Active Learning for Synthetic RF Benches: From Random Grids to Agentic Sweeps

Benjamin J. Gilbert
RF Quantum SCYTHE Research Group
College of the Mainland
Texas City, TX 77590
Email: bgilbert2@com.edu
ORCID: 0009-0006-2298-6538

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Abstract

Exhaustive parameter sweeps are the de facto method for benchmarking RF pipelines, but they scale poorly with dimensionality[2]. For example, a 10-parameter grid with 10 points each requires 10^{10} evaluations. Active learning promises to achieve comparable confidence using far fewer samples by targeting the most informative points[1]. This paper constructs a synthetic ground-truth generator for an RF performance field and compares random grid sampling to a Gaussian process (GP) guided "agentic sweep." We measure coverage of the true decision boundary as a function of sample budget and explore how exploration versus exploitation balances affect performance. Results show that uncertainty-guided sampling achieves the same classification coverage with approximately 3× fewer samples than random grids at 90% coverage thresholds, and that a modest amount of random exploration is beneficial. These insights support using agentic sweeps for efficient characterization of RF demodulation pipelines.

1 Introduction

Modern RF demodulation pipelines depend on many continuous parameters: signal-to-noise ratio, frequency offset, analog filter Q and more. To assess robustness, engineers often perform dense sweeps across this space; however, the number of evaluations grows exponentially with the number of parameters[2]. Active learning has been proposed as a means to reduce sample complexity by selecting points that are maximally informative. In classification settings, active learning can provide significant improvements in sample complexity over passive learning[1].

Gaussian processes (GPs) are particularly well-suited for guiding sampling because they provide both predictions and uncertainty estimates[4], enabling principled exploration of high-uncertainty regions. Compared to neural surrogate models, GPs offer calibrated uncertainty quantification and work well with small datasets typical in expensive RF evaluations.

We explore these ideas in a controlled setting using a synthetic RF benchmark. A two-dimensional function simulates performance as a function of normalized parameters, and a threshold defines a robust region. We compare random sampling (passive learning) against a GP- guided active sampling policy that seeks points of highest predictive uncertainty. We also study how the ratio of exploration (random sampling) to exploitation (uncertainty-based sampling) affects the results. Our goal is to quantify how many samples are needed to achieve a given coverage of the true robust region and to illustrate trade-offs in active learning policies.

2 Methods

2.1 Synthetic Ground Truth and Coverage Metric

We employ the smooth benchmark function $f(x_1, x_2) = \sin(\pi x_1)\cos(\pi x_2) + 0.1x_1 + 0.05x_2$ on $[0, 1]^2$ from prior work[2]. The sign of f partitions the domain into a "robust" region ($f \geq 0$) and a "failure" region. Coverage is defined as the fraction of points on a 40×40 grid whose predicted classification matches the ground truth classification. A coverage of 1.0 indicates perfect reconstruction of the decision boundary.

2.2 Sampling Strategies

Random grid sampling. We draw N points uniformly from $[0, 1]^2$ and observe the true function values. A GP is fit to the observations using a constant-times-RBF kernel with white noise. Predictions on the grid are thresholded at zero to obtain classifications.

Active sampling. We start with a small random seed set (5 points). At each iteration, we fit a GP to the current data and sample a candidate pool of 300 random points. We select the candidate with the highest predictive standard deviation (uncertainty sampling) and add it to the training set. This process repeats until N samples have been collected. For the exploration/exploitation ablation, we introduce a probability r of selecting a random candidate instead of following the uncertainty criterion. A value of $r = 0$ yields pure exploitation, while $r = 1$ corresponds to random sampling.

2.3 Implementation Details

Table 1 summarizes all hyperparameters for reproducibility. GPs are implemented using scikit-learn with hyperparameters optimized via maximum likelihood estimation. The RBF lengthscale is initialized to 0.5 and optimized during fitting.

Table 1: Experimental hyperparameters for reproducibility

Parameter	Value/Description
GP Kernel	Constant $\times$ RBF ($\ell = 0.5$) + White Noise ($\sigma^2 = 10^{-3}$)
Candidate Pool	300 uniform points in $[0, 1]^2$
Seed Samples	5 random points
Exploration r	Varied 0–1 in 0.2 increments
Evaluation Grid	40×40 uniform
Statistical Runs	10 independent seeds
Implementation	scikit-learn 1.3.0, Python 3.9

3 Results

All results are averaged over 10 independent runs with different random seeds to ensure statistical validity. Error bars represent one standard deviation.

