Deep learning in Astronomy

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Outline

Astronomy

A branch of science that covers the study and analysis of all extraterrestrial objects and their phenomena.

- Origin
- Evolution
- Functions

Astronomy – Method History

- Observational astronomy (OA)
    - Human eyes
    - Telescopes
    - Radio
    - Micrometer (e.g. double stars)
    - Spectrograph (e.g. redshift)
    - Photoelectric photometry using Charge-coupled Device (CCD), which can record the image nearly down to the level of individual photons.
    - Neutrino astronomy
    - Gravitational wave
- Virtual observatory (VO)

Astronomy – Fields

Astronomy is divided into many subfields, such as galactic astronomy, planetary science, extragalactic astronomy, stellar astronomy, solar astronomy, and cosmology. In general, the theoretical and the observational.

The purpose of observational study is to observe, record, and collect the data about the universe under study and theoretical scientists mainly calculate the measurable consequences of physical models.

Theoretical astronomers use the collected data to generate the simulation model, and the corresponding observations serve the purpose of evaluating the model or indicating the need for tweaking them.

Astronomy – Data

With ultra-modern technology, the astronomical data collection has been very simple, and rate is very high. And in astronomy, there are ”4Vs” – volume, variety, velocity, and value.

Volume data size – can be PB, EB, ZB.

Variety complex elements – signals, images, videos, spectra, time series, and simulations.

Velocity rate of production and transmission – sizeable synoptic survey telescopes (LSST) 20 TB per night for ten years.

Value high value to the astronomy of the data.

Data – Data type

- One-dimensional information in the form of signals;
- Two-dimensional information in images;
  - multispectral (8-10) and hyperspectral (100+).
  - From electromagnetic (EM) emissions
  - Image data
  - Spectral data
- Three-dimensional information in the video?;
- Time series (GW).

ctrum From 1 Hz to 10^{25} Hz, From km to atom size.

Tasks

- Stellar Classification[1]
    - Most potential applications
    - O, B, A, F, G, K, and M. (O and M represent the hottest and coolest types)
- Pulsar Detection and Recognition (Time series, intensity and time)
- Star / galaxy separation/classification and information analysis[2]
    - Shape and size
- Transient Analysis (暂现源, Fast ratio burst (FRB), gamma-ray burst, pulsar, gravitational wave,[3] and other transient phenomena)(FAST)
- Astronomical survey analysis (e.g. Gaia survey, Active Galactic Nuclei(AGN))
- Other applications

[1] Jing-min et al., "A New Stellar Spectral Feature Extraction Method Based on Two-dimensional Fourier Spectrum Image and Its Application in the Stellar Spectral Classification Based on Deep Network"; Chiu et al., "Searching for Young Stellar Objects through SEDs by Machine Learning".

[2] Hausen and Robertson, "Morpheus".

[3] Zhang et al., "Detecting Gravitational Waves from Extreme Mass Ratio Inspirals Using Convolutional Neural Networks".

Paper 1

- Detecting gravitational waves from extreme mass ratio inspirals (EMRI) using convolutional neural networks[4]
- By: Xue-Ting Zhang, Chris Messenger, Natalia Korsakova, Man Leong Chan, Yi-Ming Hu, and Jing-dong Zhang

[4] Zhang et al., "Detecting Gravitational Waves from Extreme Mass Ratio Inspirals Using Convolutional Neural Networks".

Gravitational waves

- Double White Dwarfs (DWDs)
- Massive Binary Black Holes (MBBHs)
- Stellar-mass Binary Black Holes (sBBHs)
- Extreme mass ratio inspirals (EMRIs)
- Stochastic gravitational-wave background (mHz frequency band)

Waveform models of EMRIs

- Teukolsky-based waveform and Numerical Kludge (NK) waveform.
- Analytic Kludge (AK) model, through post-Newtonian equations (max 4.5 now)
- Augmented Analytic Kludge (AAK). Accuracy similar to NK with the generating speed of AK

The TianQin (天琴) mission

Ground noise affects accuracy, and TianQin is in space and can accurately detect gravitational waves.

