

### **Time-Domain Astronomy ?**



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# **Classical (Bio)Statistics**

#### Jerzy Neyman

(1894 – 1981)



- Polish / American Statistician
- Founder of Hypothesis Testing
- Co-Inventor of Confidence Intervals
- Neyman-Pearson Lemma

(with his advisor Egon Pearson)

" The trouble is that what we [statisticians] call modern [orthodox] statistics was developed under strong pressure on the part of biologists. As a result, there is practically nothing done by us which is directly applicable to problems of astronomy." -- Jerzy Neyman (late in his life)

# **Modern Biostatistics**

"In academia, the Bayesian revolution is on the verge of becoming the majority viewpoint, which would have been unthinkable 10 years ago."

from The New York Times, January 20th 2004

#### - Bradley P. Carlin

Mayo Professor of Public Health Head of Division of Biostatistics University of Minnesota



# **Modern Biostatistics**



- Pathologies of Orthodox Statistics
  are more acknowledged nowadays
- Tests of statistical significance and design of clinical trials are now increasingly Bayesian
- Journals banning use of *p-values*
  - The Lancet
  - Medical J. of Australia
  - The British Heart Journal
  - American J. of Public Health
  - Int'l Committee of Medical Journal Eds

# **Sequential Analysis**

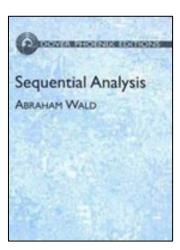
Abraham Wald (1902 - 1950)

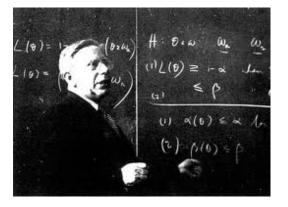


- Hungarian mathematician
- Fled Nazi Europe in late 1930s
- Invented Sequential Analysis

doing QC for Allied bombers in WW2



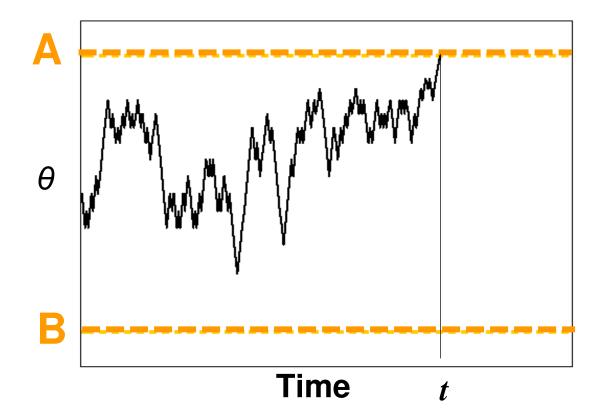




- Wrote classic text in 1947
- Sequential Probability Ratio Test (SPRT)

### **Optimal Decision Policy**

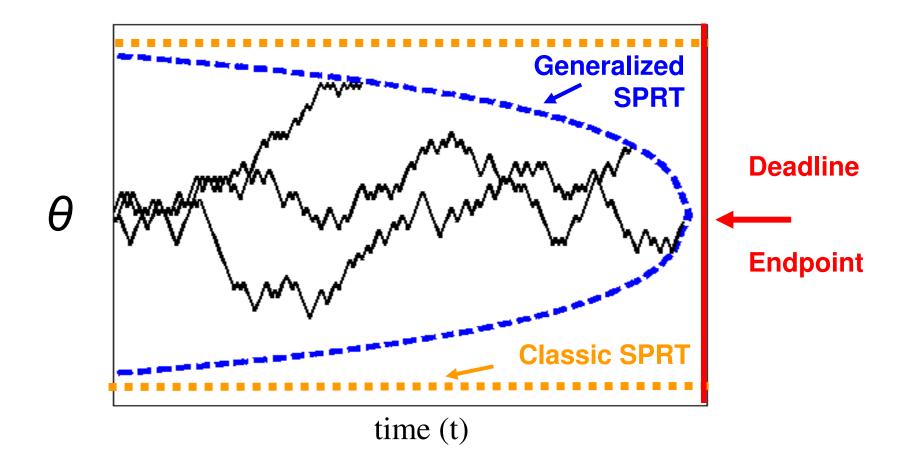
Wald & Wolfowitz (1948) showed that the optimal policy is to stop when  $\theta$ exits an interval [A,B] and to choose the more likely hypothesis

