

# Cohort State-Transition Models

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# Cohort State-Transition Modeling Overview

# Cohort State-Transition Models

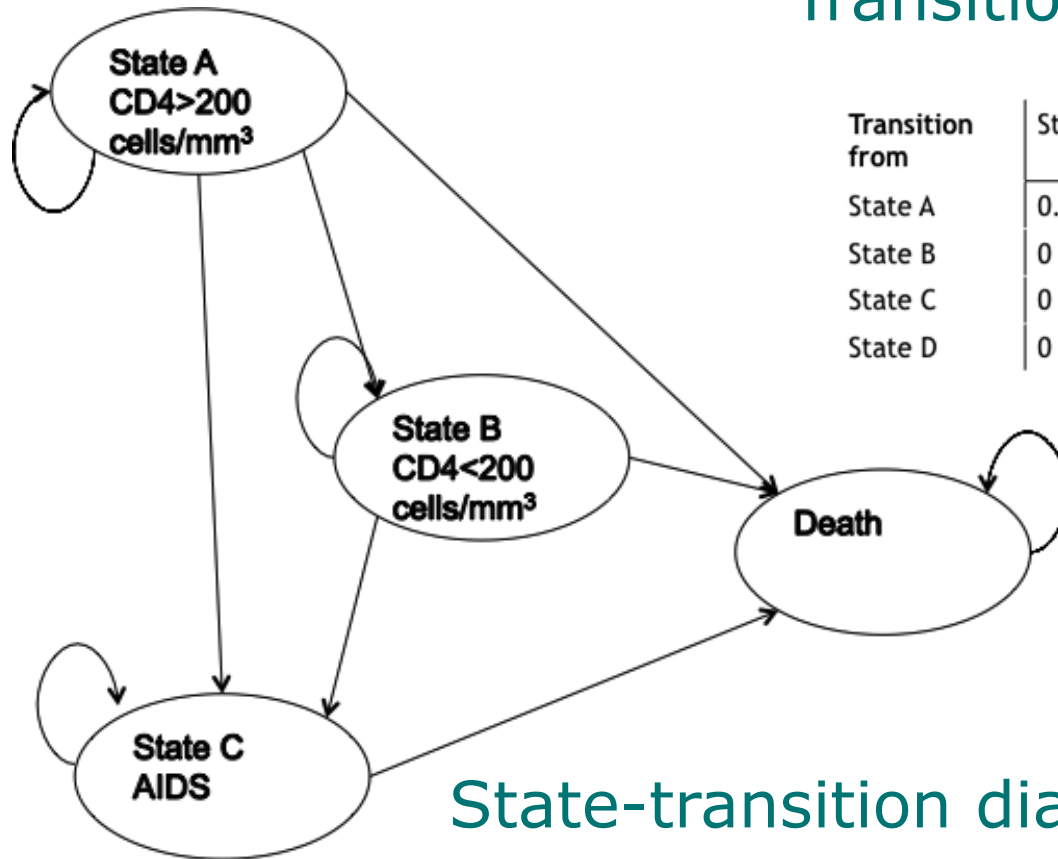
- Model that describes how a cohort is distributed across health states over time
  - e.g., healthy, sick, stable, progressed, dead
- Allow transitions between states with some probability
- Transitions are modeled in discrete time steps (e.g. weekly, monthly, yearly)

# Cohort Model Assumptions

- Health states are mutually exclusive, collectively exhaustive
- Within a given health state, population is homogeneous
- Markovian assumption: transition probabilities depends only on current health state (“memoryless”)

# Simple State-Transition Model of HIV Progression

## Transition probability matrix



Transition from	Transition to			
	State A	State B	State C	State D
State A	0.721	0.202	0.067	0.01
State B	0	0.581	0.407	0.012
State C	0	0	0.75	0.25
State D	0	0	0	1

