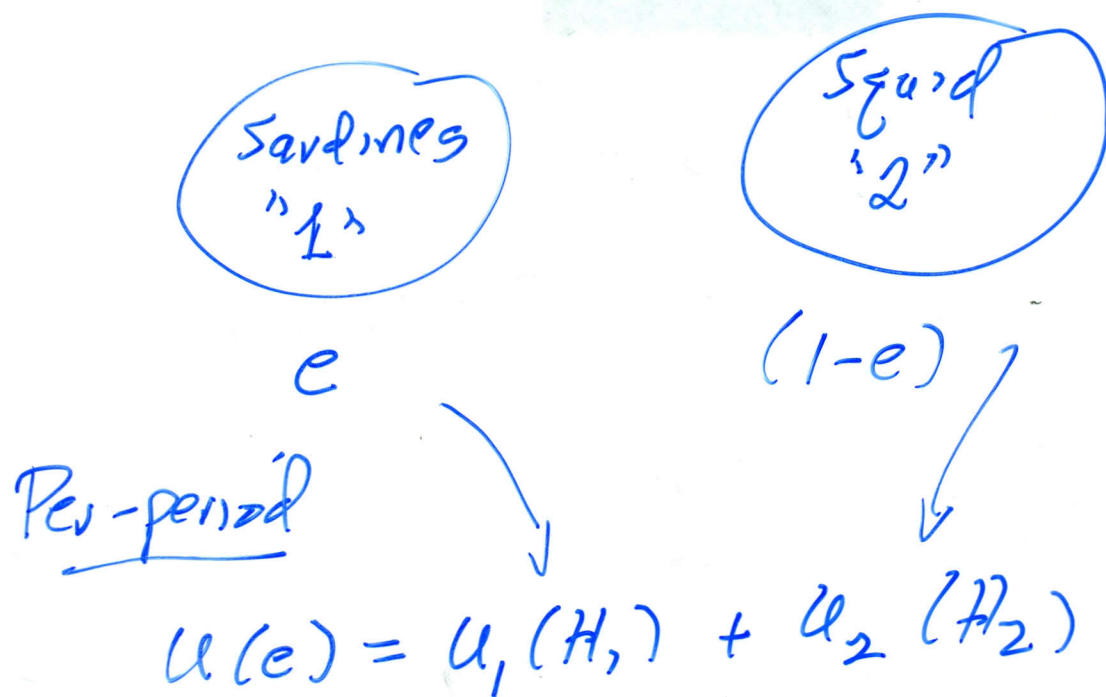


Dynamics of Information

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Deterministic / Full Knowledge Case

$$H_1 = k_1 e \quad H_2 = k_2 (1-e)$$

$$U(e) = U_1(k_1 e) + U_2(k_2 (1-e))$$

$$k_1 U_1'(k_1 e) = k_2 U_2'(k_2 (1-e))$$

Stochasticity but no uncertainty

Patch 2: deterministic & known $[k_2]$

k_1 ~ known precisely

$H_1 = K_1^{(e)}$ = outcome of a visit to patch 1
when effort allocation is e .

[random variable]

$$\Pr\{K_1 = k\} = e^{-\lambda e} \frac{(\lambda e)^k}{k!}$$

$$E\{K_1\} = \lambda e$$

Certainty Equivalence

$$u(e) = u_1(\lambda e) + u_2(k_2(1-e))$$

Boring -

Less Boring

$$U(e) = E_{K(e)} \{ U_1(K) \} + U_2(k_2(1-e))$$

$$= \sum_{k=0}^{\infty} e^{-\lambda e} \frac{(\lambda e)^k}{k!} U_1(k) + U_2(k_2(1-e))$$

Not not boring: we still assume that
 λ and k_2 are known

- ① λ has a ^{precisely} distribution
 - ② I can learn about ~~the~~ the parameters of that distribution
- } not-boring

