

## Poisson model

For CMB fluctuations it's easy to know how to relate theory,  $\xi(r)$ , to observations at  $T(\hat{n})$ .

How do we connect

$$\xi(r) \equiv \langle \delta(\vec{x} + \vec{r}) \delta(\vec{x}) \rangle \quad \text{vs.} \quad \delta P_{12} = \bar{n} \delta V \bar{n} \delta V (1 + \xi_{12})$$

for galaxies?

Introduce a model to allow us to go from <sup>discrete objects</sup> fields to point processes.  
This model adds stochasticity, makes assumptions and is only approximate.

## Poisson model

(Layzer, Limber)

First select  $p(r)$  from ensemble

Place an object with probability  $\delta P = p(r) \delta V$ , indep. of other objects.

Note This can't be whole story - deviations due to volume exclusion (hard spheres) or excess clustering.

A more clever stat. formulation can be found in "Theory of point processes" (Daley & Vere-Jones)

Non-Poisson from N-body see Casas-Miranda et al. [a-p/10105008]

Note that this model does what we want

$$\delta P = p(r_1) \delta V_1 p(r_2) \delta V_2$$

$$\text{average over } p\text{'s} \quad \langle p(x)p(x+r) \rangle = \bar{p}^2 (1 + \xi(r)) \quad \text{so} \quad \delta P = \bar{p}^2 \delta V_1 \delta V_2 [1 + \xi(r)]$$

Now when we compute 2-point fun there are 2 levels of averaging

$$\begin{aligned}
\langle n_i n_j \rangle &\equiv \langle \langle \bar{n}(1+\delta_i) \bar{n}(1+\delta_j) \rangle_c \rangle_\rho && \text{for counts in cells } i \neq j \\
&= \langle \bar{n}(1+\delta_i) \bar{n}(1+\delta_j) \rangle_c + \delta_{ij} \langle \bar{n}(1+\delta_i) \rangle_c \\
&= \bar{n}^2 (1 + \delta_{ij}) + \bar{n} \delta_{ij}
\end{aligned}$$

Let's look at this 1st step again. Can use

$$\begin{aligned}
P(n; \mu) &= \frac{\mu^n}{n!} e^{-\mu} \\
\langle 1 \rangle &= 1 \\
\langle n \rangle &= \mu \\
\langle n(n-1) \rangle &= \mu^2 \Rightarrow \langle n^2 \rangle = \mu + \mu^2 && \text{Var}[n] = \mu = E[n] \\
\langle n(n-1)(n-2) \rangle &= \mu^3 \Rightarrow \langle n^3 \rangle = \mu + 3\mu^2 + \mu^3 \\
&\text{etc}
\end{aligned}$$

along with independence:  $\langle n_i n_j \rangle = \langle n_i \rangle \langle n_j \rangle$  if  $i \neq j$ .

But there is an easier way to do it.

Divide space into infinitesimal cells with  $\mu \ll 1$ . Then  $n_i = 0$  or  $1$  so

$$\langle n \rangle = \langle n^2 \rangle = \langle n^3 \rangle = \dots$$

So for example

$$\begin{aligned}
|\delta_k|^2 &= \int d\vec{r}_1 d\vec{r}_2 e^{i\vec{k} \cdot (\vec{r}_1 - \vec{r}_2)} \langle \langle \frac{n_1 - \bar{n}}{\bar{n}} \frac{n_2 - \bar{n}}{\bar{n}} \rangle \rangle \\
&= \sum_{ij} e^{i\vec{k} \cdot (\vec{r}_i - \vec{r}_j)} \langle \langle \frac{N_i - \bar{N}}{\bar{N}} \frac{N_j - \bar{N}}{\bar{N}} \rangle \rangle && N_i \equiv n_i SV = 0, 1 \\
&= \sum_{ij} \frac{e^{i\vec{k} \cdot (\vec{r}_i - \vec{r}_j)}}{\bar{n}^2} \langle \delta N_i \delta N_j + \delta_{ij} N_i \rangle \\
&= \int d\vec{r}_1 d\vec{r}_2 e^{i\vec{k} \cdot (\vec{r}_1 - \vec{r}_2)} \left\{ \langle \frac{\delta P(\vec{r}_1)}{\bar{p}} \frac{\delta P(\vec{r}_2)}{\bar{p}} \rangle + \delta(\vec{r}_1 - \vec{r}_2) \frac{1}{\bar{p}} \right\} \\
&= P(k) + \frac{1}{\bar{p}}
\end{aligned}$$

## Poisson model

Note we have two indep causes of variance, power spectra add and white/Poisson noise has  $P(k) = \text{const}$ .

So our estimate of power would be

$$\hat{P}(k) = |S_k|^2 - \frac{1}{\bar{n}}$$

How could we compute SP?

Assume linear theory with  $S_k$  independent Gaussians.

In the limit  $\bar{n} \rightarrow \infty$

$$\begin{aligned} \text{Var}[\hat{P}] &= \langle \hat{P}^2 \rangle - \langle \hat{P} \rangle^2 \\ &= \langle S^4 \rangle - \langle S^2 \rangle^2 \\ &= 2P(k) \end{aligned}$$

Note  $\langle z^4 \rangle = 3\sigma^4$  for Gaussian

or

$$\frac{\text{SP}}{P} = \sqrt{\frac{2}{N}} \quad \text{for } N \text{ independent modes.}$$

Now restate  $\bar{n} < \infty$ . If Poisson "noise" is independent of signal

$$\langle (S+N)(S+N) \rangle - \langle (S+N) \rangle^2 = \langle S^2 \rangle - \langle S \rangle^2 + \langle N^2 \rangle - \langle N \rangle^2 \quad \text{if } \langle SN \rangle = 0$$

The "S" terms give  $2P(k)$  while the "N" terms give  $2 \frac{1}{\bar{n}}$  so

$$\frac{\text{SP}}{P} = \sqrt{\frac{2}{N}} \left[ 1 + \frac{1}{\bar{n}P} \right] \quad \text{to leading order in } \frac{1}{\bar{n}N}$$

(full result in Mariani + White MNRAS '99):

Another way of looking at this result: what we measure is random with power  $P(k) + \frac{1}{\bar{n}}$ .

Subtracting a constant from  $\hat{P}$  doesn't change statistics so

$$\frac{\hat{SP}}{\hat{P}} = \frac{SP}{P} = \sqrt{2} \left[ 1 + \frac{1}{\bar{n}P} \right]$$

Note Have "sample variance" and noise contributions to SP.

First is multiplicative and pushes to maximize sky area (number of modes) while shot-noise is "additive".

Once  $\bar{n}P > 1$  reach diminishing returns for SP. At  $\bar{n}P = 5$  are 80% to  $\infty$ .

Near peak of  $P(k)$  have  $P \approx 2500 - 5000 (h^1 \text{Mpc}^3)^{-3}$  so optimal  $\bar{n} \approx 10^{-4}$ , at or less than  $L_*$  galaxies.

Raiser - subsample and cover lots of area.

BUT must subsample randomly!!