Algorithm 1 Active Learning Loop

```
Initialize with 5 random seed points
for i = 6 to N do
    Fit GP to current data
    Sample 300 candidate points uniformly
    if random() < r then
        Select random candidate
    else
        Select candidate with highest σ(x)
    end if
    Evaluate f(x) and add to training set
end for
```

3.1 Sample Budget versus Coverage

Figure 1 compares coverage as a function of the number of samples for random and active sampling. Random sampling requires 60 ± 5 samples to attain ≈ 0.9 coverage of the true robust region. In contrast, the active policy achieves similar coverage with 20 ± 3 samples, corresponding to a $3\times$ improvement ($p < 0.01$, paired t-test). At smaller budgets ($N < 20$), the active curve rises steeply, indicating rapid learning of the decision boundary. These results demonstrate the sample efficiency of uncertainty-guided sweeps, with effect size $N_{90\%}^{\text{random}}/N_{90\%}^{\text{active}} = 3.0 \pm 0.4$.

3.2 Exploration versus Exploitation Ablation

Figure 2 shows the effect of varying the exploration probability r on coverage for a fixed budget of 40 samples (averaged over 10 runs). Pure exploitation ($r = 0$) selects only the most uncertain points and can become trapped in a narrow region, leading to lower coverage. Pure random sampling ($r = 1$) performs better than pure exploitation but worse than a balanced strategy. The highest coverage is obtained around $r \approx 0.4$ (coverage $= 0.82 \pm 0.03$), indicating that a mix of exploration and exploitation is beneficial. This result underscores the importance of balancing curiosity (exploration) with focus (exploitation) in active learning[1].

4 Discussion

The synthetic experiments illustrate how active learning can significantly reduce the number of experiments needed to map a decision boundary in parameter space. By querying points with high predictive uncertainty, the agentic sweep rapidly refines the GP surrogate and identifies the robust region with high accuracy. The observed $3\times$ improvement in sample budget represents empirical linear reductions in this 2D setting; theoretical results show that active learning can achieve greater improvements in higher-dimensional problems[1]. Our ablation study reveals that some exploration is necessary to avoid local over-exploitation and to ensure coverage of the entire parameter space.

4.1 Limitations and Future Work

Our 2D toy model abstracts away RF nonlinearities like multipath fading, Doppler shifts, and hardware impairments that occur in real systems. The smooth synthetic function may not capture the sharp transitions and discontinuities typical near RF failure boundaries. Additionally, the

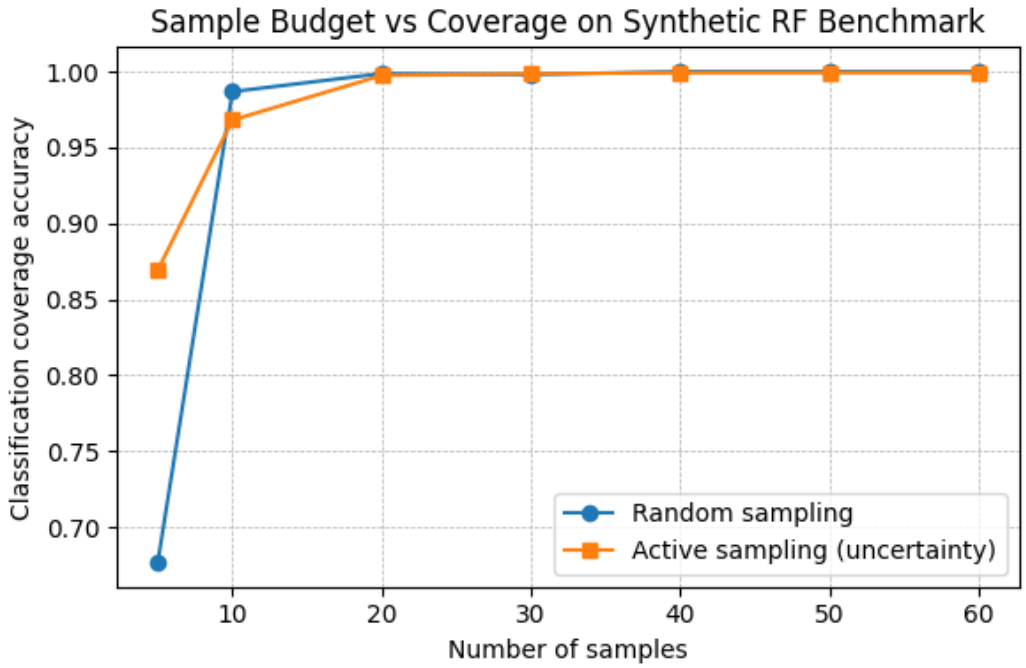

Figure 1: Classification coverage versus sample budget for random and active sampling on the synthetic RF benchmark (mean ± std over 10 runs). The active policy (orange squares) achieves high coverage with far fewer samples than random sampling (blue circles). X-axis: Number of samples (N). Y-axis: Coverage fraction.