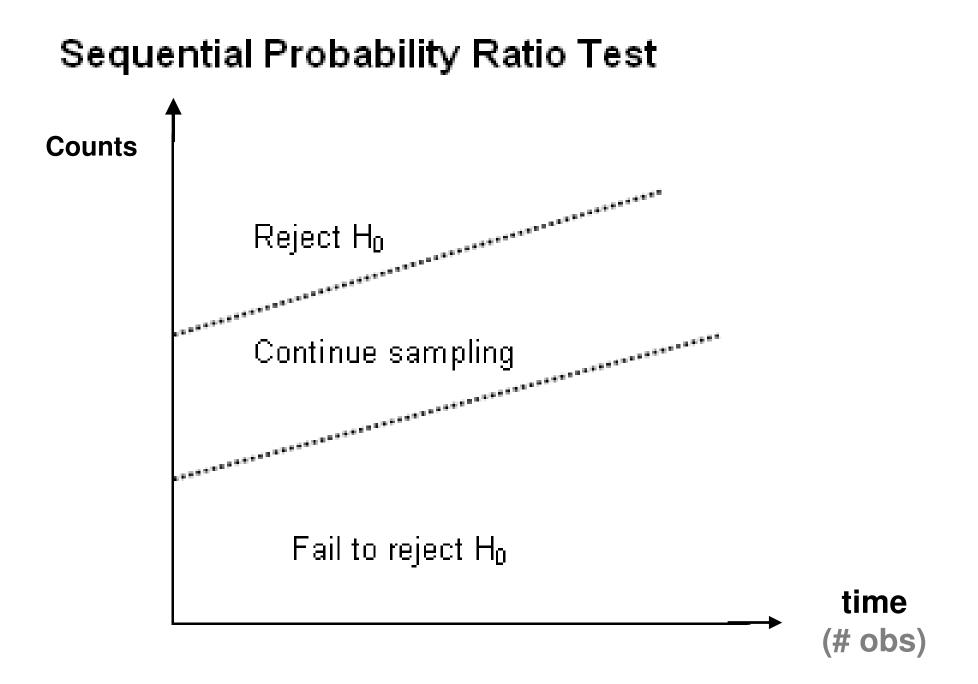


#### **Sequential Probability Ratio Test (SPRT)**

## **Optimal Decision Policy**

The optimal policy with a **time-penalty** is to stop as soon as  $\theta$  exits a region that narrows with time.



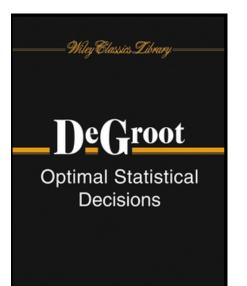


# **Optimal Decisions**

#### **Morris DeGroot**

(1931 – 1989)





- American Statistician / CMU Professor
- Extended and formalized Wald's SPRT
- Bayesian Sequential Decision Making
- Wrote seminal text book in 1970
- Optimal decision algorithms
- For example, **Backward Induction** (BI)
  - solves the problem "backward in time"
  - also used in Dynamic Programming
  - unfortunately has exponential complexity

