

exploring the SN Ia light-curve hyperparameter space by Markov Chain Monte Carlo (MCMC) sampling. We test to see how the posteriors of these hyperparameters depend on cosmology, whether using different dark energy models or reconstructions shift these posteriors. Our constraints on the SN Ia light-curve hyperparameters from our model-independent analysis are very consistent with the constraints from using different parameterizations of the equation of state of dark energy, namely the flat  $\Lambda$  CDM cosmology, the Chevallier-Polarski-Linder model, and the Phenomenologically Emergent Dark Energy (PEDE) model. This implies that the distance moduli constructed from the JLA data are mostly independent of the cosmological models. We also studied that the possibility the light-curve parameters evolve with redshift and our results show consistency with no evolution. The reconstructed expansion history of the universe and dark energy properties also seem to be in good agreement with the expectations of the standard  $\Lambda$ CDM model. However, our results also indicate that the data still allow for considerable flexibility in the expansion history of the universe. This work is published in ApJ.

**[구 CD-08] Model Independent Statistics in Cosmology**

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In this talk, I will discuss a few different techniques to reconstruct different cosmological functions, such as the primordial power spectrum and the expansion history. These model independent techniques are useful because they can discover surprising results in a way that nested modeling cannot. For instance, we can use the modified Richardson Lucy algorithm to reconstruct a novel primordial power spectra from the Planck data that can resolve the “Hubble tension”. This novel primordial power spectrum has regular oscillatory features that would be difficult to find using parametric methods. Further, we can use Gaussian process regression to reconstruct the expansion history of the Universe from low-redshift distance datasets. We can also this technique to test if these datasets are consistent with one another, which essentially allows for this technique to serve as a systematics finder.

**[석 CD-09] CMASS galaxy sample and the ontological status of cosmological principle**

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SDSS-III BOSS DR12 은하적색이동 탐사 자료 중 CMASS 표본을 사용하여 물질 분포에 대한 균일성 테스트를 수행하였다. 균일성의 비교 기준으로는 (i) 완전한 무작위 분포, (ii) Horizon Run 3 N-체 수치실험에서 얻은 헤일로 목록, 그리고 (iii) 물질 요동의 파워 스펙트럼과 로그정규분포를 가정해 얻은 모의 은하 목록을 사용하였다. 현재 관측된 영역에서 통계적으로 의미가 있는 가장 큰 규모인  $300h^{-1}\text{Mpc}$ 까지 조사한 결과, 우리는 관측된 물질 분포가 무작위 분포와 비교하여 전혀 균일하지 않지만 우주론으로부터 구한 나머지 두 목록과는 부합함을 보였다. 우주의 균일 등방성을 제시하는 우주론 원리는 우주론의 이론적 전개에서 물질의 분포가 아닌 공간곡률에 적용된다. 지금 우주모형에서는 이 원리에서 벗어난 공간곡률의 정도가 충분히 작으므로 우주론 원리를 우주론에 적용하는 데 문제가 없다. 하지만 우리는 물질 분포가 균일 등방성에서 벗어난 정도가 상당함을 보였으며, 따라서 우주론 원리가 이론적 모형에 성공적으로 적용되지만 실제로 관측된 은하 분포에는 존재하지 않는다는 기존의 결론을 새로운 자료를 이용해 강화하였다.

**특별세션-기계학습**

**[구 ML-01] Deep Learning the Large Scale Galaxy Distribution**

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I will give an overview of the recent work in deriving cosmological constraints from deep learning methods applied to the large scale distribution of galaxies. I will specifically highlight the success of convolutional neural networks in linking the morphology of the large scale matter distribution to dark energy parameters and modified gravity scenarios.

**[구 ML-02] Weak-lensing Mass Reconstruction of Galaxy Clusters with Convolutional Neural Network**

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