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لهم اخْرُجْنَا مِنَ الظُّلْمَةِ إِلَى النُّورِ

Data modeling : Table of Contents (Optimization)

Main Subjects that are Covered by my lecture are :

* Relevant Refs.

Most relevant References: Books

- 1) Modern Cosmology, S. Donelson.
- 2) The Cosmic Microwave Background, R. Bunner.
- 3) Physical foundation of Cosmology, V. Mukhanov.
- 4) Cosmology, S. Weinberg.
- 5) Neutrino Cosmology, J. lesgourges et.al
- 6) Galaxy Formation and Evolution, H. Mo, F.V. den Bosch and S. White
- 7) Statistics of Galaxy Distribution, V. Martinez, E. Saar
- 8) Cosmological Physics, J.A. Peacock
- 9) Topological Complexity of Smooth Random Functions, Adler, Robert, Taylor, Jonathan E., Springer, 2009.
- 10) Geometry, Topology and Physics, Mikio Nakahara, 1990.
- 11) Analysis and Data-Based Reconstruction of Complex Nonlinear Dynamical Systems, Using the Methods of Stochastic Processes, M. Reza Rahimi Tabar, Springer, 2019.
- 12) Zomorodian, Afra. "Topological data analysis." Advances in applied and computational topology 70 (2012): 1-39.
- 13) Edelsbrunner, Herbert, and John Harer. Computational topology: an introduction. American Mathematical Soc., 2010.

Most relevant References: Papers and Lectures

- 1) Matsubara, Takahiko. "Statistics of smoothed cosmic fields in perturbation theory. I. Formulation and useful formulae in second-order perturbation theory." The Astrophysical Journal 584.1 (2003).
- 2) Vafaei Sadr, A., and S. M. S. Movahed. "Clustering of local extrema in Planck CMB maps." Monthly Notices of the Royal Astronomical Society 503.1 (2021): 815-829.
- 3) Masoomey, H., et al. "Persistent homology of fractional Gaussian noise." Physical Review E 104.3 (2021): 034116.
- 4) Masoomey, H., S. Tajik, and S. M. S. Movahed. "Homology groups of embedded fractional Brownian motion." Physical Review E 106.6 (2022): 064115.
- 5) Lesgourges, J. "Cosmological perturbations." Searching for New Physics at Small and Large Scales: TASI 2012. 2013: 29-97.
- 6) Mostaghel, Behrang, Hossein Moshafi, and S. M. S. Movahed. "Non-minimal derivative coupling scalar field and bulk viscous dark energy." The European Physical Journal C 77 (2017): 1-22.
- 7) Pranav, Pratyush, et al. "Topology and geometry of Gaussian random fields I: on Betti numbers, Euler characteristic, and Minkowski functionals." Monthly Notices of the Royal Astronomical Society 485.3 (2019): 4167-4208.
- 8) Pranav, Pratyush. "Topology and geometry of Gaussian random fields II: on critical points, excursion sets, and persistent homology." arXiv preprint arXiv:2109.08721 (2021).
- 9) Bardeen J. M., Bond J. R., Kaiser N., Szalay A. S., 1986, Astro- phys. J., 304, 15
- 10) Bond, J. R., et al., The Astrophysical Journal 379 (1991): 440-460.

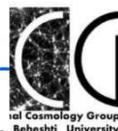
برای اینجا



Review on Data Analysis Methods & Cosmological Simulations

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Workshop on Computational Cosmology:
From Theory to Observation
1-2 August 2023



Most relevant References: Previous activities

Part A: Previous workshops

- 1) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/106-data-modeling-workshop>
- 2) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/131-workshop-on-observational-data-analysis-in-cosmology-kurdistan-1398>
- 3) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/144-school-and-workshop-on-statistical-analysis-of-cosmic-fields-1400>
- 4) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/154-school-and-workshop-on-topological-based-data-analysis-1401>

Part B: Some lectures:

- 1) <http://facultymembers.sbu.ac.ir/movahed/index.php/courses/142-optimization-and-computational-approaches-fall-2021>
- 2) <http://facultymembers.sbu.ac.ir/movahed/index.php/courses/132-advanced-course-on-computational-physics>
- 3) <http://facultymembers.sbu.ac.ir/movahed/index.php/courses/139-stochastic-processes>
- Part C: Some of my talks:
 - 1) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/102-my-talk-at-cosmology-meeting-ipm-96>
 - 2) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/148-my-talk-at-sharif-group-meeting-1401-2022>
 - 3) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/145-my-talk-at-conference-on-gravity-and-cosmology-1400>
 - 4) <http://facultymembers.sbu.ac.ir/movahed/index.php/talks-a-presentations/130-data-science>

★ Data modeling Workshop at 1397

★ Data Modeling workshop at Neyshabour 1398

① General View (Motivations and Scientific Methodology -)

X ② Different Classification of "DM"
★ Model-Based Analysis

★ Data-Based Analysis

③ Different types of DM approaches.

