

# Space-filling experimental designs using sequences of lattices

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# Outline

- Computer experiments and designs
- Applications
- New type of lattice design
- Nested structure
- Application in predictive science
- Re-cap



# Many processes are investigated using computational models

- Many scientific applications use **deterministic** mathematical models to describe physical systems
- To understand how inputs to the computer code impact the system, scientists adjust the inputs to computer simulators and observe the response
- The computer models frequently:
  1. require solutions to PDEs or use finite element analyses
  2. have high dimensional inputs
  3. have outputs which are complex functions of the inputs
  4. require a large amounts of computing time
  5. have features from some of the above

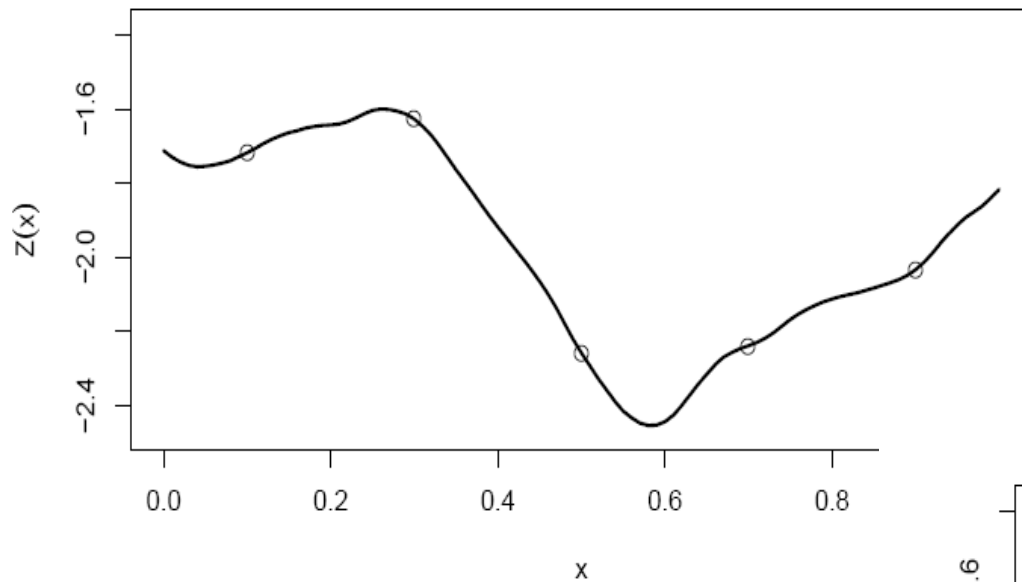


# Use Gaussian processes (GP's) for emulating computer model output

- GP's have proven effective for emulating computer model output (Sacks et al., 1989; **Jones, Schonlau and Welch, 1998**) and also data mining
- Emulating computer model output
  - output varies smoothly with input changes
  - output is essentially noise free
  - passes through the observed response
  - GP's outperform other modeling approaches in this arena

