DEEP-Theory Meeting 22 June 2017

GALFIT-type analysis of VELA simulations using deep learning — Marc Huertas-Company. New paper by Yicheng Guo on clump properties with disk subtraction nearly done.

Deep Learning for Galaxies project: Analysis of VELA Gen3 simulations is ongoing by Raymond Simons at JHU, Christoph Lee and Sean Larkin, along with Avishai's student Tomer Nussbaum: finding all satellites. Christoph is also using the DL code that classified CANDELS images to classify VELA mock galaxy images. Fernando Caro is analyzing Horizon simulations. Marc may have new results to discuss.

Deep Learning for Galaxy Environment project: Fernando Caro is working with David Koo on using DL for this. He may report on this today. James Kakos and Dominic Pasquale plan to use DL for a project to improve z and local environment estimates for galaxies with only photometric redshifts.

Galaxy size vs. local density project — Graham Vanbenthuysen, Viraj Pandya, Christoph Lee, Doug Hellinger, Aldo Rodriguez-Puebla, David Koo — We are measuring λ vs. density by various methods in Aldo's mock catalogs from Bolshoi-Planck and MultiDark-Planck, and SDSS galaxy radii vs. density by the same methods.

Elongated galaxies aligned with cosmic filaments? — Viraj Pandya will report on his work on this.

Halo properties like concentration, accretion history, and spin are mainly determined by environmental density rather than by location within the cosmic web — we are finishing the paper led by Tze Goh

DM halo mass loss and **halo radial profile** paper(s?) being drafted — Christoph Lee, Doug Hellinger. Related work this summer by SIP students Shawn Zhang and Peter Wu with Christoph.

Improved Santa Cruz Semi-Analytic Model of galaxy population evolution, including insights from high-resolution hydro simulations — Viraj Pandya, Christoph Lee, Rachel Somerville, Sandy Faber











Some useful files from Raymond Simons

Sightlines

#(0) scale factor

- #(1) camera number
- #(2) field of view (kpc)
- #(3) CAMPOSX (X position of camera in kpc; coordinate system centered on galaxy)
- #(4) CAMPOSY
- #(5) CAMPOSZ
- #(6) CAMDIRX (X comp of camera viewing dir, normalized)
- #(7) CAMDIRY
- #(8) CAMDIRZ
- #(9) CAMUPX (orientation of image-up)
- #(10) CAMUPY
- #(11) CAMUPZ

0.400	66	100.0	55156.609	-78470.582	-26245.057	-0.562	0.785	0.262	0.8274	0.5326	0.1781
0.400	01	100.0	-71089.962	-61986.836	33224.23	0.711	0.62	-0.332	-0.5616	0.7847	0.2625
0.400	02	100.0	-55156.609	78470.582	26245.057	0.562	-0.785	-0.262	0.6667	-0.6667	0.3333
0.400	63	100.0	71039.962	61986.836	-33224.23	-0.711	-0.62	0.332	-0.5616	0.7847	0.2625
0.400	64	100.0	-10559.475	-99318.392	4935.021	0.106	0.993	-0.049	-0.8998	0.1166	0.4205
0.400	05	100.0	-0.0	-0.0	100000.0	0.0	0.0	-1.0	-0.582	0.8132	0.0
0.400	06	100.0	-0.0	-100000.0	-0.0	0.0	1.0	0.0	-0.9059	0.0	0.4234
0.400	07	100.0	-100000.0	-0.0	-0.0	1.0	0.0	0.0	6.6	0.9484	0.3172
0.400	88	100.0	94215.506	29837.81	15269.04	-0.942	-0.298	-0.153	-0.3324	0.8902	0.3117
0.400	69	100.0	20753.95	93369.534	-29178.823	-0.208	-0.934	0.292	-0.8	0.3337	0.4987
0.400	10	100.0	79244.317	59703.634	12482.558	-0.792	-0.597	-0.125	-0.6071	0.7523	0.2558
0.400	11	100.0	59578.998	17290.861	-78354.6	-0.597	-0.173	0.784	-0.3498	0.9349	-0.0601
0.400	12	100.0	70318.563	49990.08	-49857.025	-0.708	-0.5	0.499	-0.4694	0.8609	0.1963
0.400	13	100.0	-15033.059	3475.392	-98802.474	0.15	-0.035	0.988	-0.5902	0.7936	0.1179
0.400	14	100.0	-50927.997	53397.663	-58621.401	0.609	-0.534	0.586	-0.2411	0.5795	0.7785
0.400	15	100.0	-52373.249	-19918.474	75583.28	0.624	0.199	-0.756	-0.3445	0.9331	-0.0371
0.400	16	100.0	-1758.208	-93767.284	34706.915	0.018	0.938	-0.347	-0.7413	0.2452	0.6248
0.400	17	100.0	-95359.088	-26211.855	14818.332	0.954	0.262	-0.148	-0.2259	0.9432	0.2236
0.400	18	100.0	-87554.36	42460.962	23049.952	0.876	-0.425	-0.23	0.4595	0.8793	0.1256