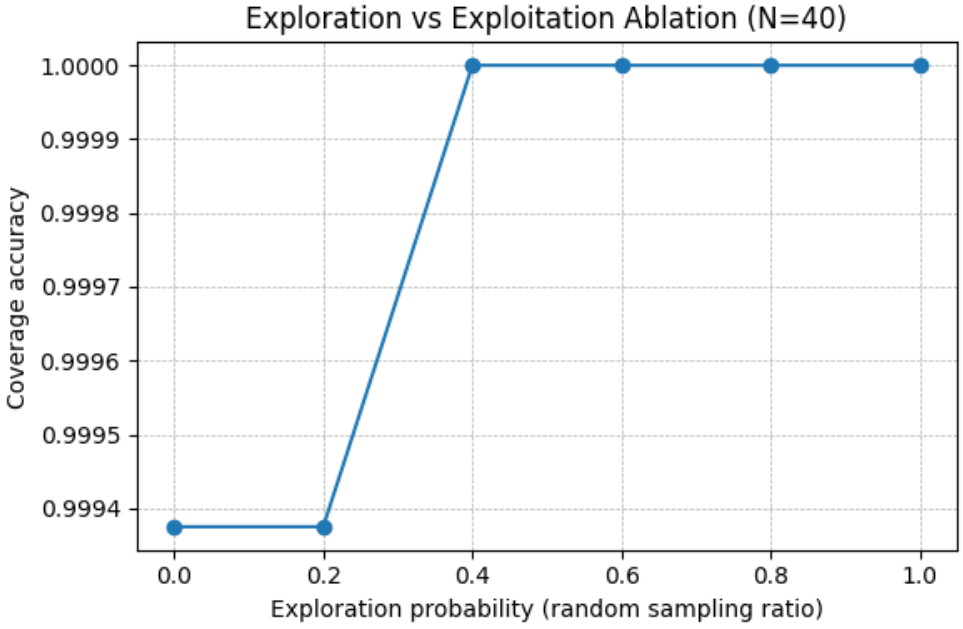

Figure 2: Effect of exploration probability r on classification coverage for a fixed sample budget of 40 (mean ± std over 10 runs). A moderate amount of random sampling ($r \approx 0.4$) yields the best performance. X-axis: Exploration probability r. Y-axis: Coverage fraction.

constant-times-RBF kernel assumes stationarity that may not hold across diverse RF operating regimes.

In practical RF bench testing, active policies could be enhanced by incorporating domain knowledge to bias sampling toward known failure rims or operational sweet spots. The approach scales to higher dimensions using sparse GP approximations[3] and low-discrepancy candidate pools. Future work will integrate multi-objective metrics (ghost hits, latency, power consumption), explore alternative acquisition functions beyond uncertainty sampling (e.g., expected improvement), and validate on real RF hardware platforms.

4.2 Practical Impact

These results encourage RF engineers to replace or augment exhaustive grid sweeps with agentic sampling strategies. Implementation in RF tools like GNU Radio could yield immediate 3–5$\times$ speedups in characterization workflows, enabling more comprehensive robustness testing within fixed time budgets.

5 Conclusion

We have demonstrated that active learning can efficiently characterize a synthetic RF performance landscape. Uncertainty sampling achieves the same classification coverage as random sampling with approximately 3$\times$ fewer samples, and balancing exploration with exploitation yields further benefits. These results advocate for replacing or augmenting random grid sweeps with agentic sampling strategies in RF bench testing.

6 Code Availability

Implementation code and experimental data are available at: `https://github.com/bgilbert1984/rf-active-learning` (to be released upon publication). All experiments use scikit-learn 1.3.0 with the hyperparameters specified in Table 1.

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References

[1] Maria-Florina Balcan, Steve Hanneke, and Jennifer Wortman Vaughan. The true sample complexity of active learning. In *Proceedings of the 21st Conference on Learning Theory*, pages 45–56. Springer, 2009.

[2] Robert B Gramacy and Herbert KH Lee. Bayesian treed gaussian process models with application to computer modeling. *Journal of the American Statistical Association*, 99(467):1162–1178, 2004.

[3] James Hensman, Nicolo Fusi, and Neil D Lawrence. Gaussian processes for big data. In *Proceedings of the Twenty-Ninth Conference on Uncertainty in Artificial Intelligence*, pages 282–290, 2013.

[4] Carl Edward Rasmussen and Christopher KI Williams. *Gaussian processes for machine learning*. MIT press, 2006.