## State-transition diagram

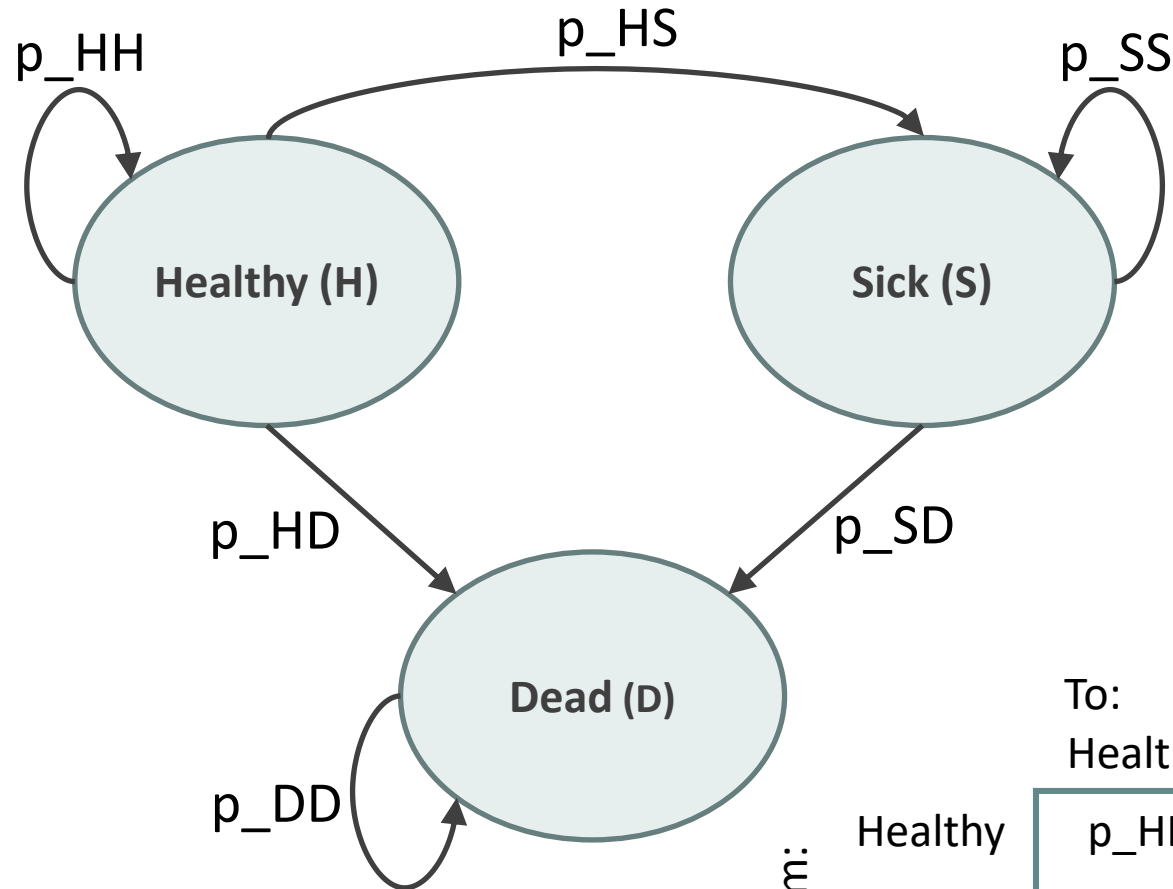
Cycle	State A	State B	State C	State D	Total
0	1000	0	0	0	1000
	$1000 \times 0.721$	$1000 \times 0.202$	$1000 \times 0.067$	$1000 \times 0.01$	
	↓	↓	↓	↓	
1	721	202	67	10	1000
2	520	263	181	36	1000
3	375	258	277	90	1000
4	270	226	338	166	1000
5	195	186	363	256	1000
6	140	147	361	351	1000
7	101	114	340	445	1000
8	73	87	308	532	1000
9	53	65	271	611	1000
10	38	48	234	680	1000
11	27	36	197	739	1000
12	20	26	164	789	1000
13	14	19	135	831	1000
14	10	14	110	865	1000
15	7	10	89	893	1000
16	5	7	72	916	1000
17	4	5	57	934	1000
18	3	4	45	948	1000
19	2	3	36	959	1000
20	1	2	28	968	1000