★ Bayesian approach

★ frequentism approach

④ Various Parts of a typical DM approach

⑤ The Mathematical Foundation of Bayesian
"DM" approach.

⑥ Bayesian Model averaging (BMA)

⑦ Analytical algorithm for "DM" [Optimization]

⑧ Computational algorithm for "DM"

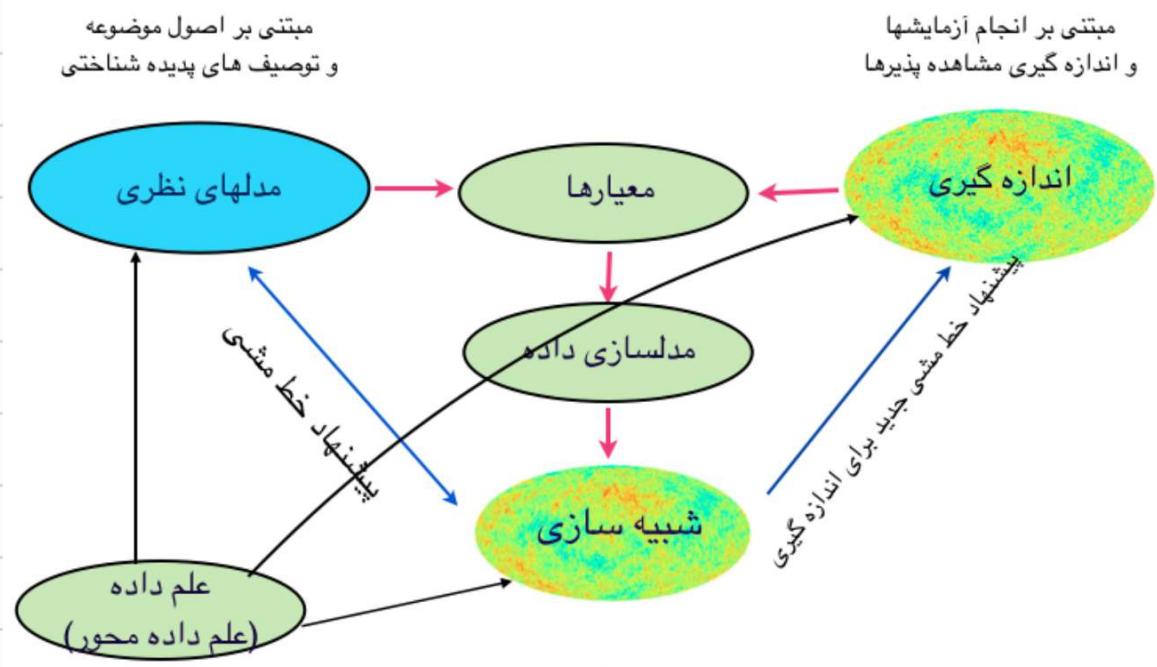
⑨ Fisher forecast (Fisher Information Matrix)

⑩ Goodness of fit and Confidence Interval
for Model's free Parameters.