Learning About λ : Parametric, Bayesian
Approach Based on a
Conjugate Prior

$$P\{A|B\} = \frac{P\{A, B\}}{P\{B\}} \quad \text{MCMC}$$

Assume that λ has a gamma density
with parameters ν and α

$$\lambda \sim f(\lambda) = \frac{e^{-\alpha\lambda} \lambda^{\nu-1} \alpha^\nu}{\Gamma(\nu)}$$

$$0 \leq \lambda < \infty$$

$$E\{\lambda\} = \int_0^\infty \lambda f(\lambda) d\lambda = \nu/\alpha$$

$$CV\{\lambda\} = 1/\sqrt{\nu} = \text{SD}/\text{mean}$$

Quiz

$$\int_0^\infty e^{-\alpha\lambda} \lambda^{\nu-1} d\lambda = \frac{\Gamma(\nu)}{\alpha^\nu}$$

$$\Gamma(\nu+1) = \nu \Gamma(\nu)$$

$$Pr\{K=k\} = \int_0^{\infty} Pr\{K=k, \lambda\} d\lambda$$

$$= \int_0^{\infty} Pr\{K=k | \lambda\} f(\lambda) d\lambda$$

$$= \int_0^{\infty} \frac{e^{-\lambda e} (\lambda e)^k}{k!} \frac{e^{-\alpha \lambda} \lambda^{\nu-1} \alpha}{\Gamma(\nu)} d\lambda$$

$$= \frac{e^k}{k!} \frac{\alpha^\nu}{\Gamma(\nu)} \int_0^{\infty} e^{-\lambda(\alpha+e)} \lambda^{\nu+k-1} d\lambda$$

II V H:

$$= \frac{e^k}{k!} \frac{\alpha^\nu}{\Gamma(\nu)} \frac{\Gamma(\nu+k)}{(\alpha+e)^{\nu+k}}$$

$$= \left(\frac{\alpha}{\alpha+e}\right)^\nu \left(\frac{e}{\alpha+e}\right)^k \frac{\Gamma(\nu+k)}{\Gamma(\nu) k!}$$

Negative
Binomial
Distribution

$$= P_{k|\nu, \alpha, e}$$

$$\Pr\{K=0\} = \left(\frac{\alpha}{\alpha+e}\right)^v$$

$$E\{K\} = \frac{v}{\alpha} e$$

$$\text{Var}\{K\} = \frac{ve}{\alpha} + \frac{1}{v} \left(\frac{\alpha ve}{\alpha}\right)^2$$

Bayesian Updating

$$\Pr\{A|B\} = \frac{\Pr\{A, B\}}{\Pr\{B\}} = \frac{\Pr\{B|A\} \Pr\{A\}}{\Pr\{B\}}$$

$$\Pr\{\lambda | K=k\}$$

$$= \frac{\Pr\{K=k | \lambda\} f(\lambda)}{\int [\text{numerator}] d\lambda}$$

prior

$$= \frac{e^{-\lambda e} (\lambda e)^k}{k!} \frac{e^{-\alpha \lambda} \lambda^{v-1} \alpha^v}{\Gamma(v)}$$

$$\propto \frac{e^{-(\alpha+e)\lambda} \lambda^{v+k-1}}{\lambda}$$

$$\int [\text{numerator}] d\lambda$$

posterior

Before

After

—

α

}

Effort e

$\alpha + e$

harvest k

$v + k$

v

v/α

Mean

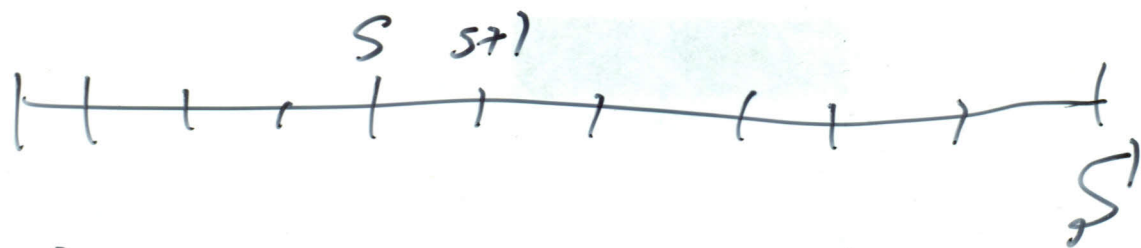
$\frac{v+k}{\alpha+e}$

$1/\sqrt{v}$

CV

$1/\sqrt{v+k}$

SDP with Information Dynamics



~~$F(v, \phi)$~~

$F(v, \phi, s) = \text{maximum } E \{ \text{accumulation of utility from } s \text{ to } s' \mid \text{parameters at } s \text{ are } (v, \phi) \}$