# Why use a GP for emulation?

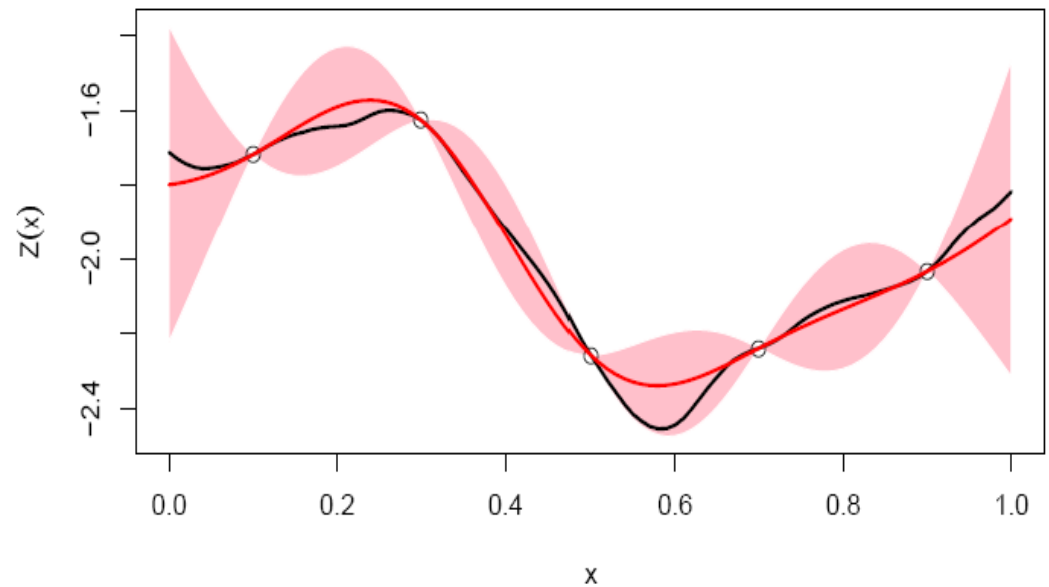
True function and observations



$$y(x) = \mu + z(x)$$

$$E(z(x)) = 0; \quad \text{var}(z(x)) = \sigma^2$$

$$\text{cov}(z(x), z(x')) = \sigma^2 R(x, x')$$

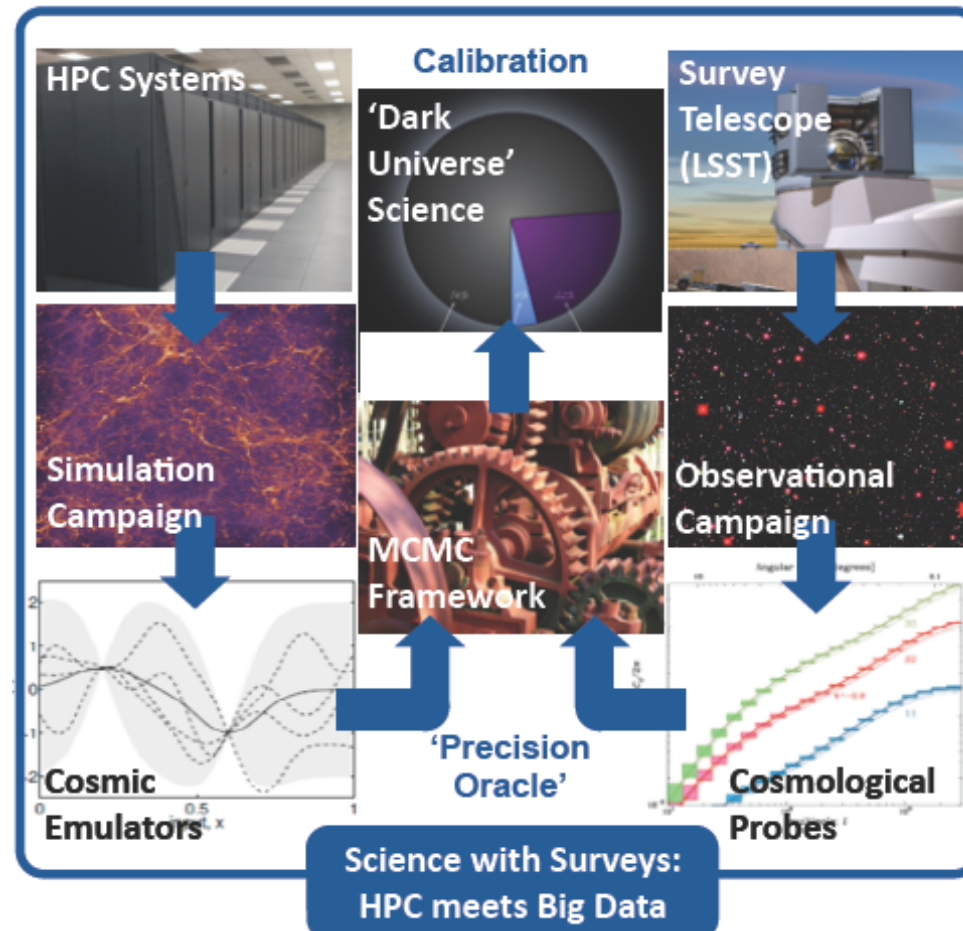


# Applications of interest



- Upcoming space based cosmology missions promise exquisite measurements of the large-scale structure distribution of the Universe (e.g., including weak lensing, baryon acoustic oscillations, clusters of galaxies, and redshift space distortions)
- Currently exploring an 8-dimensional input space that, when combined with observations, should shed light into the initial conditions of the Universe and also the nature of dark energy