# Cohort "Trace"

Number or proportion  
of individuals at each  
time step

# Simple 3-State Example

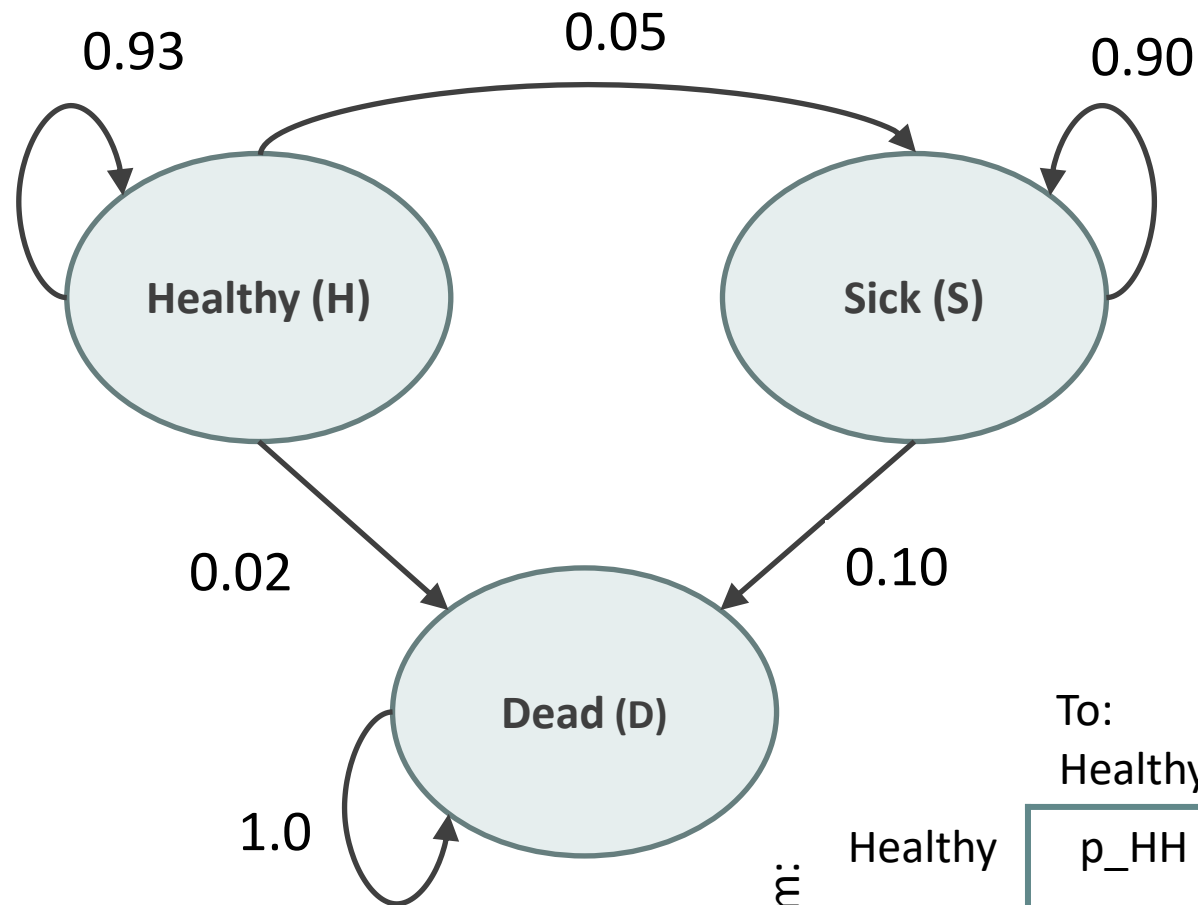
# Three-State Model



From:	To:		
	Healthy	Sick	Dead
Healthy	$p_{HH}$	$p_{HS}$	$p_{HD}$
Sick	0	$p_{SS}$	$p_{SD}$
Dead	0	0	$p_{DD}$