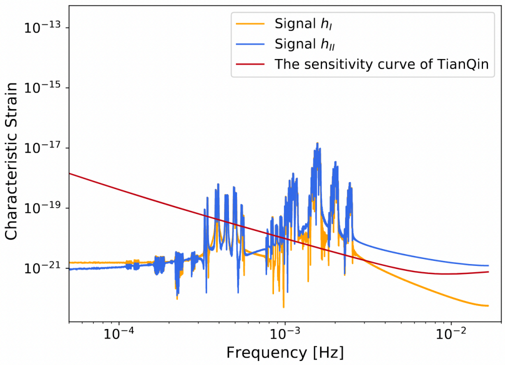


Figure: An example EMRI signals compared with the sensitivity curve of TianQin. A total length of 3 months observation time is assumed. From Zhang et al., "Detecting Gravitational Waves from Extreme Mass Ratio Inspirals Using Convolutional Neural Networks"

Data

Two categories. One can express the data d as the addition of random Gaussian noise n and the GW signal h.

- $d(t) = h(t) + n(t)$, if signal is present
- $d(t) = n(t)$, if there is no signal.

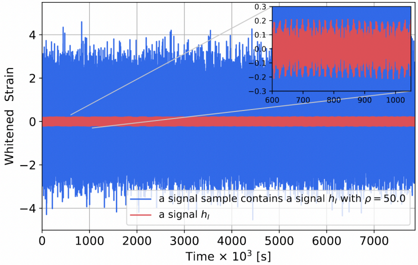


Figure: An example of whitened data in channel I in comparison with signal hI alone. For this event, the SNR is set to be 50. We draw the reader' s attention to the difference in scale for the noise and the signal. From Zhang et al., "Detecting Gravitational Waves from Extreme Mass Ratio Inspirals Using Convolutional Neural Networks"

Model

Input Simulation data for TianQin, using AK and AKK.

- 7864320 seconds (three months)
- 1/30 Hz
- 262144 size

TABLE III. the architecture of the CNN

	Layers	kernel number	kernel size	Activation function
1	Input	/	matrix(size: 2×262144)	/
2	Convolution	32	matrix(size:1×34)	relu
3	Pooling	16	matrix(size:1×8)	relu
4	Convolution	16	matrix(size: 1×8)	relu
5	Pooling	16	matrix(size: 1×6)	relu
6	Convolution	16	matrix(size: 1×6)	relu
7	Pooling	16	matrix(size: 1×4)	relu
8	Flatten	/	/	/
9	Dense	/	vector(size: 128)	relu
10	Dense	/	vector(size: 32)	relu
11	Output	/	vector(size: 2)	softmax

Experiment and Results

M is MBH mass, $10^4, 10^7$; ρ is Signal-to-Noise Ratio (SNR); z is redshift.

TABLE IV. Different waveform setups used as testing data. The first column indicates the index; the second column is the waveform model; the third column describes the parameter distribution, where to some astrophysical parameters the range shown in the table will be applied, but other unspecified parameters will remain in the same range as the training data(See table II).

number	**waveform model**	**physical parameters distribution**		**signal samples number**
1	AK	$\rho \in$ uniform [50,120]		500
2	AK	$\rho > 50$, astrophysical model M12		500
3	AAK	$\rho \in$ uniform [50,120]		500
4	AK	ρ enumerates $10, 20, ..., 130$		1000 $\times 13$
5	AK	M enumerates $10^4, 10^{4.5}, ..., 10^7 M_\odot$, $a = 0.98$	$z = 0.1$ $z = 0.2$ $z = 0.3$	1000 $\times 7 \times 3$
6	AK	$M = 10^6 M_\odot$, a enumerates $0.0, 0.2, 0.4, 0.6, 0.8, 0.98$	$z = 0.1$ $z = 0.2$ $z = 0.3$	1000 $\times 6 \times 3$
7	AK	$M = 10^{5.5} M_\odot, a = 0.98,\ z$ enumerates $0.1, 0.2, 0.3$ $M = 10^6 M_\odot, a = 0.0,\ z$ enumerates $0.1, 0.2, 0.3$ $M = 10^6 M_\odot, a = 0.98,\ z$ enumerates $0.1, 0.2, 0.3$		1000 $\times 3 \times 3$

Experiment and Results

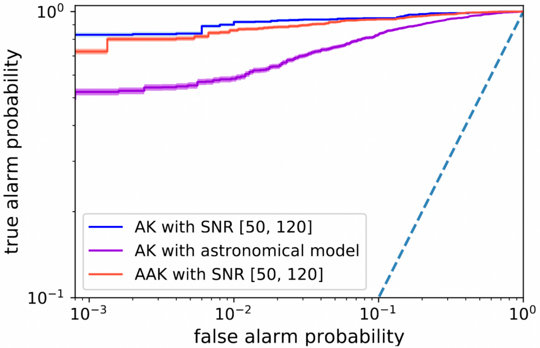


Figure: The ROC curve of the signals from testing groups 1-3 is shown with the blue, purple, and red lines, respectively. The blue line indicates the expected effectiveness for group 1, the parameters have identical distribution to the training data; for group 2, the distribution is drawn from an astrophysical model; for group 3, the distribution is the same as group 1 and the training data, but switched to the AAK waveform model. The 1-σ confidence intervals are indicated by the shaded regions.