# Applications of interest



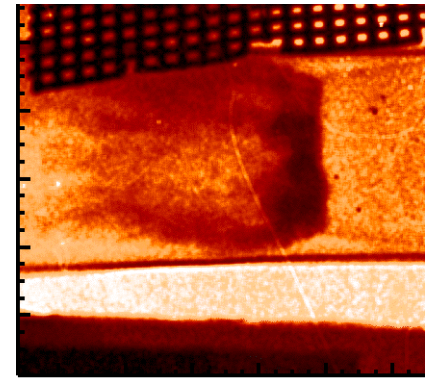
# Applications of interest



- Will be running about 100 simulations that should take between 1 and 2 years to complete ... **can run several of these in sequence**
- Can investigate the response in intermediate stages while other simulations are running



# Applications of interest



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Target Coord. X ( $\mu\text{m}$ )

- At the Center for Radiative Shock Hydrodynamics (CRASH), computational models were employed to simulate features of radiative shocks
- The CRASH codes consisted of high and low fidelity models
- It was helpful to run the high and low fidelity codes with the same inputs to explore the discrepancy between the two models
- The low fidelity code was run at far more input settings (high fidelity design was **nested** within the low fidelity design)

# Design for computer experiments

- Johnson et al. (1990) and others (e.g., Kunsch et al., 2005) demonstrate that designs with good *space-filling* properties are essential for prediction using GPs
- Latin hypercube designs (McKay et al, 1989) and other variants (Tang, 1993) have proven popular
- For type of sequence of designs and low/high fidelity models, work by Qian (2009), Qian, Tang and Wu (2009) is related
- Designs based on Cartesian lattices have also been proposed (Beattie and Lin, 2004; Qian and Ai, 2010)
- Single state lattice designs have been discussed (Bates et al., 1996; **Pronzato and Müller, 2012**; He 2016, 2017)
- **Here, a new type of lattice design is proposed** (based on Heitmann, Bingham et al., 2016)

# Would like our designs to have specific properties

1. Would like  $n$ -run designs where each design point is a  $d$ -dimensional input vector to the computer model
2. In our setting would like experiment designs ( $D$ ) with good  $d$ -dimensional space-filling properties
3. Would like the designs to have the nesting property
  - Important for applications where good **intermediate-stage designs** are required, as well as the **final experiment design**
  - Important for applications with high- and low-fidelity simulators where the **high-fidelity simulator design is a sub-set of the larger, low-fidelity simulator design**