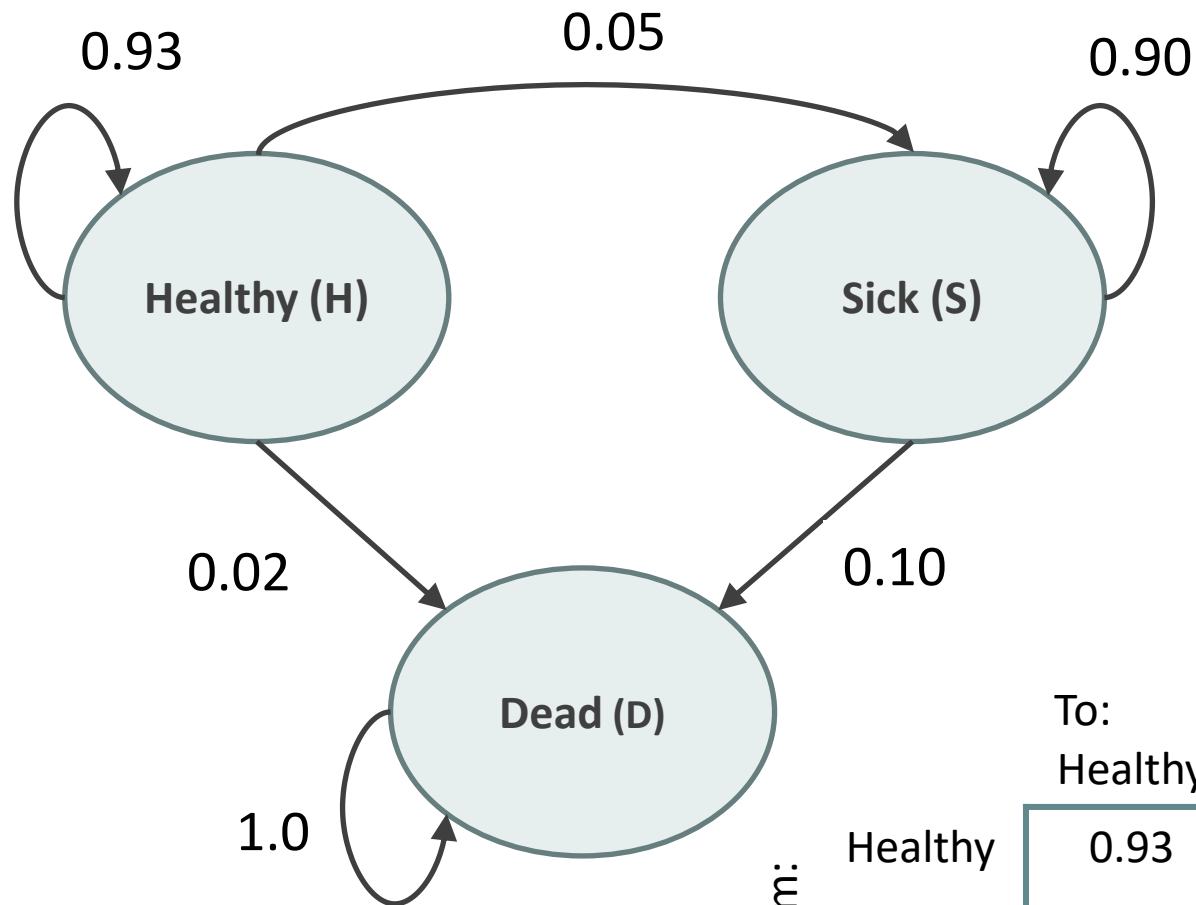


# Three-State Model



From:	To:		
	Healthy	Sick	Dead
Healthy	$p_{HH}$	$p_{HS}$	$p_{HD}$
Sick	0	$p_{SS}$	$p_{SD}$
Dead	0	0	$p_{DD}$

# Three-State Model



From:	To:		
	Healthy	Sick	Dead
Healthy	0.93	0.05	0.02
Sick	0	0.90	0.10
Dead	0	0	1.0

# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{bmatrix} \text{---} x_{t+1} \text{---} \end{bmatrix} = \begin{bmatrix} \text{---} x_t \text{---} \end{bmatrix} \begin{bmatrix} \text{Transition} \\ \text{Probability} \\ \text{Matrix} \\ P \end{bmatrix}$$

# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{bmatrix} x_1 \end{bmatrix} = \begin{bmatrix} x_0 & 1.0 & 0.0 & 0.0 \end{bmatrix} \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix}$$

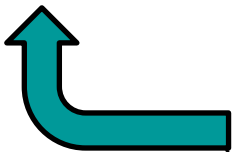
# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{matrix} x_1 \\ \begin{bmatrix} 0.93 \end{bmatrix} \end{matrix} = \begin{matrix} x_0 \\ \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \end{matrix} \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix}$$

  $(0.93)(1.0) + (0.0)(0.0) + (0.0)(0.0)$

$$(p_{Healthy,Healthy}) * \Pr(healthy) + (p_{Sick,Healthy}) * \Pr(sick) + (p_{Dead,Healthy}) * \Pr(dead)$$

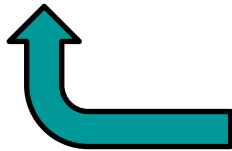
# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{bmatrix} x_1 \\ 0.93 & 0.05 \end{bmatrix} = \begin{bmatrix} x_0 \\ 1.0 & 0.0 & 0.0 \end{bmatrix} \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix}$$


 $(0.05)(1.0) + (0.90)(0.0) + (0.0)(0.0)$

# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{matrix} & x_1 \\ \begin{bmatrix} 0.93 & 0.05 & 0.02 \end{bmatrix} & = & \begin{bmatrix} & x_0 \\ 1.0 & \cdot & 0.0 & \cdot & 0.0 \end{bmatrix} & \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix} \end{matrix}$$

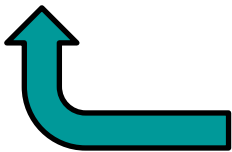
# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{matrix} & x_2 & \\ \begin{bmatrix} 0.87 & & \end{bmatrix} & = & \begin{matrix} & x_1 \\ \begin{bmatrix} 0.93 & 0.05 & 0.02 \end{bmatrix} & \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix} \end{matrix}$$


 $(0.93)(0.93) + (0.0)(0.05) + (0.0)(0.02)$



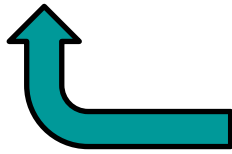
# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{bmatrix} x_2 & & \\ 0.87 & 0.09 & \\ & & \end{bmatrix} = \begin{bmatrix} x_1 & & \\ 0.93 & 0.05 & 0.02 \end{bmatrix} \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix}$$

  $(0.05)(0.93) + (0.90)(0.05) + (0.0)(0.02)$


# Simulate the Cohort over Time

- Initial cohort distribution:

$$x_0 = \begin{bmatrix} 1.0 & 0.0 & 0.0 \end{bmatrix} \quad (\text{everyone starts healthy})$$

- Cohort distribution at next time step is calculated through matrix multiplication

$$\begin{array}{c} x_2 \\ \left[ \begin{array}{ccc} 0.87 & 0.09 & 0.04 \end{array} \right] \end{array} = \begin{array}{c} x_1 \\ \left[ \begin{array}{ccc} 0.93 & 0.05 & 0.02 \end{array} \right] \end{array} \begin{bmatrix} 0.93 & 0.05 & 0.02 \\ 0 & 0.90 & 0.10 \\ 0 & 0 & 1.0 \end{bmatrix}$$