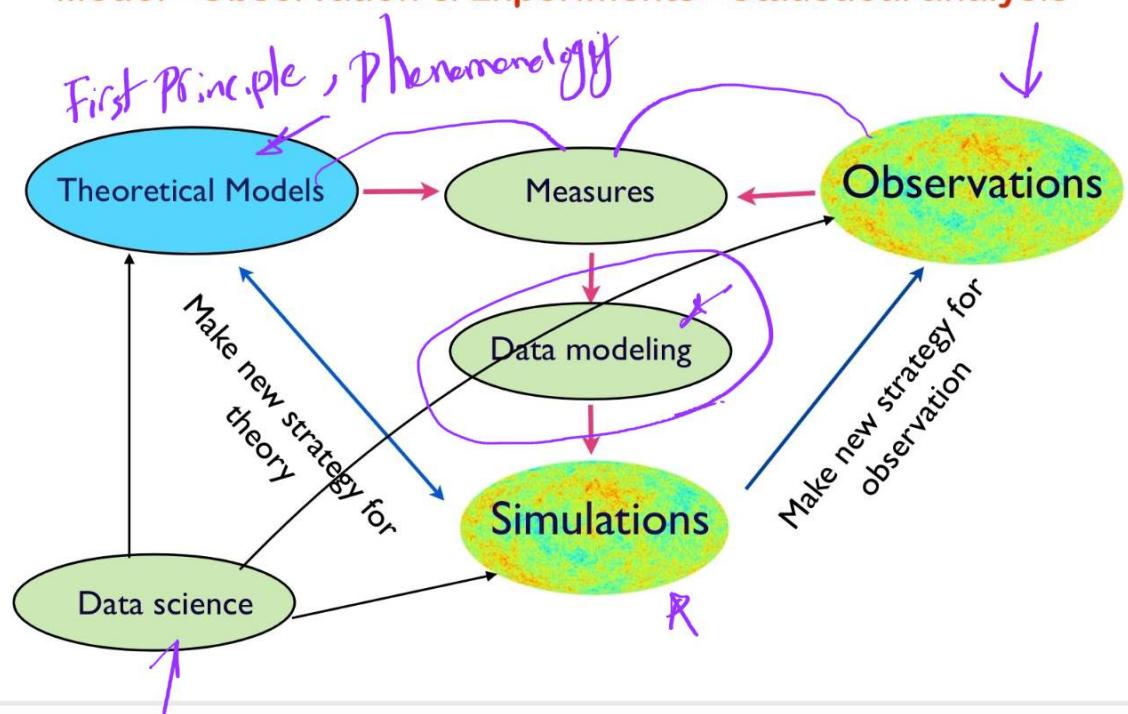
⑪ Simulation Based Inference (SBI)

① General View :

چرخه روش شناسی علمی



Scientific Methodology Model - Observation & Experiments - Statistical analysis

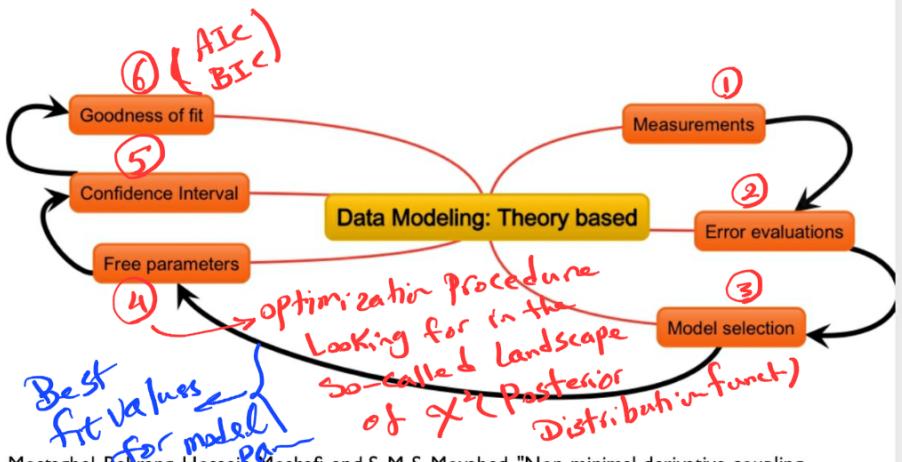


② Different Classifications of Data Modeling.

- Model-Based
 - Data-Based

(Theory-Based approach)

General view on Theory based



Mostaghel, Behrang, Hossein Moshafi, and S. M. S. Movahed. "Non-minimal derivative coupling scalar field and bulk viscous dark energy." *The European Physical Journal C* 77 (2017): 1-22.

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Ex 1: Suppose that in an Experimental Set up

We measured Internal Energy of a System.

{ E }

from a theoretical point of view we have a

Theory for Internal Energy of a N-Body System

with subtraction

$$H = H_0 + U$$

Free Part

$\langle p^2 \rangle_m$

$$U(r) \in \left[\left(\frac{\alpha}{r} \right)^a - \left(\frac{\sigma}{r} \right)^b \right]$$

$$r = |\vec{r}_i - \vec{r}_j|$$

$\{\theta\} : \{e, \alpha, a, \sigma, b\}$: Model's free Parameters.

