

BUQ Phase II

Bayesian Probabilistic Methods to Enable Cross-Cutting AI Research in Nuclear Science

Lead Institution

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University of California, San Diego: A. Li
Wayne State University: C. Shen

<https://sites.google.com/lbl.gov/bayesianuqproject/documents?authuser=0>

Table 1: Proposed project budget.

Project role	Name	Institution	Year 1 (\$K)	Year 2 (\$K)	Total(\$K)
Lead PI	Jacobs	LBNL/UCB	855	881	1,736
Co-PI	Mak	Duke	171	180	351
Co-PI	Li	UCSD	191	222	413
Co-PI	Shen	Wayne State	142	145	288
Total			1,359	1,429	2,787

Project approved for \$2.3M

- need to reduce by \$490K (20%)

DOE will provide guidance where to reduce, not yet received

However, Phase I will have a carryover at end of FY25 of \$191K

Net result: only modest reduction in scope needed, all major elements of proposal can be supported

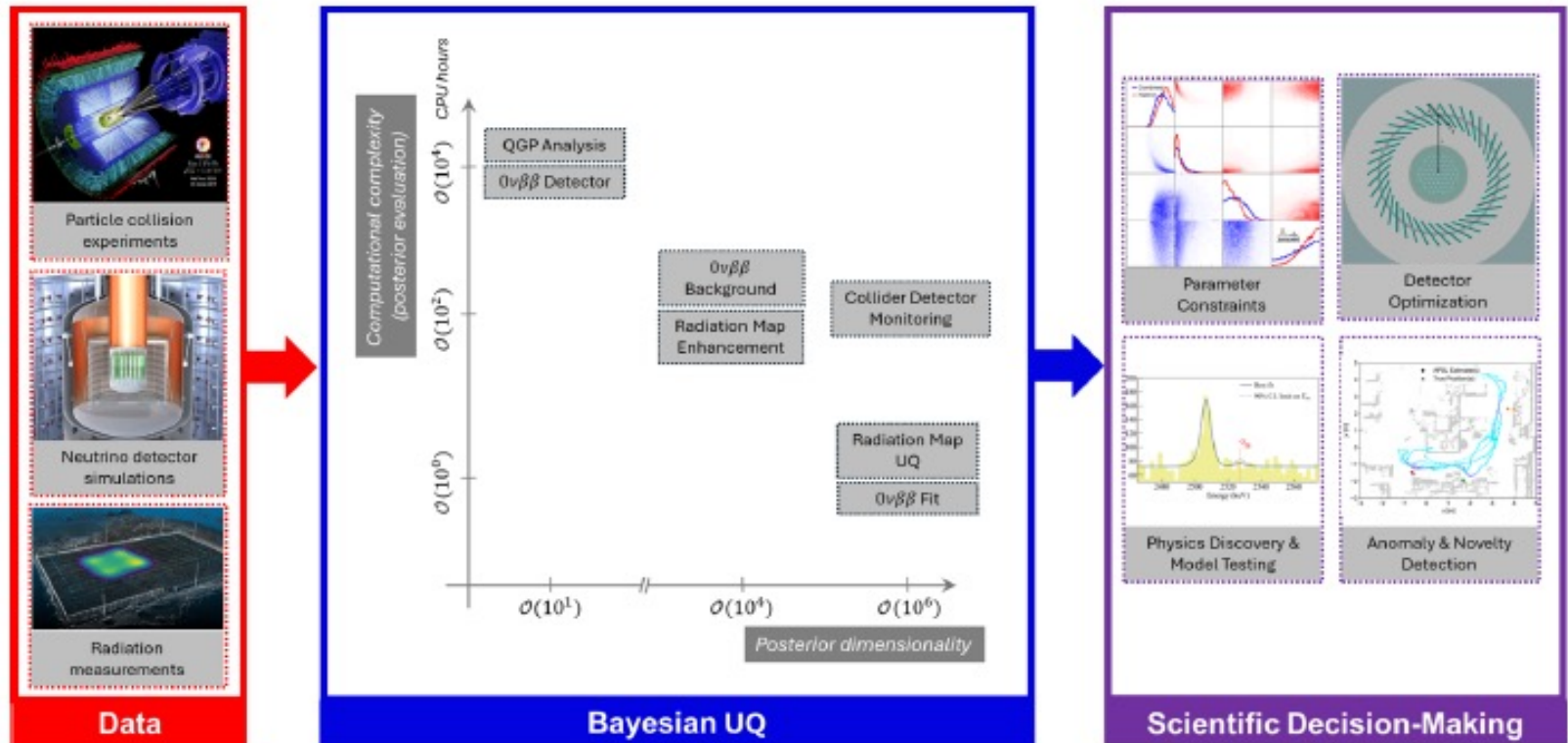


Figure 1: Schematic representation of the key computational requirements for probabilistic Bayesian analysis and UQ of the NP projects considered in the proposal. The left column indicates the various data sources, while the right column specifies the target analyses. The middle box places each project in a two-dimensional space of computational complexity of the forward model (vertical) and posterior dimensionality (horizontal).

	$0\nu\beta\beta$ Detector Optimization	$0\nu\beta\beta$ Background & Fit	QGP Collider Monitoring	QGP Analysis	Radiation Map Enhancement	Radiation Map UQ
Bayesian Transfer Learning				✓	✓	
Bayesian Multi-Fidelity Learning	✓ ○			✓	✓	
Langevin Monte Carlo		✓ ○		✓		✓ ○
Bayesian Manifold Learning	○			○		
Bayesian Optimization	○					○
Boundary-Informed Surrogates	○			○		
Bayesian Image Change Detection			○			

✓: BUQ Phase 1

○: BUQ Phase 2

Figure 2: Tabulation of BUQ methods and physics projects, indicating the method applied to each project in BUQ Phase 1 and proposed for BUQ Phase 2.

