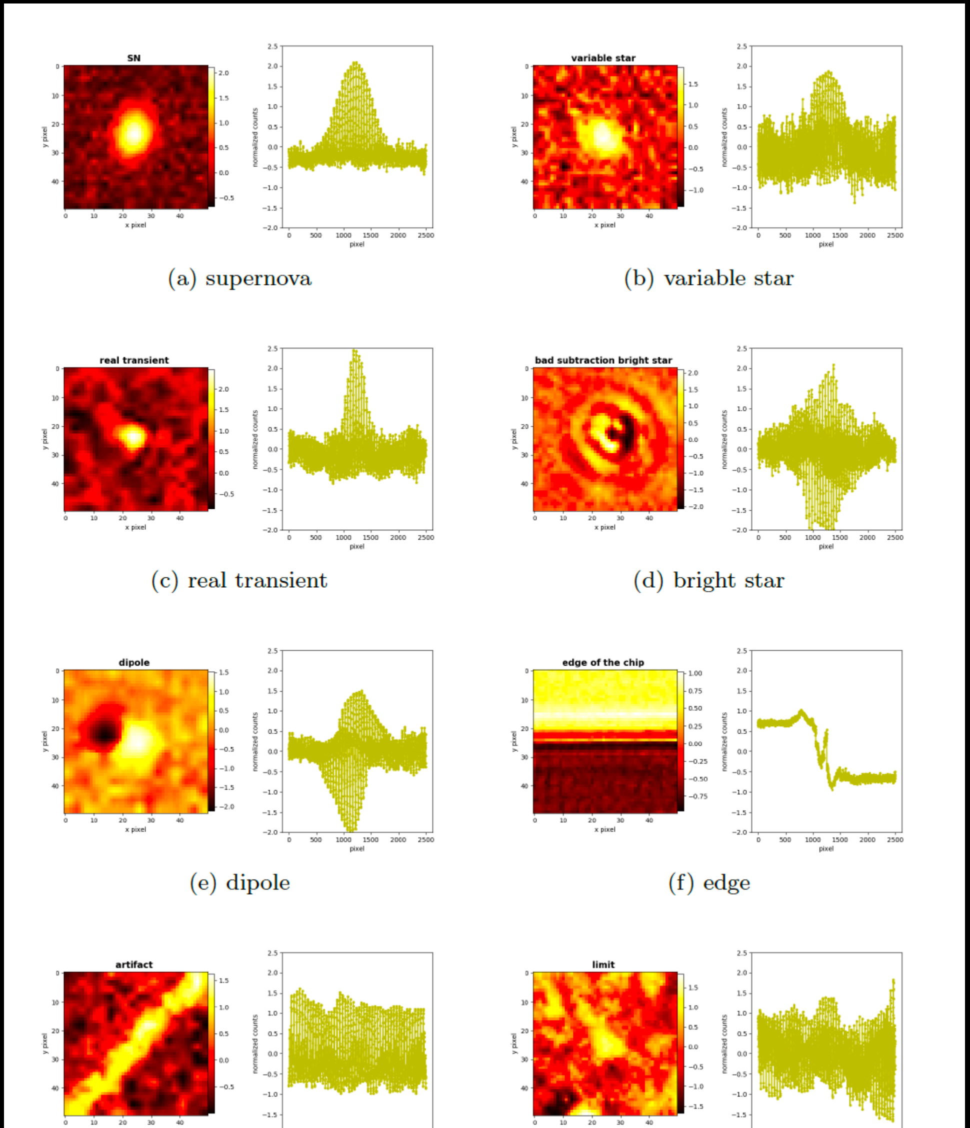
Future - Machine learning

Feature (considering only the source detection)
- Parameters from hotpants and sextractor
- Matrix of the image stamps

Methods:
Supervised (feature + label), unsupervised (feature), semi-supervised (mix)
- scikit-learn for traditional learning
- tensorflow for deep learning