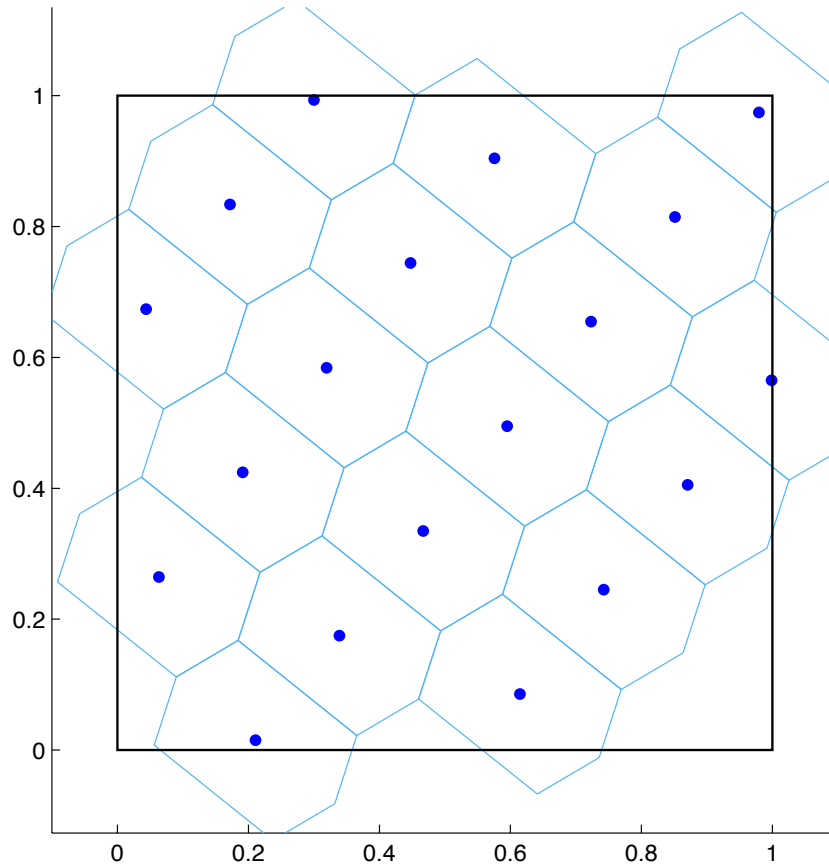


# Suggestion ...

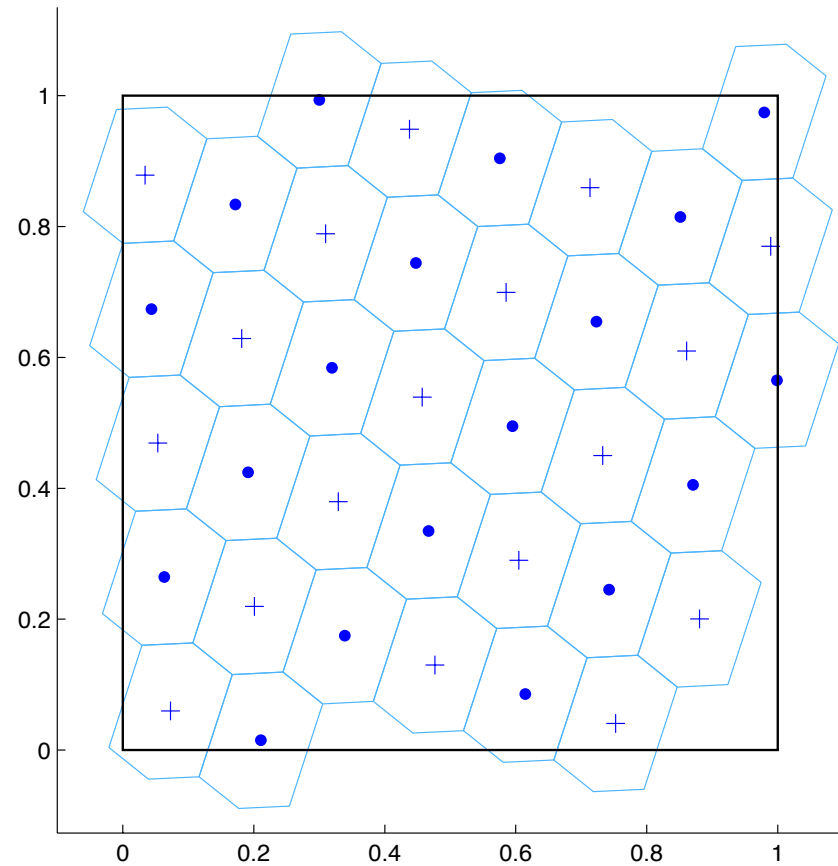
- Use a lattice
- For one-stage designs, can use already computed lattices (Conway and Sloane, 1999) that have good space filling properties
- Not quite as easy as you might think ...
- Is more challenging for our setting where nesting is required

# Example

First stage (high-fidelity) design



First and second stage (low-fidelity) design



# Notation and definitions

- A **point lattice** is an infinite, discrete set of points in  $\mathbb{R}^d$  that is constructed from integer multiples of a set of basis vectors in the columns of a  $d \times d$  **generating matrix**,  $\mathbf{G}$ ,

$$\Lambda(\mathbf{G}) = \mathbf{G}\mathbb{Z}^d = \{\mathbf{G}\mathbf{k} : \mathbf{k} \in \mathbb{Z}^d\} \subset \mathbb{R}^d$$

- A **lattice design**  $D(\Lambda, \mathcal{M}, \mathbf{p}) = \mathcal{M} \cap \{\Lambda + \mathbf{p}\}$  is the intersection of a point lattice and region  $\mathcal{M} \subseteq \mathbb{R}^d$  that is shifted by a vector,  $\mathbf{p}$
- See Conway and Sloane, 1999 or Patterson, 1954