$F(v, \phi, s')$

NB

↓

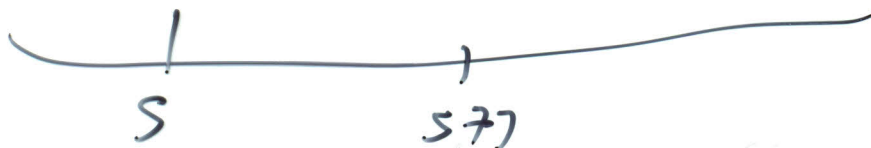
$$= \max_e \left[\sum_{k=0}^{\infty} \gamma^k (v, \phi_k, e) u_1(k) + u_2(k_2(1-e)) \right]$$

What about previous periods

$$\begin{array}{ccc} S & \longrightarrow & S+1 \\ (v, \alpha) & & (v+k, \alpha+e) \\ e & & \text{or } P_k(v, \alpha, e) \end{array}$$

$$F(v, \alpha, S)$$

$$= \max_e \left\{ \sum_{k=0}^{\infty} P_k(v, \alpha, e) \left[U_1(k) + U_2(k_2(1-\alpha)) + F(v+k, \alpha+e, S+1) \right] \right\}$$



Computational Considerations

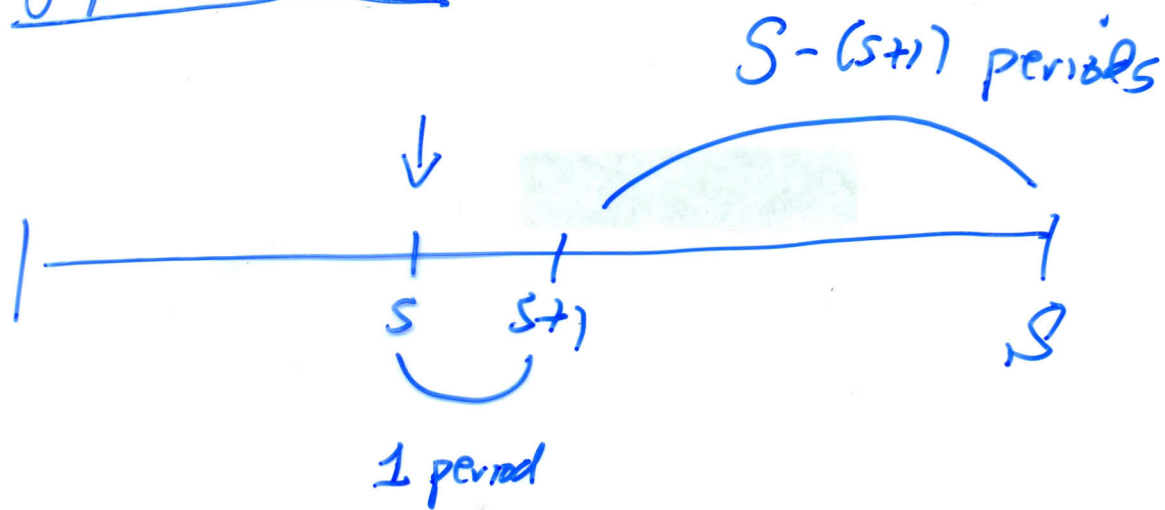
$$\sum_{k=0}^{\infty} \varphi_k(v, \alpha, \epsilon)$$

$$\rightarrow \sum_{k=0}^{k_{\max}(\epsilon)} \varphi_k(v, \alpha, \epsilon) = 1 - \epsilon$$

Renormalize

$$\sum_{k=0}^{k_{\max}} p'_k(v, \alpha, \epsilon) = 1$$

"Myopic Approach"



$$F_m(v, \alpha, s) \quad \text{key}$$
$$= \max_e \left\{ \sum_{k=0}^{\infty} \varphi_k'(v, \alpha, e) \left[U_1(k) + U_2(k, (1-e)) \right. \right. \\ \left. \left. + F_m(v+k, \alpha+e, s') (s' - (s+1)) \right] \right\}$$