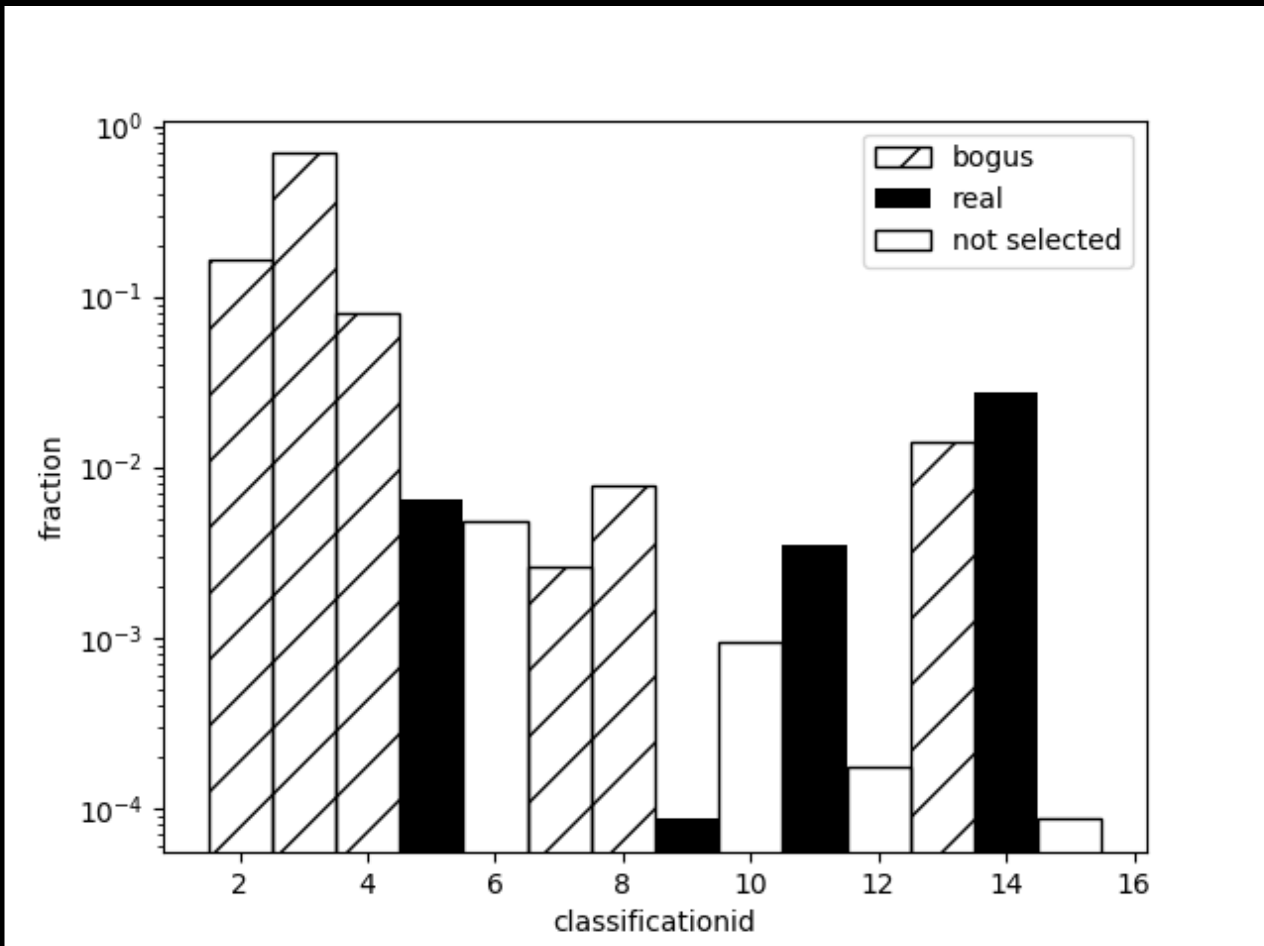
Stamp size: 5*FWHM



(a) supernova
(b) variable star
(c) real transient
(d) bright star
(e) dipole
(f) edge
(g) artifact
(h) limit