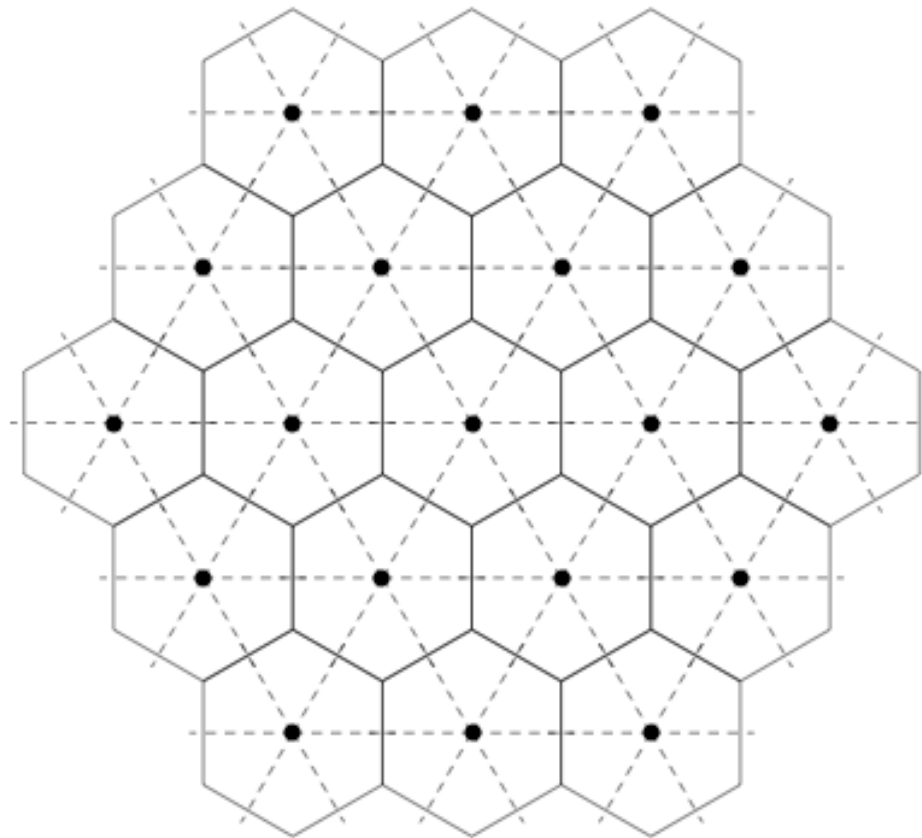
Usually the  $d$ -dimensional unit hypercube

# Fun facts about lattices

- As a linear transformation of the integers, lattices inherit their abelian group structure
  - ... this implies that the neighborhood around each lattice point is the same
  - This region is also called the **Vornoi cell**
- The space between the lattice points are described by the **fundamental parallelepiped**



# Fun facts about lattices





# Example

- Factorial design (Cartesian lattice):
- Have  $d$  inputs with levels  $\mathbf{s} = (s_1, s_2, \dots, s_d)$
- Here  $\mathbf{G} = \mathbf{I}_d$  and the lattice is  $\Lambda(\mathbf{G}) = \mathbf{G}\mathbb{Z}^d = \{\mathbf{G}\mathbf{k} : \mathbf{k} \in \mathbb{Z}^d\} \subset \mathbb{R}^d$
- Region of interest is  $[0,1)^d$  scaled by  $\text{diag}(\mathbf{s})$

# We are looking for specific designs

- A sequence of designs, is said to be nested if

$$D_l \subseteq D_{l+1} \text{ for all } l \in \mathbb{Z}$$

- Increasing  $l$  is called a **refinement** and decreasing  $l$  is called **coarsening**



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THE END



## A result

- For two lattices,  $\Lambda_1$  and  $\Lambda_2$ ,  $\Lambda_1 \subseteq \Lambda_2$  iff there exists a matrix  $\mathbf{K} \in \mathbb{Z}^{d \times d}$  that relates the generating matrices of the two lattices by  $G_1 = G_2\mathbf{K}$ . And under these conditions, if  $|\det K| = 1$  then  $\Lambda_1 = \Lambda_2$ .

# More notation and definitions

- A **dilation matrix**,  $\mathbf{K} \in \mathbb{Z}^{d \times d}$ , with  $|\det \mathbf{K}| = \beta > 1$ , applied to a lattice forms a nested sequence of lattices,  $\Lambda_{l-1} \subset \Lambda_l$  via  $\Lambda_{l-1} = \Lambda_l \mathbf{K}$



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- For this setting, an **admissible dilation matrix** is one where
  - (a)  $\mathbf{K}$  is a dilation matrix;
  - (b) magnitude of all eigen-values of  $\mathbf{K}$  are larger than 1; and
  - (c)  $\det \mathbf{K} = \alpha^d$ , where  $\alpha$  is the eigen-value for  $\mathbf{K}$



# Theoretical results we can prove

- In  $[0,1)^d$ , the expected number of lattice points is  $1/\det \mathbf{G}$
- $\mathbf{K}$  must be an integer matrix
- For refinement (i.e.,  $l$  goes up) the volume of the fundamental parallelepiped decreases by  $|\det \mathbf{K}| = \beta$
- Can show that to get a nested lattice  $\beta > 1$ , thus best refinement is to half the volume between points as the run-size is doubled