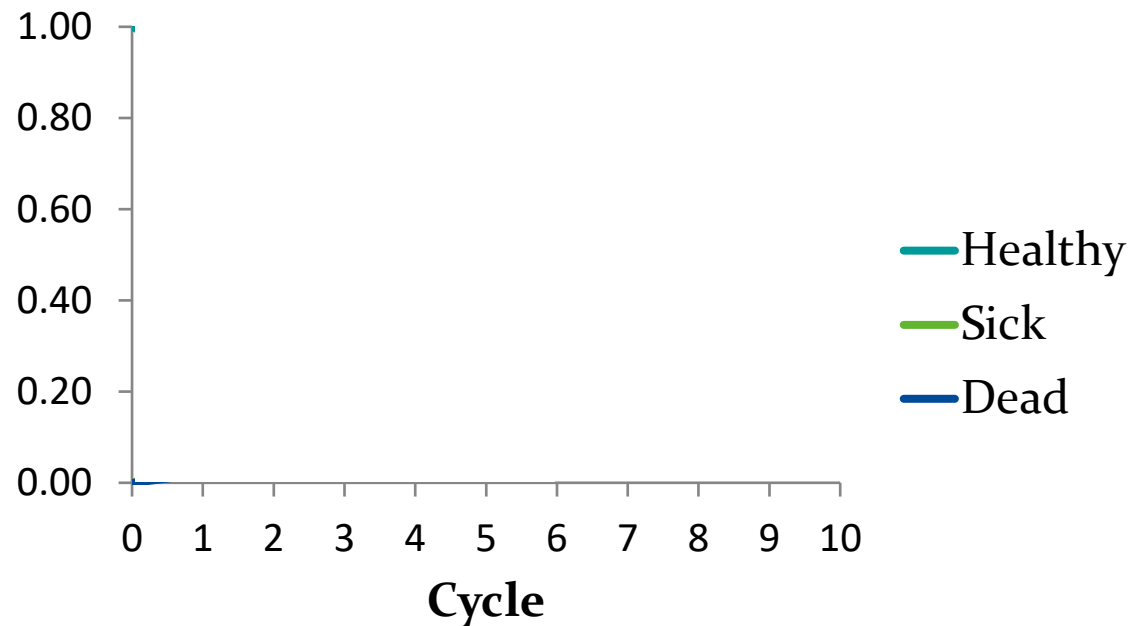
  $(0.02)(0.93) + (0.10)(0.05) + (1.0)(0.02)$

# Simulate the Cohort over Time

- Cohort distribution over time:

$$x_4 = [0.75 \quad 0.15 \quad 0.10]$$

- Cohort trace:



# Calculating Model Outcomes

# Expected outcomes

- Expected remaining life-years, quality-adjusted life-years (QALYs), costs
  - Generally calculated over lifetime
- Multiply cohort distribution by state-specific values to calculate expected value at each cycle
- Sum expected values over time
  - discount if desired

# Remaining Life-Expectancy

- State-specific values: 1 if alive, 0 if dead

State values:    1.0                    1.0                    0.0

Time	Healthy	Sick	Dead	E[LYs]
0	1.0	0.0	0.0	--
1	0.93	0.05	0.02	
2	0.87	0.09	0.04	
3	0.80	0.13	0.07	
	...	...	...	

Total life years:    21.0 years

# Remaining QALE

- Remaining quality-adjusted life-expectancy (QALE)
- State-specific values: utility of that state

State values:    0.8                      0.5                      0.0

Time	Healthy	Sick	Dead	E[QALYs]
0	1.0	0.0	0.0	--
1	0.93	0.05	0.02	
2	0.87	0.09	0.04	
3	0.80	0.13	0.07	
	...	...	...	

Total QALYs:    14.7 QALYs

# Remaining costs

- Remaining lifetime health care costs
- State-specific values: cost of spending one cycle in that health state

State values:   \$400           \$1,000           \$0

Time	Healthy	Sick	Dead	E[costs]
0	1.0	0.0	0.0	--
1	0.93	0.05	0.02	
2	0.87	0.09	0.04	
3	0.80	0.13	0.07	
	...	...	...	

Total health care costs:   \$12,531



# Discounting

- In cost-effectiveness analysis, costs and QALYs are discounted at some rate,  $r$
- At each cycle  $t$ , multiply expected outcome by the discount factor:  $\frac{1}{(1+r)^t}$

State values:

0.8

0.5

0.0

Time	Healthy	Sick	Dead	E[QALYs]
0	1.0	0.0	0.0	--
1	0.93	0.05	0.02	0.77
2	0.87	0.09	0.04	0.74
3	0.80	0.13	0.07	0.71
	...	...	...	