Future - Machine learning

Database for training samples

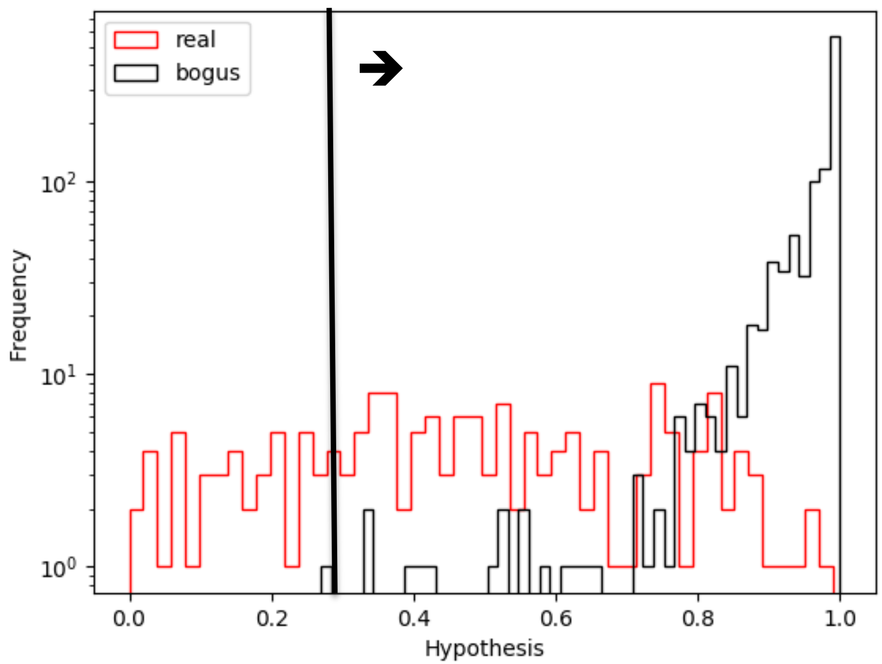


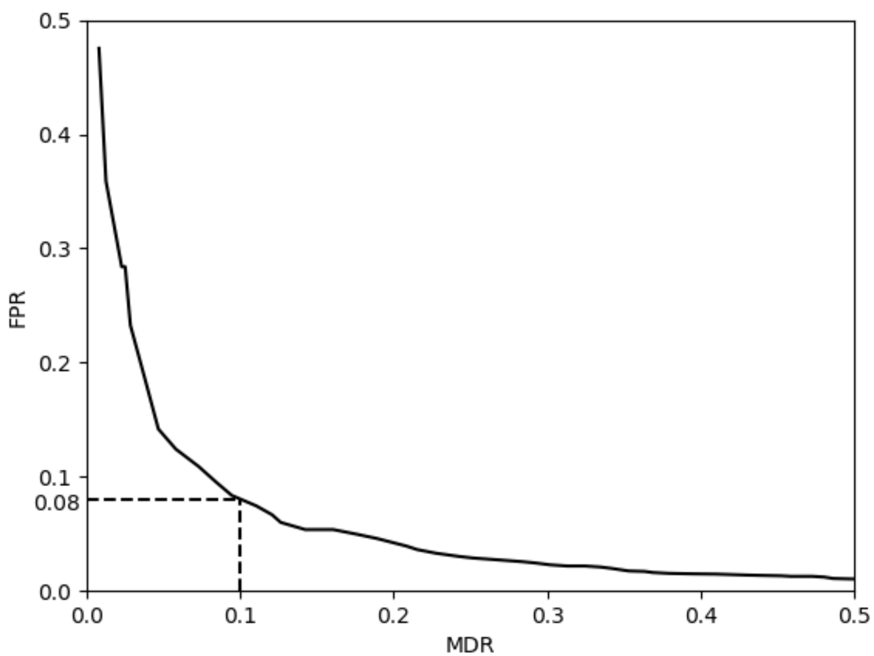
DLT40 log

id	classification	ML_id
1	eyeball	NULL
2	bad subtraction	0
3	bad subtraction bright star	0
4	dipole	0
5	real transient	1
6	moving object	NULL
7	edge of the chip	0
8	artifact	0
9	AGN	NULL
10	artificial star	1
11	SN	1
12	CV	NULL
13	rings	0
14	variable star	NULL
15	limit	0
16	kilonova	1

Future - Machine learning

Supervised:
1. feature + label as training set for ML
2. New feature, hypothesis estimated by ML