Experiment and Results

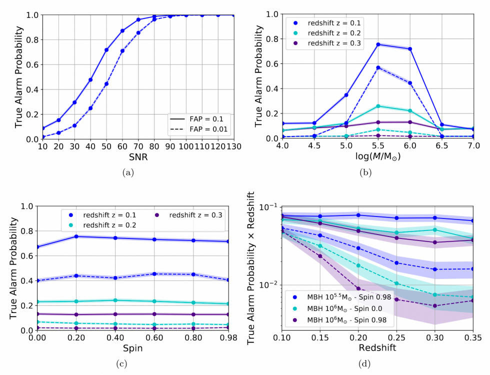


Figure: The comparison of the CNN sensitivity over EMRIs with different parameters.The vertical axis is the TAP, while the horizontal axis is the single varying parameter. The 1- confidence intervals are indicated by the shaded regions. The 1-σ confidence intervals are indicated by the shaded regions.

Paper 2

- Morpheus: A Deep Learning Framework for the Pixel-level Analysis of Astronomical Image Data[5]
- By: Ryan Hausen and Brant E. Robertson.

[5] Hausen and Robertson, "Morpheus".

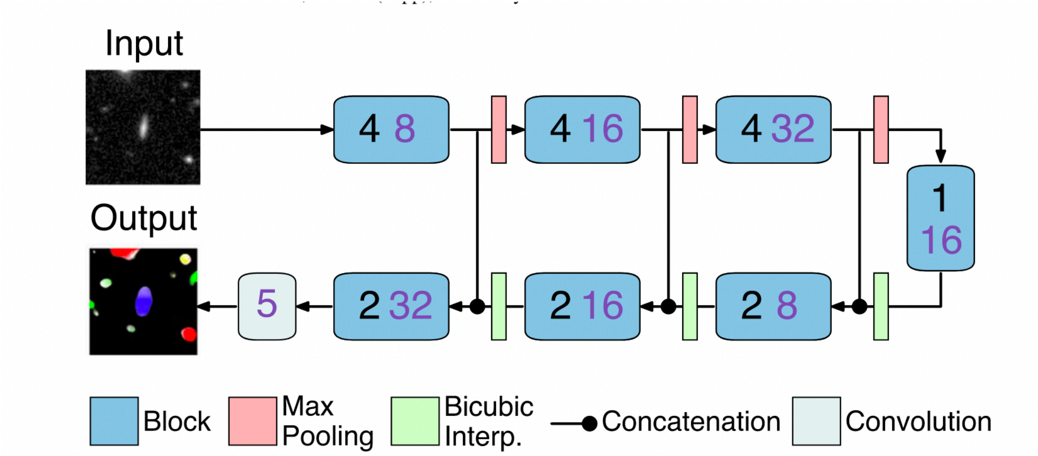
Target

- Source detection,
- Source segmentation,
- Morphological classification

Model

A U-Net.

- **Input** astronomical FITS images
- **Output** types – spheroid, disk, irregular, point source/compact, and background.



