## Combining large-scale surveys and the CMB: the why and the how

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## Why we combine datasets



## Which datasets to combine ?

- Probes of different "sectors":
- Background evolution: all standard rulers/candles
- Perturbations: probes of structure growth


## Which datasets to combine?

- Probes of different "sectors":
- Background evolution: all standard rulers/candles
- Perturbations: probes of structure growth
- Probes of different epochs:



## Outline

## I. Forecasting the CMB-LSS combination

## How do we combine probes?

## Combining "existing" datasets

When analyzing data, fitting a model, running an MCMC,... :

## $\mathcal{L}_{\text {probe } 1+\text { probe } 2}=\mathcal{L}_{\text {probe } 1} \times \mathcal{L}_{\text {probe } 2}$

$\rightarrow$ assumes "probe 1" and "probe 2" are uncorrelated

## Combining "future" datasets

Fisher formalism :

- Approximates the posterior (~likelihood) as a Gaussian of the model parameters

$$
\mathcal{L}(\boldsymbol{\Theta}) \propto \exp \left[-\frac{1}{2}\left(\boldsymbol{\Theta}-\boldsymbol{\Theta}_{\mathrm{fid}}\right)^{T} \mathcal{F}\left(\boldsymbol{\Theta}-\boldsymbol{\Theta}_{\mathrm{fid}}\right)\right]
$$

- Fisher matrix :

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\mathcal{F}=\left(\begin{array}{ccc}
-\left.\frac{\partial^{2} \ln \mathcal{L}}{\partial \theta_{1}^{2}}\right|_{\text {fid }} & -\left.\frac{\partial^{2} \ln \mathcal{L}}{\partial \theta_{1} \partial \theta_{2}}\right|_{\text {fid }} & \cdots \\
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\end{array}\right)\left(=\frac{1}{2} \Sigma_{a b}^{-1} \frac{\partial \Sigma_{b c}}{\partial \theta_{\alpha}} \Sigma_{c d}^{-1} \frac{\partial \Sigma_{d a}}{\partial \theta_{\beta}}+\Sigma_{a b}^{-1} \frac{\partial \mu_{a}}{\partial \theta_{\alpha}} \frac{\partial \mu_{b}}{\partial \theta_{\beta}}\right)
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\end{array}\right)=\begin{aligned}
& \text { Forecasted errors } \\
& \text { on parameters }
\end{aligned}
$$

- Then
$\mathcal{L}_{\text {probe } 1+\text { probe } 2}=\mathcal{L}_{\text {probe } 1} \times \mathcal{L}_{\text {probe } 2}$
is equivalent to $\mathcal{F}_{\text {probe1 }}$ probe2 $=\mathcal{F}_{\text {probe1 }}+\mathcal{F}_{\text {probe } 2}$


## Combining future \& existing datasets ?

E.g. : Planck constraints + Euclid-like LSS forecasts

- LSS $\rightarrow$ Natural to use Fisher matrices
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- CMB $\rightarrow$ Could use "Planck-like" Fisher, but Planck is already here!
llić 2018 (in prep.):
- Produce a well-converged MCMC
- Perform an analytical fit of the posterior
- Combine it with any "classical" Fisher matrix


## Fitting the posterior



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## Fitting the posterior

Posterior from MCMC


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Posterior from MCMC Gaussian fit, with smoothly varying mean and covariance


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Either: MCMC with CMB fit + LSS Fisher (very quick)

## Fitting the posterior

Posterior from MCMC Gaussian fit, with smoothly varying mean and covariance


Typical next-gen
LSS

Either: MCMC with CMB fit + LSS Fisher (very quick)
Or: Gauss. approx of CMB fit + LSS Fisher



## Outline

## I. Forecasting the CMB-LSS combination

II. Forecasting the CMB-LSS correlation

## CMB-LSS cross-correlation



## CMB-LSS cross-correlation



## The integrated Sachs-Wolfe effect

In matter-dominated


## The Сюня́ев-Зельдо́вич effect



## Test case for LSS x CMB via Fisher

- Probes considered:
- Planck-like CMB: T, E, Ф
- Euclid-like LSS: GC phot. (10 z-bins)
- Model : $\gamma 0-\gamma 1-C D M \quad\left(f(a)=\Omega_{m}(a)^{\gamma_{0}+\gamma_{1} \ln a}\right)$
- Two cases:
- All cross-correlations accounted for
- Euclid-CMB correlations neglected (T-GC, Ф-GC)


## Test case for LSS x CMB



## Test case for LSS x CMB

## Without cross-correlations



## Even with a low S/N...

$$
\text { Stölzner et al. } 2018
$$

| catalog | $A_{\text {ISW }}$ |  | $\frac{A}{\sigma_{A}}$ | $\chi_{0}^{2}$ | $\chi_{\min }^{2}$ |
| :--- | :--- | ---: | ---: | ---: | ---: |
| SDSS | $1.89 \pm 0.57$ | 3.29 | 30.96 | 20.11 | 8.46 |
| WIxSC | $0.93 \pm 0.56$ | 1.67 | 13.16 | 10.39 | 2.76 |
| Quasars | $2.41 \pm 1.13$ | 2.13 | 14.55 | 10.01 | 2.99 |
| 2MPZ | $0.87 \pm 1.07$ | 0.81 | 4.04 | 3.38 | 0.65 |
| SDSS+WIxSC | $1.39 \pm 0.40$ | 3.49 | 44.12 | 31.94 | 11.21 |
| SDSS+Quasars | $1.99 \pm 0.51$ | 3.9 | 45.51 | 30.28 | 11.45 |
| SDSS+WIxSC+Quasars | $1.51 \pm 0.38$ | 4 | 58.67 | 42.66 | 14.2 |
| SDSS+WIxSC+Quasars+NVSS+2MPZ | $1.51 \pm 0.30$ | 5 | 77.61 | 52.61 | 22.16 |
| SDSS+WIxSC+Quasars+NVSS | $1.56 \pm 0.31$ | 4.97 | 73.57 | 48.85 | 21.52 |
| SDSS+WIxSC+NVSS+2MPZ | $1.44 \pm 0.31$ | 4.6 | 63.06 | 41.92 | 19.17 |
| SDSS+Quasars+NVSS+2MPZ | $1.75 \pm 0.36$ | 4.88 | 64.45 | 40.67 | 19.41 |
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## .already stringent constraints

From arXiv:1707.02263<br>Galileon Gravity in Light of ISW, CMB, BAO and H0 data

 We constrain three subsets of Galileon gravity separately known as the Cubic, Quartic and Quintic Galileons. The cubic Galileon model predicts a negative $C_{\ell}^{\mathrm{Tg}}$ and exhibits a $7.8 \sigma$ tension with the data, which effectively rules it out. For the quartic and quintic models the ISW data also rule out a significant portion of the parameter space but permit regions where the goodness-of-fit is comparable to $\Lambda \mathrm{CDM}$. The data prefers a non zero sum of the neutrino


## Beyond LCDM hints ?

$$
\text { Stölzner et al. } 2018
$$

| catalog | $\mu_{\text {IS }} \mathrm{V}$ | $\frac{A}{\sigma_{A}}$ | $\chi_{0}^{2}$ | $\chi_{\text {min }}^{2}$ | $\Delta \chi^{2}$ |
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## iSW effect of superstructures



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## Thank you <br> for your attention!