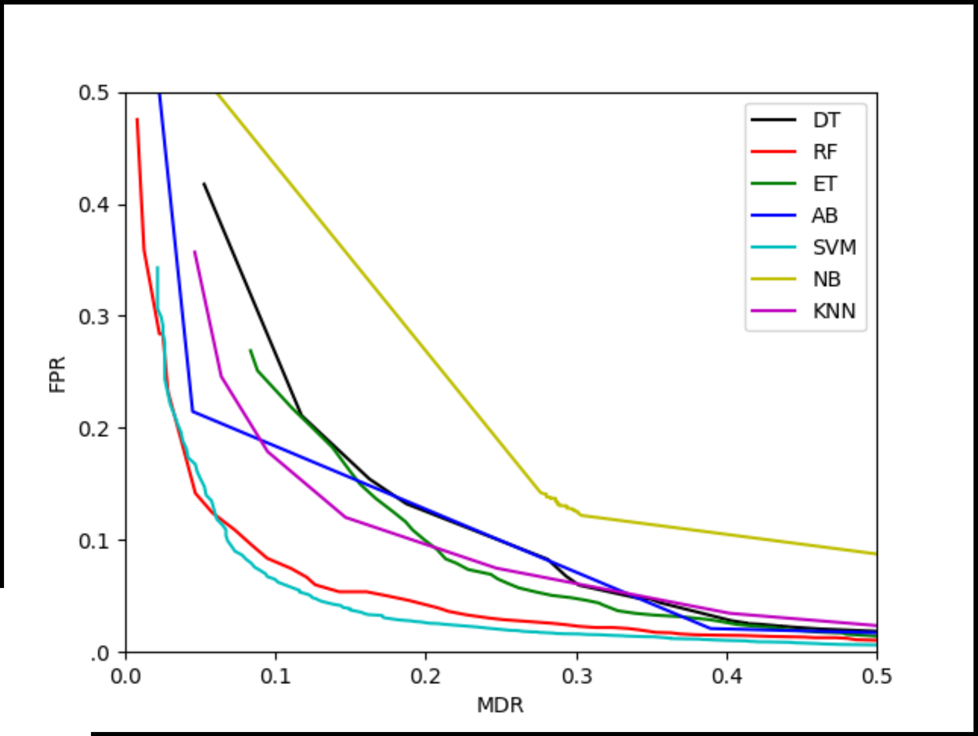


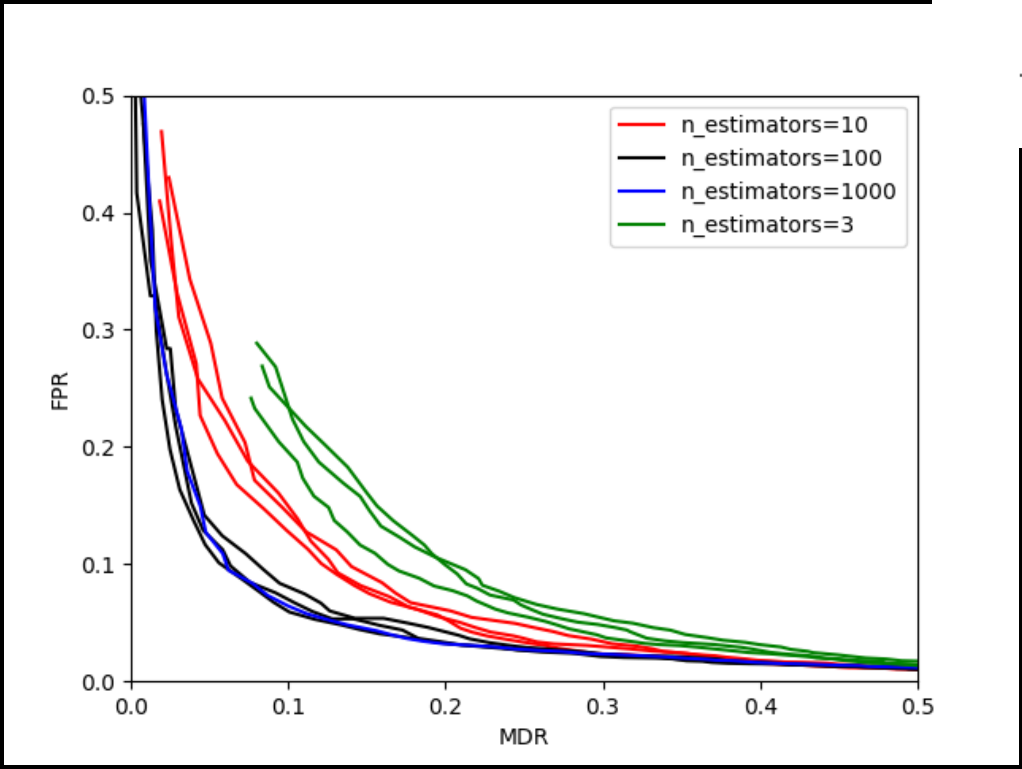


MDR:
missed detection rate, how much real missed
FPR:
false positive rate, how much bogus included
Merit:
FPR when MDR=0.1