Camera Orientations

As with the full SUNRISE suite, the general camera positions follow the scheme:

- (0) face-on
- (1) edge-on
- (2) reverse face-on
- (3) reverse edge-on
- (4) 45 degrees
- (5) Z-axis
- (6) Y-axis
- (7) X-axis
- (8-11) random and fixed to simulation box, same snapshot to snapshot
- (12-18) random between snapshots

Some useful files from Raymond Simons

Central Galaxy and Merging Satellites (file is called Mergers)

#(0) scale	#(10) merger 1 stellar mass (1.e10 Msun)
#(1) mean jz/jcirc of young stars in central galaxy	#(11) merger 1 mean location (kpc)
#(2) std jz/jcirc of young stars in central galaxy	#(12) merger 1 std location (kpc)
#(3) mean location of young stars in central galaxy (kpc)	#(13) merger 1 mean jz/jcirc
#(4) std location of young stars in central galaxy (kpc)	#(14) merger 1 std jz/jcirc
#(5) central stellar mass (1.e10 Msun)	#(15) merger 2 stellar mass (1.e10 Msun)
#(6) central mean location (kpc)	#(16) merger 2 mean location (kpc)
#(7) central std location (kpc)	#(17) merger 2 std location (kpc)
#(8) central mean jz/jcirc	#(18) merger 2 mean jz/jcirc
#(9) central std jz/jcirc	#(19) merger 2 std jz/jcirc

#(20:) etc.

Example from VELA 20 at a=0.20

0		1	2	3	4	5	6	7	8	9
10	11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30	31
32	33	34								
200		0.73	0.29	1.70	1.93	0.805	1.34	2.36	0.46	0.47
0.342	25.91	1.87	-0.65	0.53	0.051	53.14	3.44	-0.03	0.20	0.0016
42.84	0.39	-0.08	0.11	0.001	14.90	0.80	-0.82	0.07	0.001	34.7 1
0.30	-0.97	0.10	nan							

Unfortunately the Mergers file only includes mergers, not all satellites but Raymond told me that he will send all the satellite data within 2 weeks

nan

young stars (age < 20 Myr)







z = 1.5 stars

- 16j ·

10 kpc

Deep Learning for Galaxy Environment project: James Kakos and Dominic Pasquale plan to use DL for a project to improve z and local environment estimates for galaxies with only photometric redshifts. Fernando Caro and David Koo are also using DL for this. Fernando may report on this here.

From David Koo - recent astrophs on photometric redshifts and machine or deep learning

arXiv:1706.02467 Photometric redshift estimation via deep learning Antonio D'Isanto, Kai Lars Polsterer

arXiv:1703.01979 Uncertain Photometric Redshifts with Deep Learning Methods Antonio D'Isanto

arXiv:1608.08016 Uncertain Photometric Redshifts Kai Lars Polsterer, Antonio D'Isanto, Fabian Gieseke

arXiv:1706.03501 Probability density estimation of photometric redshifts based on machine learning <u>Stefano</u> <u>Cavuoti, Massimo Brescia, Valeria Amaro, Civita Vellucci, Giuseppe Longo, Crescenzo Tortora</u> Comments: 2016 IEEE Symposium Series on Computational Intelligence

arXiv:1703.02292 METAPHOR: Probability density estimation for machine learning based photometric redshifts Valeria Amaro, Stefano Cavuoti, Massimo Brescia, Civita Vellucci, Crescenzo Tortora, Giuseppe Longo

<u>arXiv:1701.08120</u> Cooperative photometric redshift estimation <u>Stefano Cavuoti</u>, <u>Crescenzo Tortora</u>, <u>Massimo Brescia</u>, <u>Giuseppe Longo</u>, <u>Mario Radovich</u>, <u>Nicola R. Napolitano</u>, <u>Valeria Amaro</u>, <u>Civita Vellucci</u>

arXiv:1612.02173 A cooperative approach among methods for photometric redshifts estimation: an application to KiDS data Stefano Cavuoti, Crescenzo Tortora, Massimo Brescia, Giuseppe Longo, Mario Radovich, Nicola R. Napolitano, Valeria Amaro, Civita Vellucci, Francesco La Barbera, Fedor Getman, Aniello Grado Accepted by MNRAS **DM halo mass loss** and **halo radial profile** paper(s?) being drafted — Christoph Lee, Doug Hellinger. Related work this summer by SIP students Shawn Zhang and Peter Wu with Christoph.





Deep Learning for Redshifts project: Fernando Caro, James Kakos, and Dominic Pasquale may use DL for a project to improve distance and local environment estimates for galaxies with only photometric redshifts. This is related to the following work:



Circumgalactic medium (CGM): VELA mock quasar absorption spectra compared with observations - Clayton Strawn. Hassen Yesuf is working with X Prochaska to look at evidence for **outflows** in galaxies at z ~ 0.5 and compare with our ART simulations. Hassen is being hooded by David Koo today at the PhD graduation.