↑↑↑↑↑

3-D for N-Body syst

Un-Weighted TPCF

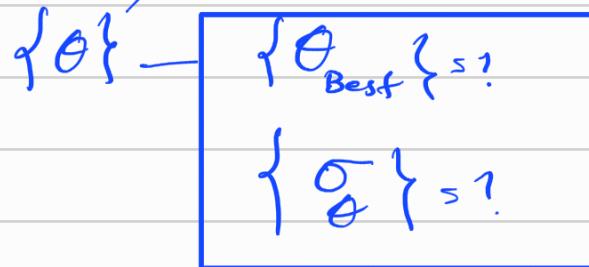
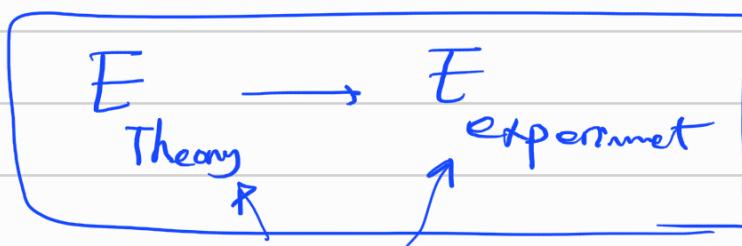
$$E = \frac{3K_B NT}{2} + \frac{n}{2} \int dr^3 \underline{w(r)} (4(r) + 1)$$

Theory.

T	E	Error \rightarrow
T_1	E_1	σ_{E_1}
T_2	E_2	σ_{E_2}
T_3	E_3	σ_{E_3}
.	.	.
T_p	E_p	σ_{E_p}

almost a Well-Defined
relation between
Model free Param
and measures from
Experiment

We are looking for $\{\theta_{\text{Best}}\}$. in such that



Model (Theory)-Based
approach.

$$EK2: \quad T_{\mu\nu} = (\overset{\rho + \tilde{P}}{\uparrow}) u_\mu u_\nu + \tilde{P} g_{\mu\nu}$$

$$\tilde{P} = P + \Pi$$

← Induced by Viscosity term

$$\nabla_\mu T^\mu_\nu = 0$$

Π : (Induced term for Pressure from Bulk Viscosity.)

$$(\dot{\rho}) + 3H(\rho + P) - 9H^2\xi = 0$$

↙

Viscosity term

$$H^2 = \frac{8\pi G}{3}\rho \left(\frac{5-3\eta}{2} \right) - \frac{K}{a^2}$$

$$\ddot{\frac{a}{a}} = -\frac{4\pi}{3} \left(\frac{5-3\eta}{2} \right) G(\rho + 3P)$$

$$H^2 = \frac{8\pi G}{3} \left(\frac{5-3\eta}{2} \right) (\dot{\rho}_r + \dot{\rho}_m + \dot{\rho}_{DE}) \quad \left. \right\}$$

$$\dot{\rho}_r + 4H\rho_r = 0$$

$$\dot{\rho}_m + 3H\rho_m = 0$$

$$\dot{\rho}_{DE} + 3H(1+\omega_{DE})\rho_{DE} = 9H^2\xi$$

Suppose (Ansatz)

$$\xi = \eta H$$

$$\frac{H^2}{H_0^2} = \left(\frac{5-3\eta}{2} \right) \left[\Omega_r (1+z)^4 + \Omega_m (1+z)^3 + \Omega_{DE} \left(1 - \frac{9\eta}{2\sqrt{\alpha_0}} \ln(1+z) \right)^2 \right]$$

$$d_L(z) = \sqrt{(1+z)^2 + \frac{1}{H(z)}}$$

$$\{\theta\} = \{\Omega_m, S_r, S_{DE}, w_{DE}, \xi, H_0\}$$

Desired
free params

Free params

observe SNIa.

Well Defined

Relation

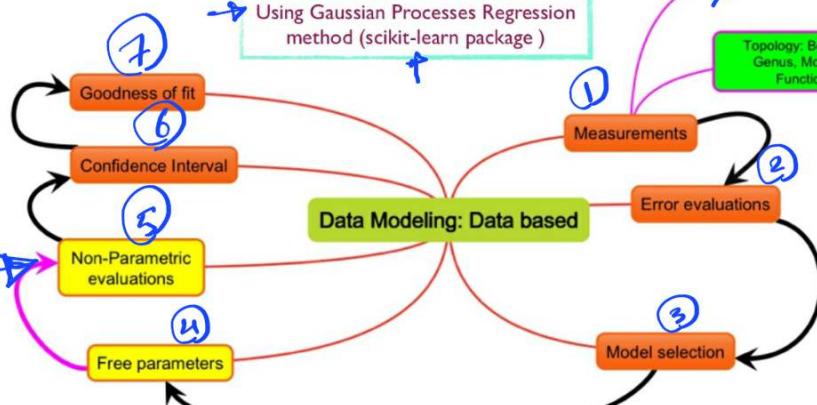
$$\text{Flux} \rightarrow d_L$$

z	Flux	σ_F
z_1	F_1	σ_{F_1}
z_2	F_2	σ_{F_2}
.	.	.
z_p	F_p	σ_{F_p}

$$\{\theta\} = \{\theta_{\text{Best}}\} \rightarrow \text{Flux}_{\text{observed}} \leftrightarrow F_{\text{theory}}$$