Future - Machine learning

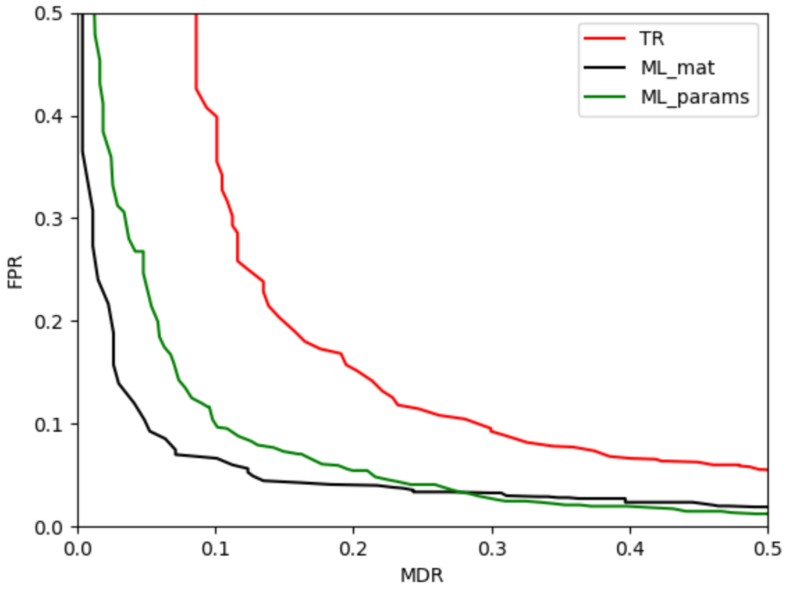
ML comparison: RF





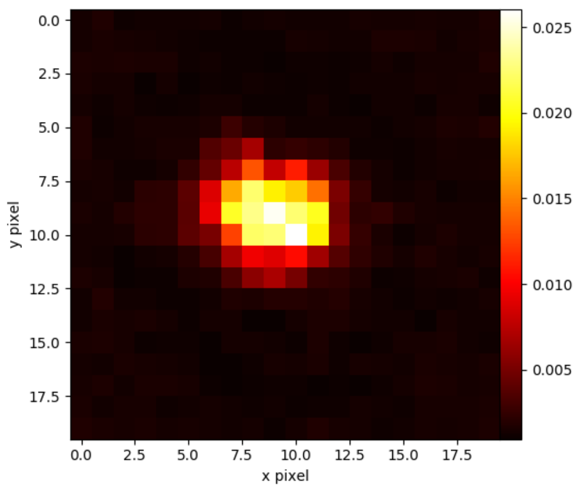
Parameter selection: RF, n_estimators=100

Future - Machine learning

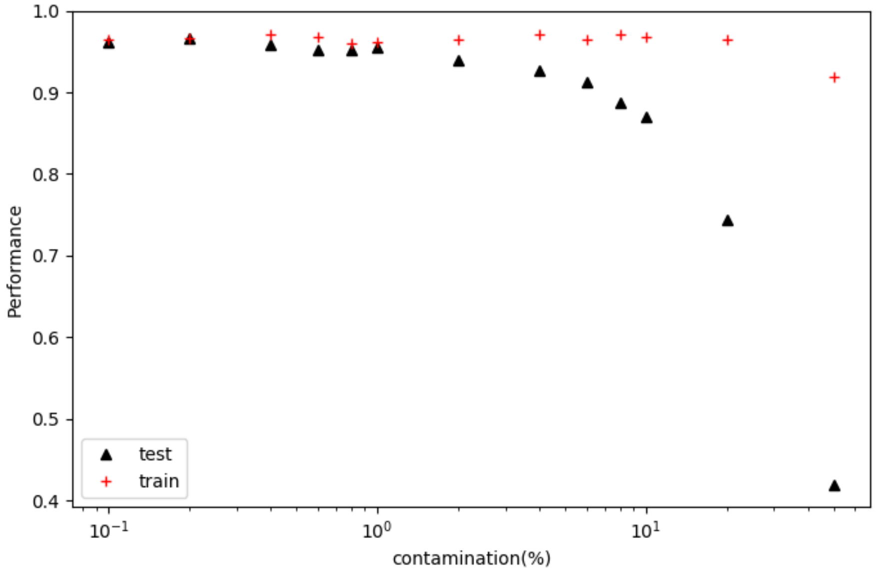


Comparison:

- Traditional ranking algorithm
- ML by using parameters as the features
- ML by using matrix as the features

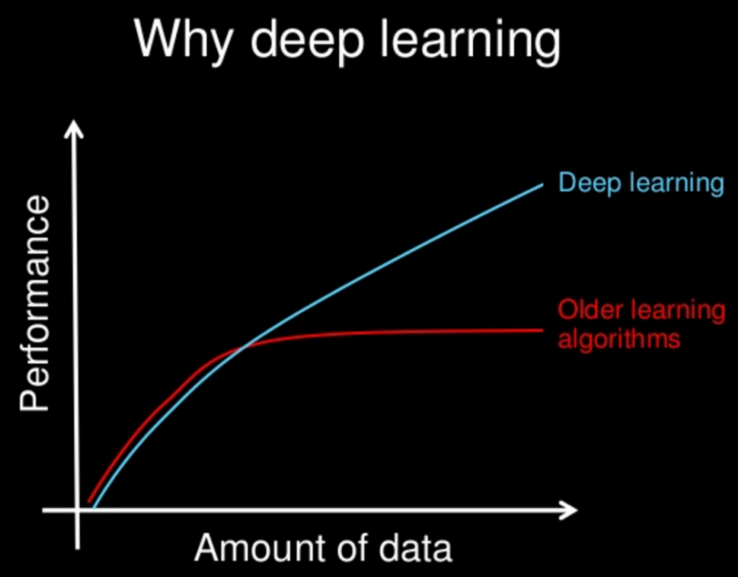


Feature importance



Contamination test

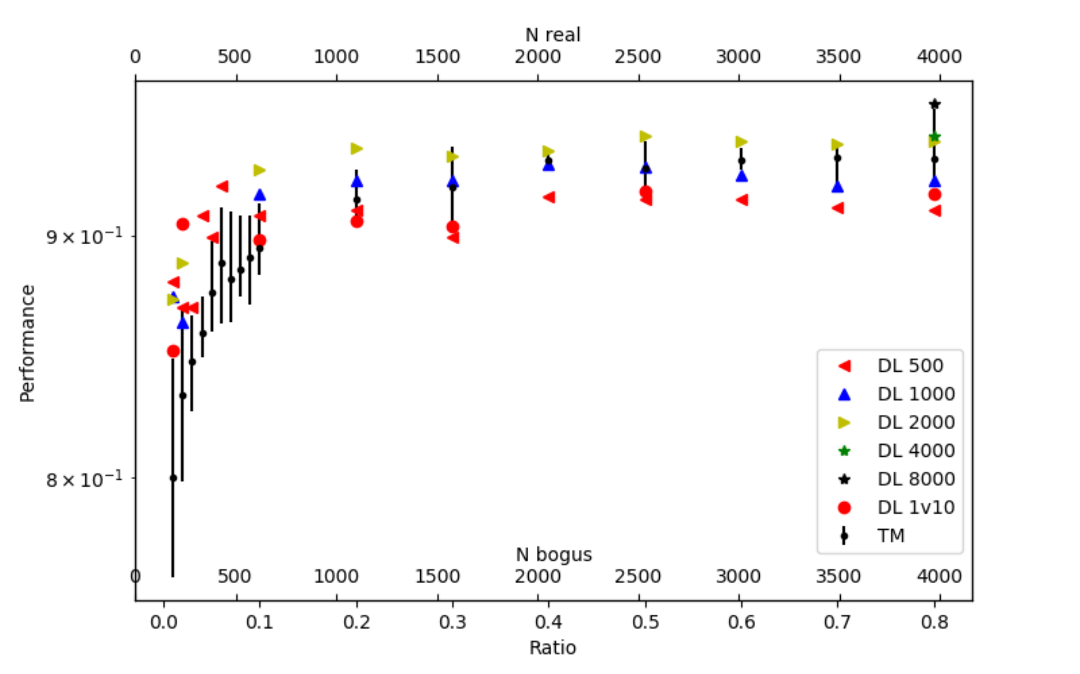
