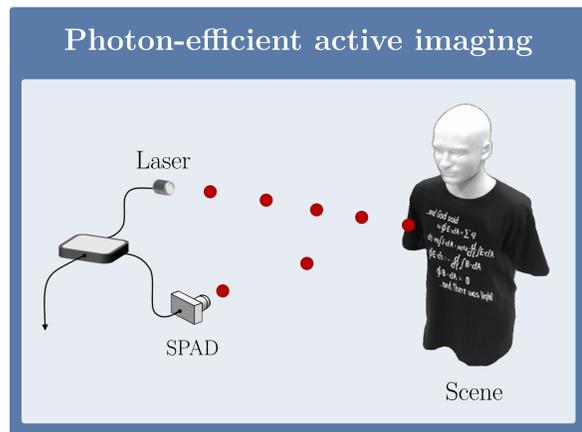


Optimal Stopping Times for Estimating Bernoulli Parameters with Applications to Active Imaging

Safa C. Medin, John Murray-Bruce, Vivek K Goyal
Boston University Electrical and Computer Engineering Department

Introduction

Estimating the parameter of a **Bernoulli process** p is a fundamental statistical problem with many applications, e.g.:



- **Conventional systems:** *nonadaptive*, i.e. number of trials fixed a priori.
- **Alternative system:** data-dependent stopping, known as *sequential estimation*.
- **Motivation:** understanding whether such adaptive systems improve estimation performance.
- **Goal:** Given some trial budget constraint, devise an *optimal stopping strategy* under a mean-squared error loss function.

Contributions

- 1 Propose a **stopping rule** through a greedy algorithm that seeks for the least achievable error.
- 2 Generalize stopping rule to a rectangular array of Bernoulli processes, representing pixels in a natural scene.
- 3 Demonstrate a 4.45 dB improvement in simulated active imaging scenarios.

A Single Bernoulli Process

Probability of continuing observations after trial t :

$$\pi_t : \{0, 1\}^t \rightarrow [0, 1], \quad t = 0, 1, \dots$$

Number of observed trials T satisfies $\mathbb{E}[T] \leq n$.

- Any stopping rule can be represented by a sequence of **continuation probabilities**.

Adaptive Stopping Rule

Under Beta(α, β) prior, observing k successes in m trials yields a Beta($\alpha + k, \beta + m - k$) distribution.

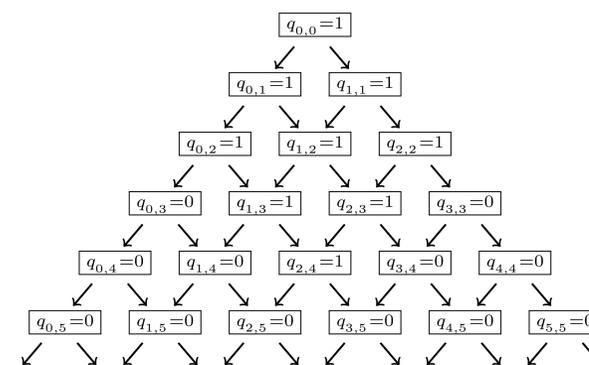
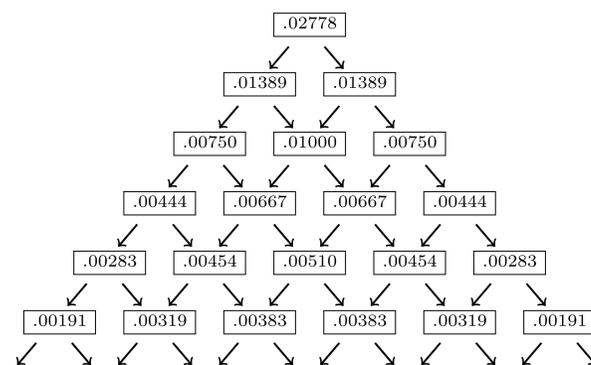
Bayes risk reduction **from one additional trial**:

$$\Delta R(k, m; \alpha, \beta) = \frac{(\alpha + k)(\beta + m - k)}{(\alpha + \beta + m)^2(\alpha + \beta + m + 1)^2}$$

Proposed data-adaptive stopping rule

Stop when Bayes risk reduction $\Delta R(k, m; \alpha, \beta)$, for an additional trial, is below a specified threshold.

- Visualization of a stopping rule \rightarrow **Binary tree** with continuation probability labels.
- All observation sequences with k successes in m trials yield the same continuation probability $q_{k,m} \rightarrow$ **Trellis**.



$\Delta R(k, m; \alpha, \beta)$ under Beta(1, 1) (uniform) prior (left) and continuation probabilities for a threshold of 0.005 (right).

- The lower the threshold, the higher the mean number of trials becomes.
- Only certain values of $\mathbb{E}[T]$ are achievable with binary continuation probabilities.
- Small improvement gained for a single Bernoulli process. Byproduct is a significant improvement in imaging applications, due to more efficient allocation of trials across spatial locations.

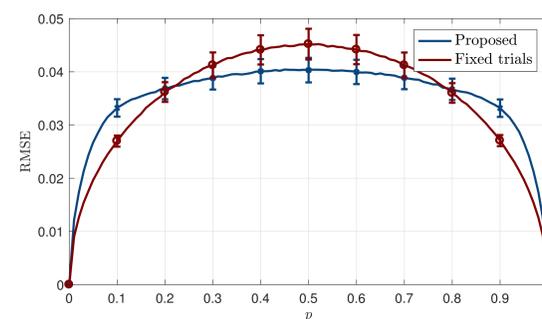


Figure 1: RMSE vs. true Bernoulli parameter, assuming Beta(1,1) prior (uniform) and budget $n = 123$. Mean-squared error reduces from 0.00134 to 0.00129, when averaged over 100 000 experiments.

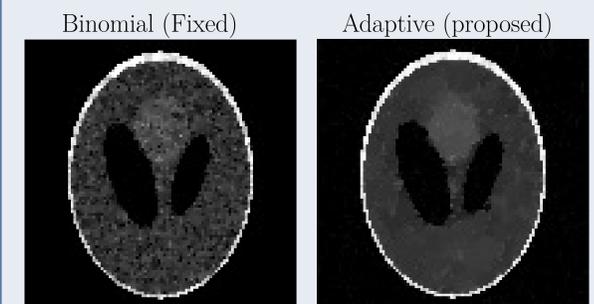
Arrays of Bernoulli Processes

Scene raster-scanned using pulsed illumination guided by *proposed stopping rule*.

- **Data:** arrays of number of pulses $[m_{i,j}]_{i,j}$ and detections $[k_{i,j}]_{i,j}$.
- **Reconstruction:** TV-regularized ML estimation to exploit spatial correlations.

Results

- True image reflectivity in $[0.001, 0.101]$.
- Beta(2, 152) prior assumed. Trial budget $n = 200$.



MSE = 3.4056×10^{-5}

MSE = 1.1779×10^{-5}

- Average over 100 experiments.

Budget	Method	
	Binomial + TV	Adaptive (proposed) + TV
$n = 58$	9.14e-05	3.43e-05
$n = 196$	3.37e-05	1.26e-05

Conclusion

- Proposed adaptive stopping rule that yields significant improvements over non-adaptive rule.
- Binomial and Negative Binomial stopping strategies are *rarely* optimal.

References

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