Model – Block

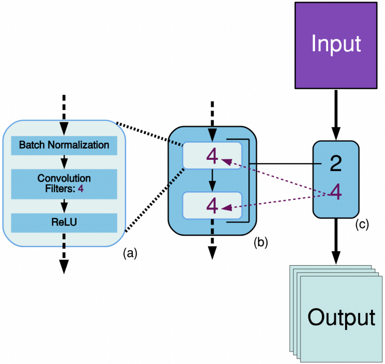
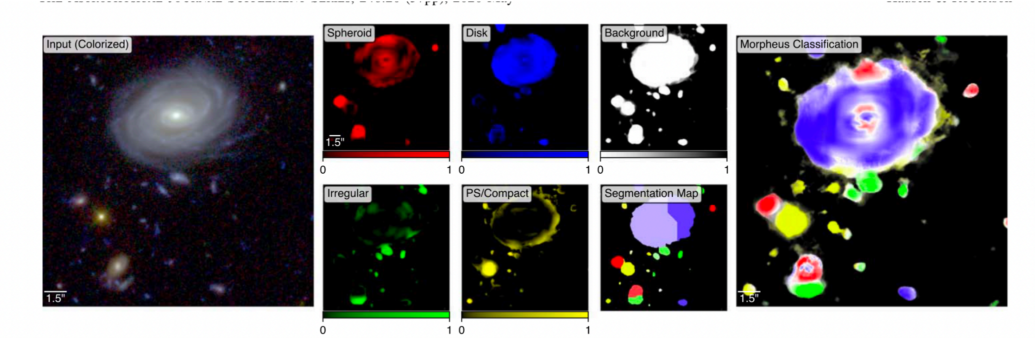
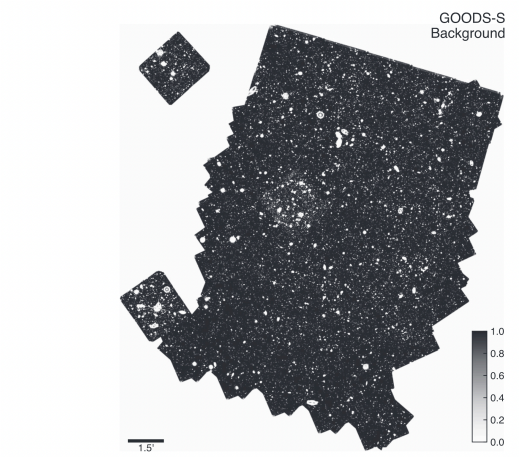


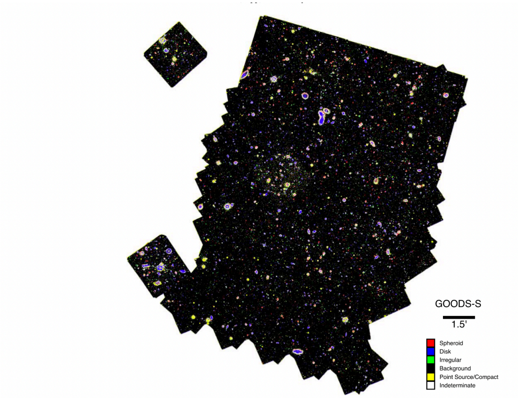
Figure: A single block in the neural network architecture. Panel (c) shows a single block from the architecture, parameterized by the number P (black) of block operations and the number Q (purple) of convolutional artificial neurons. Panel (b) shows an example zoom-in where there are P = 2 groups of Q = 4 block operations. Panel (a) shows a zoom-in on a block operation, which consists of batch normalization, Q = 4 CANs, and a rectified linear unit (ReLU).

Classification results



Classification results





Refs I

- Chiu, Y. -L. et al. “Searching for Young Stellar Objects through SEDs by Machine Learning”. In: *Astronomy and Computing* 36 (July 1, 2021), p. 100470. ISSN: 2213-1337. DOI: 10.1016/j.ascom.2021.100470. URL: https://www.sciencedirect.com/science/article/pii/S221313372100024X (visited on 07/29/2022).
- Hausen, Ryan and Brant E. Robertson. “Morpheus: A Deep Learning Framework for the Pixel-level Analysis of Astronomical Image Data”. In: *ApJS* 248.1 (May 2020), p. 20. ISSN: 0067-0049. DOI: 10.3847/1538-4365/ab8868. URL: https://doi.org/10.3847/1538-4365/ab8868 (visited on 07/29/2022).
- Jing-min, ZHANG et al. “A New Stellar Spectral Feature Extraction Method Based on Two-dimensional Fourier Spectrum Image and Its Application in the Stellar Spectral Classification Based on Deep Network”. In: *Chinese Astronomy and Astrophysics* 44.3 (July 1, 2020), pp. 334–344. ISSN: 0275-1062. DOI: 10.1016/j.chinastron.2020.08.004. URL: https://www.sciencedirect.com/science/article/pii/S0275106220300771 (visited on 07/29/2022).

Refs II

Zhang, Xue-Ting et al. "Detecting Gravitational Waves from Extreme Mass Ratio Inspirals Using Convolutional Neural Networks". In: *Phys. Rev. D* 105.12 (June 24, 2022), p. 123027. DOI: 10.1103/PhysRevD.105.123027. URL: https://link.aps.org/doi/10.1103/PhysRevD.105.123027 (visited on 07/29/2022).