Future - Machine learning

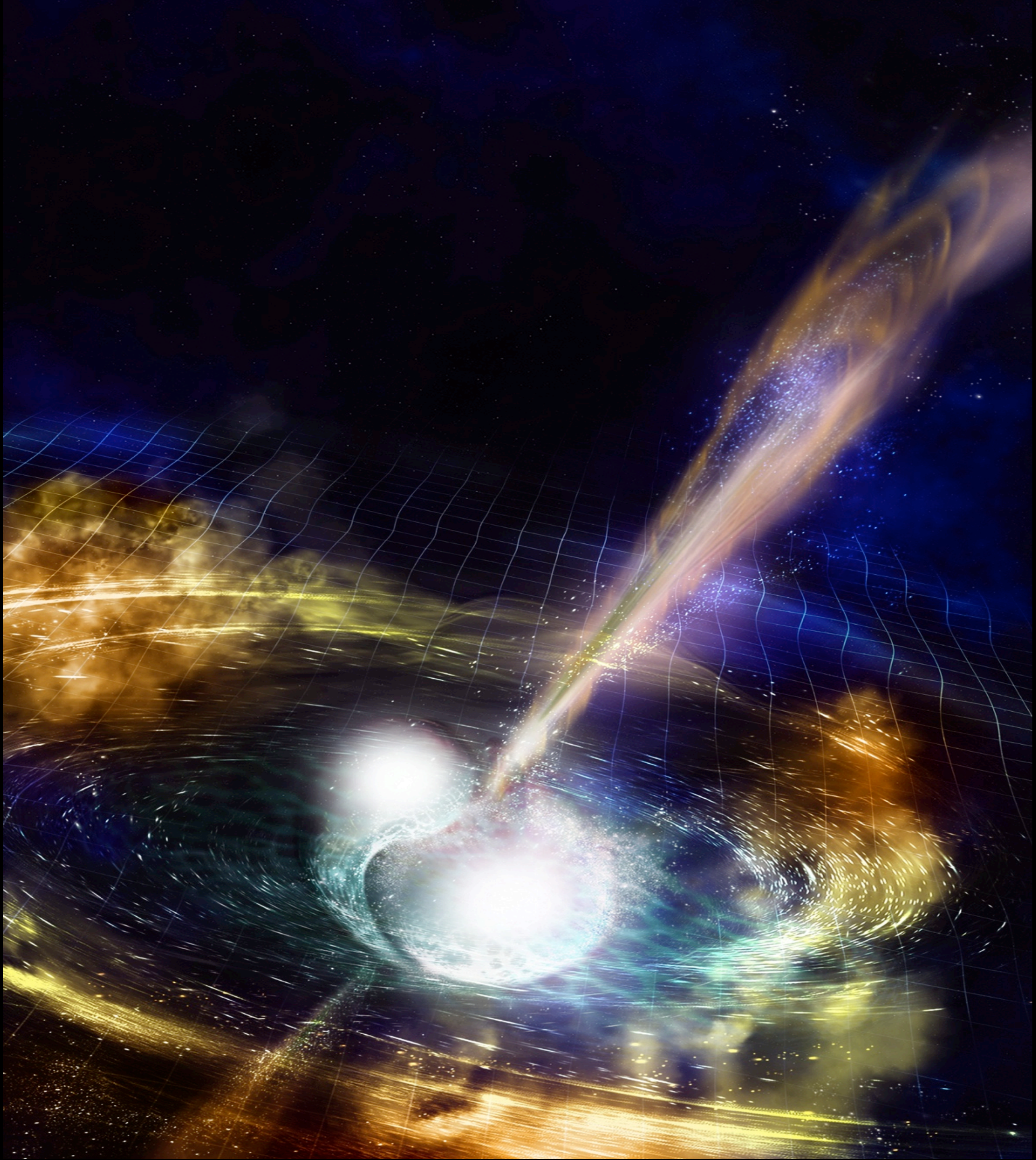


How do data science techniques scale with amount of data?

Credit by Andrew Ng

Deep learning or traditional ranking?





Thank you!