# Why do all this fancy stuff?

- Dyadic sub-sampling is impossible for Cartesian lattices with  $d > 2$
- For Cartesian lattices, number of lattice points grows exponentially with dimension
- **The main idea is to:**
  - use more general, non-diagonal generators,  $\mathbf{G}$
  - allow for sub-sampling rates that are 2, 3, 5, ... (2 is most useful)

# Why do all this fancy stuff?

- **Benefits:**
  - Sometimes can use general bases for known best packing or covering lattices, leading to a direct construction of maxi-min or mini-max designs, respectively
  - can consider virtually any run size
  - allows a sequence of designs that can be used in practical applications
  - Once bases are computed, do not need to recompute



# How do we find designs

- Assume that the design region is  $[0,1)^d$
- $n$  is the experiment run size
- looking for a non-singular lattice generating matrix  $G$  that, when sub-sampled by a dilation matrix  $K$  with reduction rate  $\beta = |\det K|$
- Need to find
  1.  $G$
  2.  $K$
  3. **Shift, rotation and scaling** to fit  $n$  points in the design region

# How do we find designs

- Need some more theory:
- Restrict attention to designs where sub-sampled lattice is a scaled or rotated version of the original lattice
- **GK=QG**
- Preserves nice geometric properties... rotationally similar
- Imposes restrictions on **K**



# How do we find designs... more theory

- The restriction ( $\mathbf{G}\mathbf{K}=\mathbf{Q}\mathbf{G}$ ) implies the choice of  $\mathbf{G}$  up to rotation and scale ... reason is that this implies that  $\mathbf{K}$  and  $\mathbf{Q}$  have same characteristic polynomial
- Can prove that: (i) for even  $d$ , there are 5 different  $\mathbf{K}$ ; and (ii) for odd  $d$  there is only 1  $\mathbf{K}$
- Restricting to diagonalizable  $\mathbf{K}$  and  $\mathbf{Q}$ , finding  $\mathbf{K}$  allows us to find  $\mathbf{G}$  and  $\mathbf{Q}$
- We can still warp these  $\mathbf{G}$  and we do so to optimize a desirable property (e.g., mini-max, maxi-min, correlation between columns of the design matrix)
- Finally,  $\mathbf{G}$  is scaled so that  $\mathbf{G}^* = \det \mathbf{c}\mathbf{G} = 1/n \dots$

# How do we find designs

- Finally, we can use the generating matrix  $\mathbf{G}^*$  and  $\mathbf{K}$  to construct our lattice design
- However, the number of points in the region of interest is only expected to be  $n$
- So, we randomly rotate  $\mathbf{G}^*$  and also shift the lattice to achieve the desired run-size in  $[0,1)^d$



# Algorithms

**Algorithm 1:** Obtain a lattice with isotropic dilation matrix  $\mathbf{K}$

1. For given input dimension and sub-sampling rate construct isotropic dilation matrix  $\mathbf{K}$
2. Form the generating matrix,  $\mathbf{G}$

**Algorithm 2:** Produce a lattice design in the unit hypercube

1. Consists of finding possible designs under random shifts,  $\mathbf{p}$ , of the lattice given  $\mathbf{G}$ ,  $\mathbf{Q}$  and  $\mathbf{K}$
2. Effective to first determine points in a bounding box of design region and then find which of these points are in design region