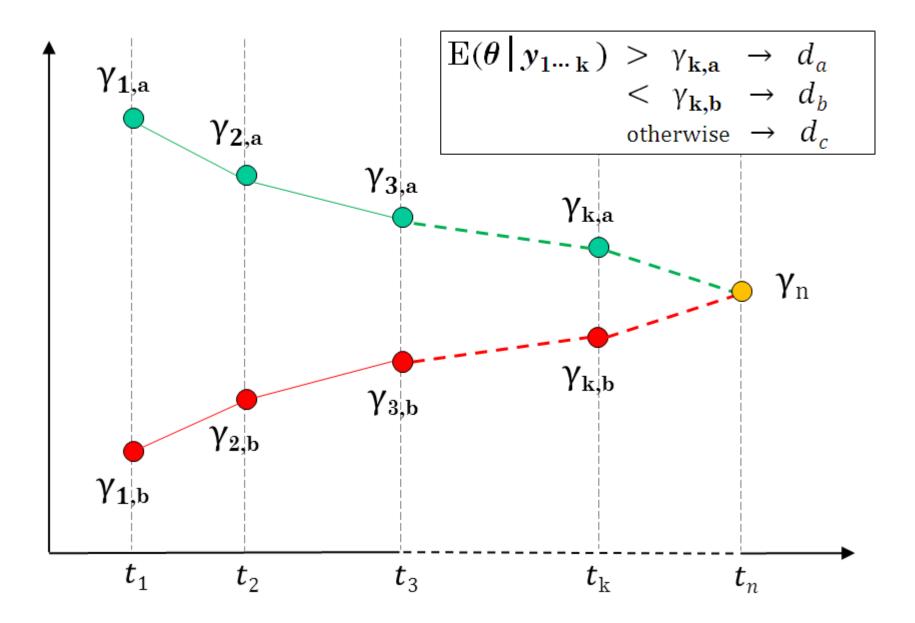
# **Sequential Decision Theory**

- Observations "trickle-in"
- Update current beliefs
- Must "act" (make decisions)
- Which leads to losses
  - timeliness (efficiency)
  - decision-induced costs
  - various domain-specific trade-offs
- Need an optimal policy (usually beforehand)
   minimize posterior expected loss

 $\{ \boldsymbol{y}_{i} \} \quad i = 1 \dots k$   $p(\boldsymbol{\theta} \mid \boldsymbol{y}_{1}, \dots, \boldsymbol{y}_{k})$   $\boldsymbol{d}_{a}, \boldsymbol{d}_{b}, \boldsymbol{d}_{c}$   $\boldsymbol{L}_{a}, \boldsymbol{L}_{b}, \boldsymbol{L}_{c}$ 

#### **Sequential Hypothesis Tests** $y_1$ $y_3$ $\boldsymbol{y}_2$ d<sub>c</sub> wait d<sub>c</sub> wait $p(\theta | y_1)$ $p(\theta | \mathbf{y}_{123})$ $p(\boldsymbol{\theta}|\mathbf{y}_{12})$ $cost C_1$ cost C<sub>2</sub> $d_{\rm b}$ d $d_{a}$ $d_{\rm b}$ $d_{\rm b}$ В В В $E[\boldsymbol{l}_{3}(\boldsymbol{d},\boldsymbol{\theta})|\boldsymbol{y}_{123}]$ $E[\boldsymbol{l}_1(\boldsymbol{d},\boldsymbol{\theta})|\boldsymbol{y}_1]$ $E[\boldsymbol{l}_2(\boldsymbol{d},\boldsymbol{\theta})|\boldsymbol{y}_{12}]$

