

NB10
case
study

$$(\mu, \sigma^2 | \text{[PM] } B) \sim p(\mu, \sigma^2)$$
$$(\bar{Y}_i | \mu, \sigma^2 | \text{[SMTT] } B) \sim \prod_{i=1}^n f_{\sigma^2}$$

STAT 206
2 Mar 21

$$t_r(\mu, \sigma^2)$$

$$(i=1, \dots, n)$$

Lecture

BIC
DIC

Gaussian ^①
model doesn't
fit

A conj. prior for this SM

we want a LI prior

hard
to implement

rejection
sampling
(von Neumann)

there
does
not
exist

(1953) A. Rosenblatt
(1942) M. Rosenblatt
Metropolis et al.
(not Ulan) (1949)

this SM
Metropolis
Hastings (MH)
algorithm

Markov Chain Monte Carlo (MCMC)

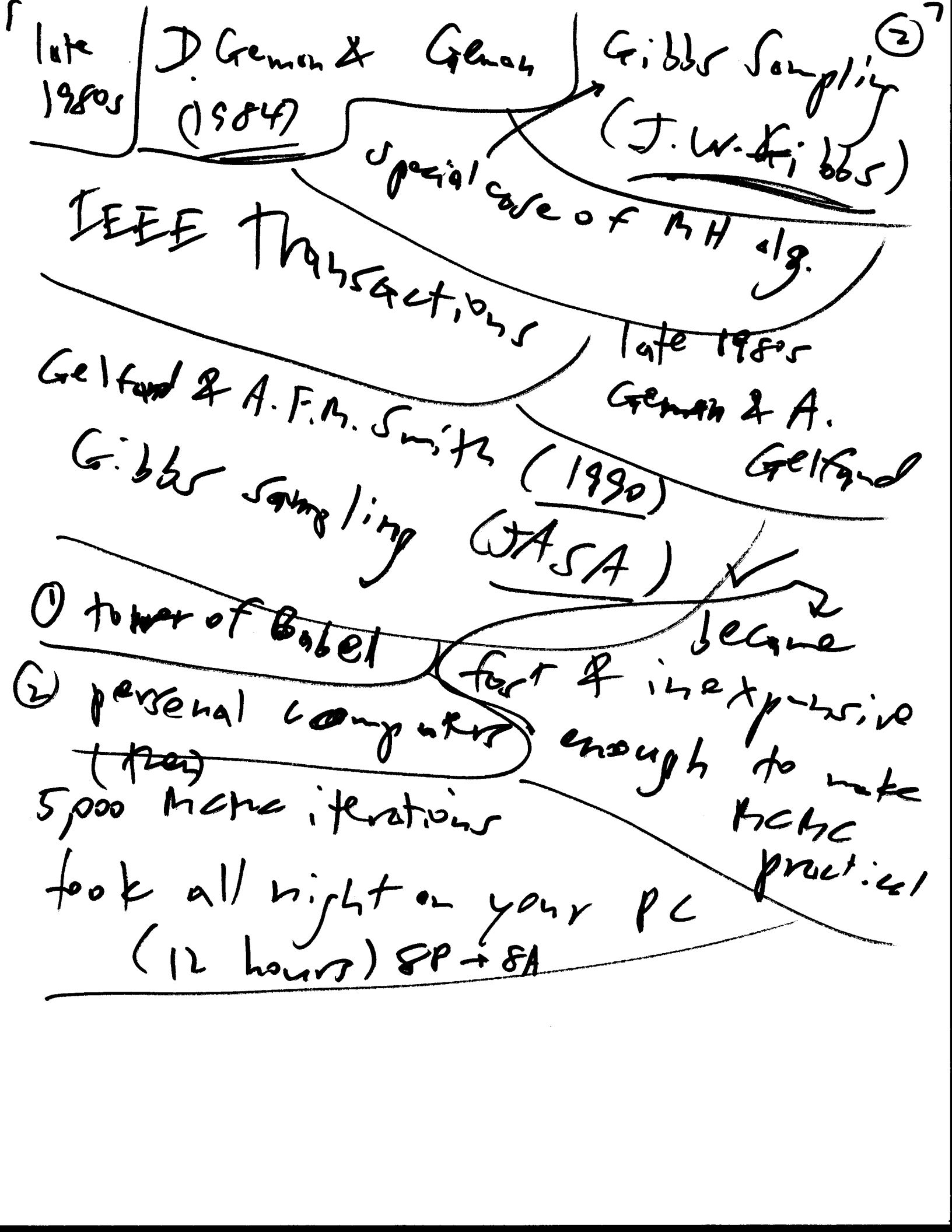
Chemical
Physics

analogy engine

"similar to,
in all relevant
ways"

(1970) Hastings

Bionetika (General AI)



late 1980s

J. Geman & Geman (1984)

Gibbs Sampling (J.W. Gibbs) ⁽²⁾

special case of MH alg.