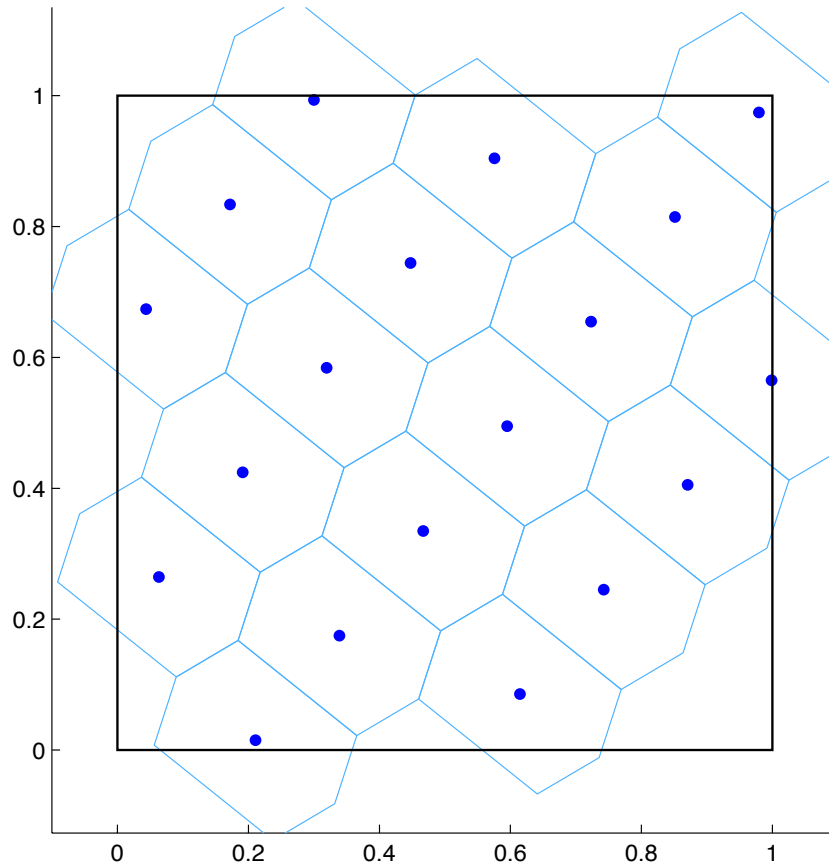
**Algorithm 3:** Can further refine based on random shifts,  $\mathbf{p}$ , and rotations  $\mathbf{Q}^*$ , to optimize additional properties



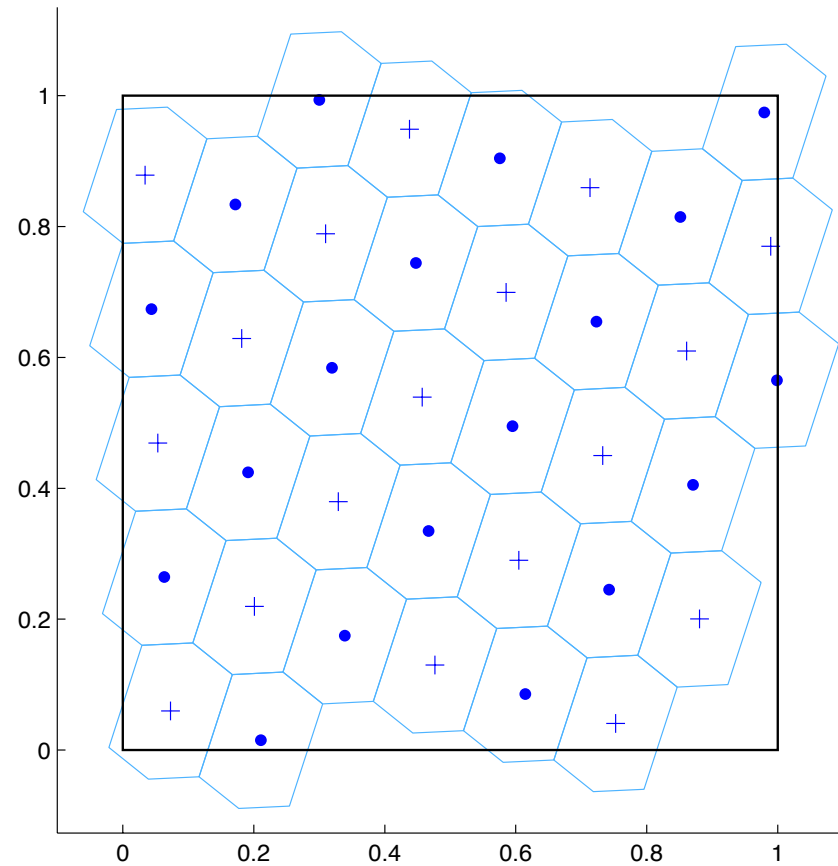


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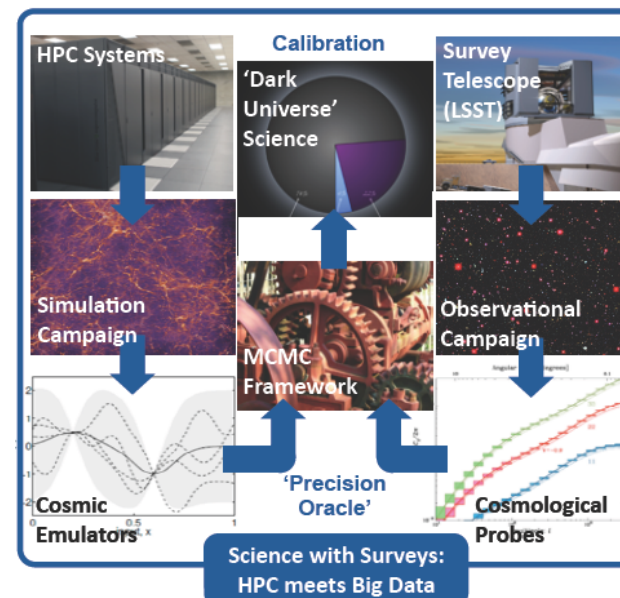