Table 2: Timeline for project objectives. Parentheses in columns 3 and 5 show postdoc effort in fractions of FTE.

Topic	Y1 PI + staff	Y1 PD + students	Y2 PI + staff	Y2 PD + students
Neutrinos				
Bayesian background model	Li, Poon, Fujikawa, Mak	LBNL(0.5), UCSD(0.5), UCSD(students), Duke(students)		
Enhance/Benchmark RESuM			Li, Poon, Fujikawa, Mak	LBNL(0.5), UCSD(0.5), UCSD(students), Duke(students)
Advanced Sampling Techniques	Kolomensky, Poon, Fujikawa, Seljak	LBNL(0.25), UCB(0.5)	Kolomensky, Poon, Fujikawa, Seljak	LBNL(0.25), UCB(0.75)
Spectrum Modeling KATRIN	Poon	LBNL(0.25)	Poon	LBNL(0.25)
Source Design CUPID	Kolomensky	UCB (0.25)	Kolomensky	UCB (0.25)
QGP				
Heteroskedastic GP	Shen, Jacobs, Mak	WSU (0.25), LBNL (0.20), Duke (students)		
Boundary-Safe Model Selection			Shen, Jacobs, Mak	WSU (0.25), LBNL (0.1), Duke (students)
Theory UQ	Shen	WSU (0.25)	Shen	WSU (0.25)
High-dim Analysis	Shen, Seljak, Mak	WSU (0.25), UCB (0.25), Duke (students)		
Generative AI			Shen, Jacobs, Mak	WSU (0.25), LBNL (0.1), Duke (students)
Iterative Multi-Messenger Analysis	Shen, Jacobs	WSU (0.25), LBNL (0.20)	Shen, Jacobs	WSU (0.25), LBNL (0.20)
Collider Monitoring	Jacobs, Mak	LBNL (0.1), Duke (students)	Jacobs, Mak	LBNL (0.1), Duke (students)
Radiation mapping				
Data sufficiency	Vavrek, Mak	LBNL (0.25)	Vavrek, Mak	LBNL (0.25)
Langevin UQ	Vavrek, LBNL staff (0.1)		Vavrek, LBNL staff (0.1)	

PMJ Comments

BUQ Phase I was a success by many measures :

- supported multiple good projects
- a few conference talks, more to come
- publications now starting to come out

However, integration of the various physics sub-areas of the project, which is the basic reason for putting them together in one project, largely did not succeed.

That is an observation, not a criticism. The integration challenge is difficult, and in the end may not be realistic or worthwhile. We are asking that question.

So then, what can we do differently in Phase II, and what should we do differently in Phase II?