IEEE Transactions

late 1980s
Geman & A. Gelfand

Gelfand & A.F.M. Smith (1990)

Gibbs Sampling (JASA)

became fast & inexpensive enough to make MCMC practical

- ① tower of Babel
- ② personal computer (1982)

5,000 Monte iterations

took all night on your PC (12 hours) SP + SA

von Neumann's rejection sampling

IID draws from

$$p(\theta | \text{---})$$

$$\theta = (\theta_1, \dots, \theta_k)$$

works well when k is small (e.g., in special cases, $k \leq 10$)

takes too

long in clock time for large k

doesn't scale as kT

MC method
M-U insight

anything you want to know about $p(\theta | \text{---})^*$ can

be estimated to arbitrary accuracy

by (a) finding a way to make lots of

IID draws from $(*)$ and (b) making graphical

and numerical summaries of the draws

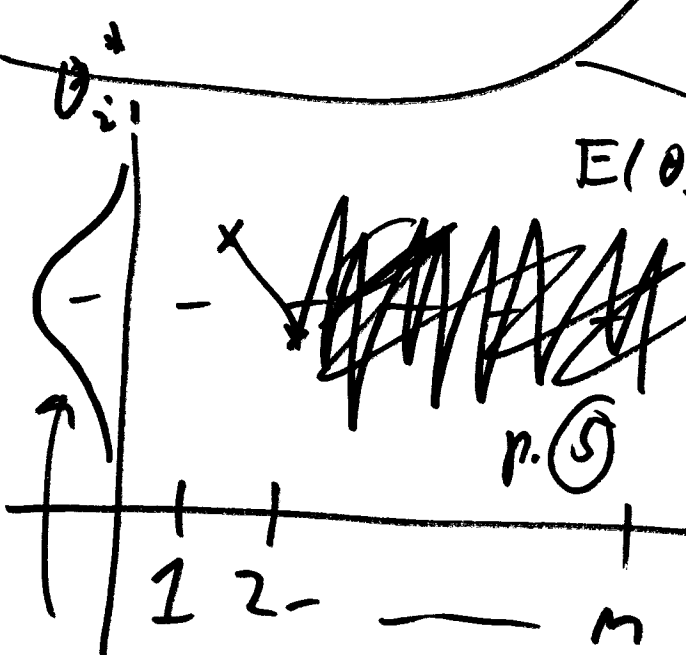
Metropolis et al. insight (independence not needed)

	θ_{11}^*	\dots	θ_{1k}^*	derived quantities			\uparrow M \downarrow
1	θ_{11}^*	\dots	θ_{1k}^*				
2	θ_{21}^*	\dots	\dots				
\vdots	\vdots	\vdots	\vdots				
M	\vdots	\vdots	\vdots				

MC data set

$$\theta_i^* = (\theta_{i1}^*, \dots, \theta_{iM}^*)$$

iteration #
(life time index)



iteration number

does not depend on

$$(\theta_{i,1}^*, \dots, \theta_{i-1,1}^*, \dots, \theta_{i,1}^*)$$

$$\theta_{i+1,1}^*$$

1st order Markov chain

$\theta_{i,t+1}^*$ is allowed to depend on $\theta_{i,t}^*$ but not on any previous $\theta_{i,t}^*$

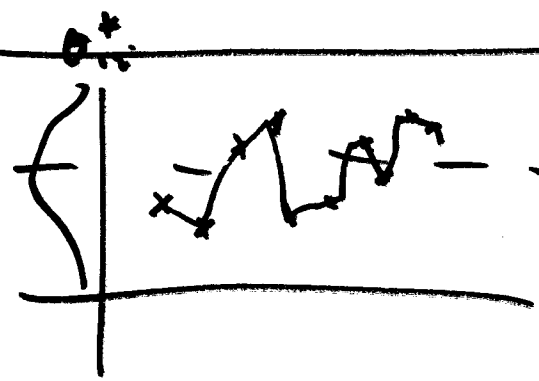
nice Markov chains

settle down, after (a few) initial iterations (starting with an initial value), into a

steady-state behavior called the equilibrium or stationary distribution

of the Markov chain

take $t=1$
 $\theta_{k=1} = \theta_{i,1}$



haphazard, no pattern