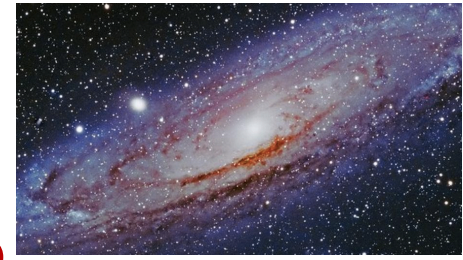


# Cosmology – what did we do?

- Had 8-dimensional input space,  $n=100$  runs in 3 stages:

$$\begin{aligned} 0.12 &\leq \omega_m \leq 0.155 \\ 0.0215 &\leq \omega_b \leq 0.0235 \\ 0.7 &\leq \sigma_8 \leq 0.9 \\ 0.55 &\leq h \leq 0.85 \\ 0.85 &\leq n_s \leq 1.05 \\ -1.3 &\leq w_0 \leq -0.7 \\ -1.5 &\leq w_a \leq 1.15 \\ 0.0 &\leq \omega_\nu \leq 0.01. \end{aligned}$$





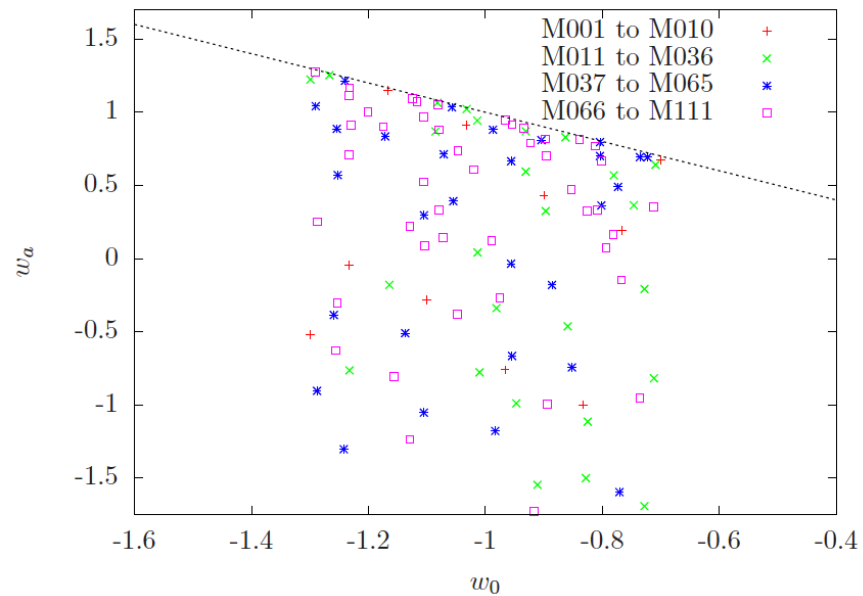
# Cosmology – what did we do?

- Had a low-fidelity model (linear power spectrum) to test the efficacy of the designs
- Used a 3-stage lattice design  $n_1=25$ ;  $n_2=25$ ;  $n_3=50$  (optimized via maximin criterion)
  - Ran each design on the low-fidelity code and did intermediate analyses (i.e., after 25 runs, 50 runs and finally 100 runs)
  - Turned out that several of the runs produced non-physical results
  - Had to do with implicit constraints on the dark energy parameters



# Cosmology – what did we do?

- Instead, re-did the design procedure using the constraint  $w_a + w_0 < 0$



# Re-cap

1. Have proposed a new type of lattice design that is useful in a variety of applications
2. Can be used to find designs with good space filling properties
3. Can find large designs from small ones
4. We are pre-computing good bases for different  $d$



*Thank you for indulging me*



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- Sub-sampling a lattice such that the chosen sample is **also a lattice** is performed by right-multiplying an integer dilation matrix onto  $G$
- **Dyadic sub-sampling**: discards every second point in each basis vector direction ( $\mathbf{K}=2\mathbf{I}$ ;  $\beta = 2^d$ )