There is No
Well Defined
Relation between
Observations
and desired
free params

General view on Data based



$\langle n_{cc} \rangle$
 $\langle n_{pk} \rangle$
 $\langle n_{tr} \rangle$
 $\langle n_{cmd} \rangle$
 $\langle n_{cm8cmd} \rangle$
 $\langle \dots \rangle$

1) Pedregosa, Fabian, et al. "Scikit-learn: Machine learning in Python." *the Journal of machine Learning research* 12 (2011): 2825-2830.
 2) Heydenreich, Sven, Benjamin Brück, and Joachim Hartmann-Déraps. "Persistent homology in cosmic shear: constraining parameters with topological data analysis." *Astronomy & Astrophysics* 648 (2021): A74.

Betti numbers are highly non-linear functions to cosmological parameters

Table A.1. Cosmological parameters of the cosmo-SLICs wCDM simulations. Other fixed parameters are $\Omega_b = 0.0447$ and $n_s = 0.969$.

	Ω_m	S_8	h	w_0	σ_8	Ω_{dm}
00	0.3282	0.6934	0.6706	-1.2376	0.6677	0.2869
01	0.1019	0.7826	0.7104	-1.6154	1.3428	0.0456
02	0.2536	0.6133	0.6238	-1.7698	0.667	0.2063
03	0.1734	0.7284	0.6584	-0.5223	0.9581	0.1261
04	0.3759	0.8986	0.6034	-0.9741	0.8028	0.3286
05	0.4758	0.7618	0.7459	-1.3046	0.6049	0.4285
06	0.1458	0.768	0.8031	-1.4498	1.1017	0.0985
07	0.3099	0.7861	0.694	-1.8784	0.7734	0.2626
08	0.4815	0.6804	0.6374	-0.7737	0.5371	0.4342
09	0.3425	0.7054	0.8006	-1.501	0.6602	0.2952
10	0.5482	0.6375	0.7645	-1.9127	0.4716	0.5009
11	0.2898	0.7218	0.6505	-0.6649	0.7344	0.2425
12	0.4247	0.7511	0.6819	-1.1986	0.6313	0.3774
13	0.3979	0.8476	0.7833	-1.1083	0.736	0.3506
14	0.1691	0.8618	0.789	-1.6903	1.1479	0.1218
15	0.1255	0.6131	0.7567	-0.9878	0.9479	0.0782
16	0.5148	0.8178	0.6691	-1.3812	0.6243	0.4675
17	0.1928	0.8862	0.6285	-0.8564	1.1055	0.1455
18	0.2784	0.65	0.7151	-1.0673	0.6747	0.2311
19	0.2106	0.8759	0.7388	-0.5667	1.0454	0.1633
20	0.443	0.8356	0.6161	-1.7037	0.6876	0.3957
21	0.4062	0.662	0.8129	-1.9866	0.5689	0.3589
22	0.2294	0.8226	0.7708	-0.8602	0.9407	0.1821
23	0.5095	0.7366	0.6988	-0.7164	0.5652	0.4632
24	0.3652	0.6574	0.7271	-1.5414	0.5958	0.3179
fid	0.2905	0.8231	0.6898	-1.0	0.8364	0.2432

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Euler characteristic

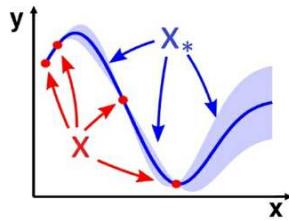
LSS
Betti numbers

persistent Betti numbers

To Topological Invariants

Using Gaussian Process Regression method (scikit-learn package)

Pedregosa, Fabian, et al. "Scikit-learn: Machine learning in Python." the Journal of machine Learning research 12 (2011): 2825-2830.



Gaussian Processes Regression

Wang, Jie, and Offroad Robotics. "An Intuitive Tutorial to Gaussian Processes Regression." stat 1050 (2021): 2.