Sum

↓

\*  $1/(1+r)$

\*  $1/(1+r)^2$

\*  $1/(1+r)^3$

Total QALYs: 14.7 QALYs

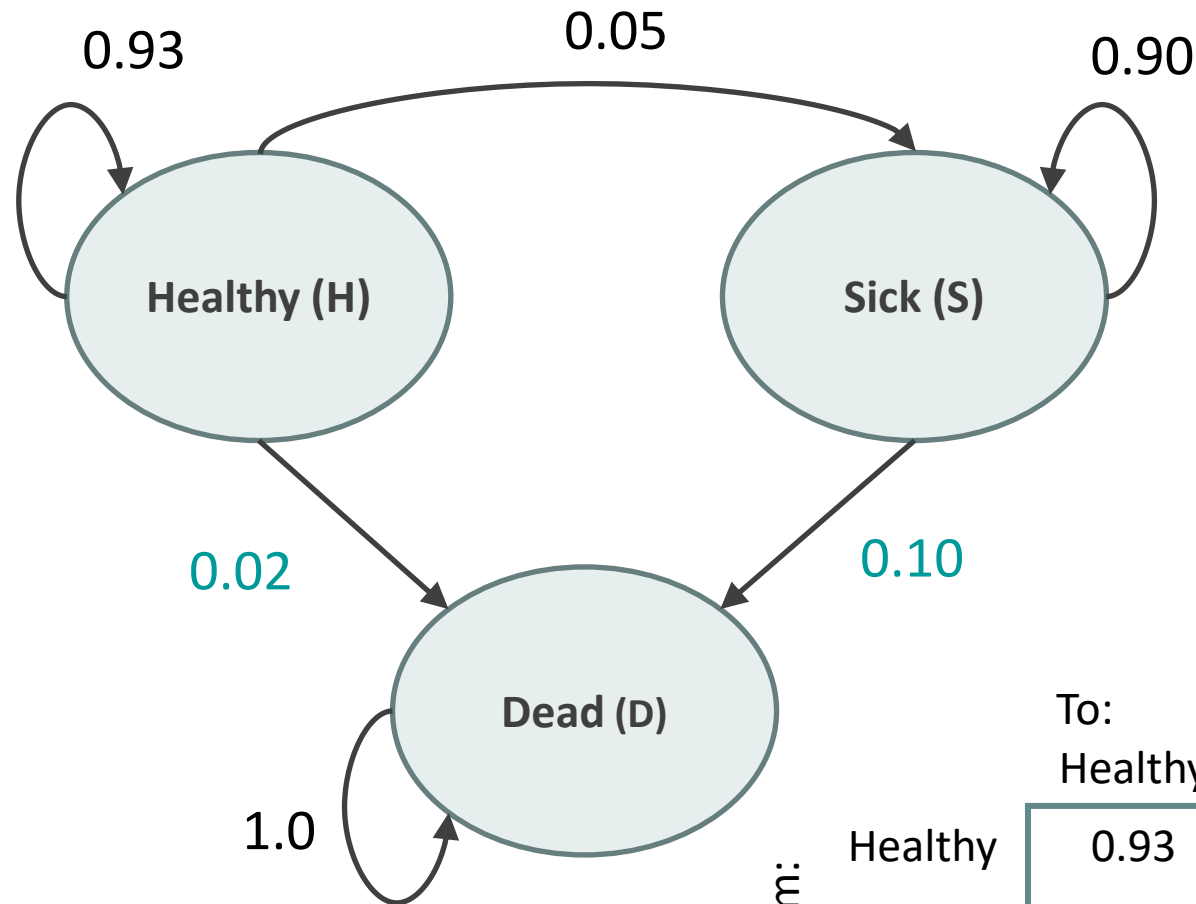
Total *discounted* (3% per year) QALYs: 10.2 QALYs