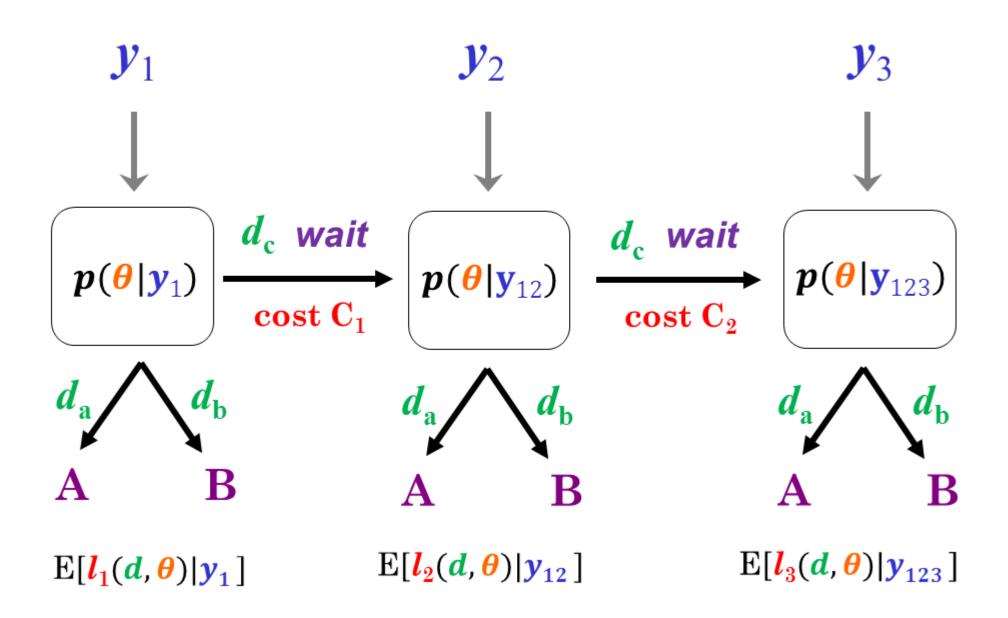
### **Sequential Hypothesis Tests**



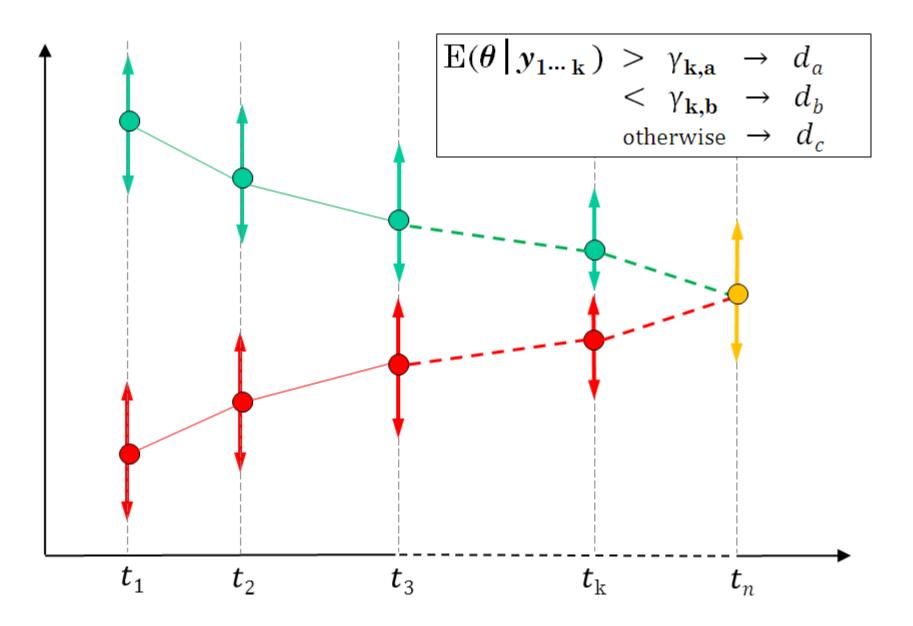
# Alternative to Bl

- For ~ 30 years **BI** was the best solution
- Then a new method: Forward Sampling
  - Carlin, Kadane and Gelfand, "Approaches to Optimal Sequential Decision Analysis in Clinical Trials," *Biometrics*, 54, 964-975, 1998
- Forward (generative) Monte Carlo sampling
- No complex integration required
- Handles arbitrary loss functions
- Complexity is **linear** in **#** of decision points

#### MC sample : $\{\theta, y_1, y_2, y_3\} \sim p(\theta, y_1, y_2, y_3)$



#### **min** E[total loss] wrt $\{\gamma_{k,d}\}$



## Forward Sampling vs. Bl

- Complexity is linear vs. exponential for BI
- FS finds the **optimal** policy (same as BI)
   for single-parameter exp-family models, *etc*
- Unlike BI, FS is a (parallelizable) *continuous* optimization problem (grid search, ICM, *etc*)
- FS offers far greater flexibility in terms of loss functions & probability distributions

### for further inspiration ...