# Time-Varying State-Transition Models

# Time-Varying Probabilities

- Often transition probabilities change over time as the cohort ages
  - Background mortality
  - Risk of developing disease or experiencing an event
- In other words, the transition probability matrix  $P$  is not the same every cycle
- Replace matrix  $P$  with matrices  $P_t$ , where  $t$  is time from the start of the simulation

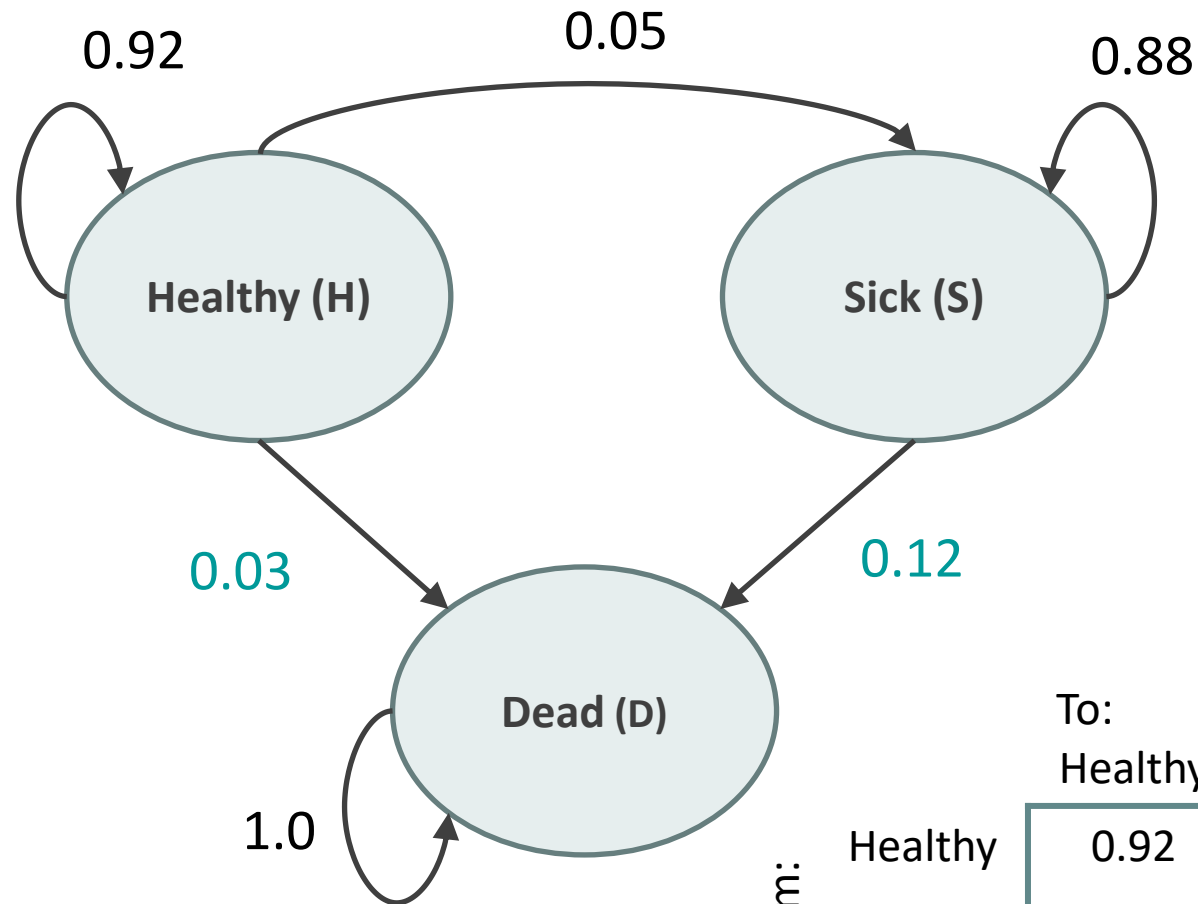
# Three-State Model



$t = 0$

From:	To:		
	Healthy	Sick	Dead
Healthy	0.93	0.05	0.02
Sick	0	0.90	0.10
Dead	0	0	1.0

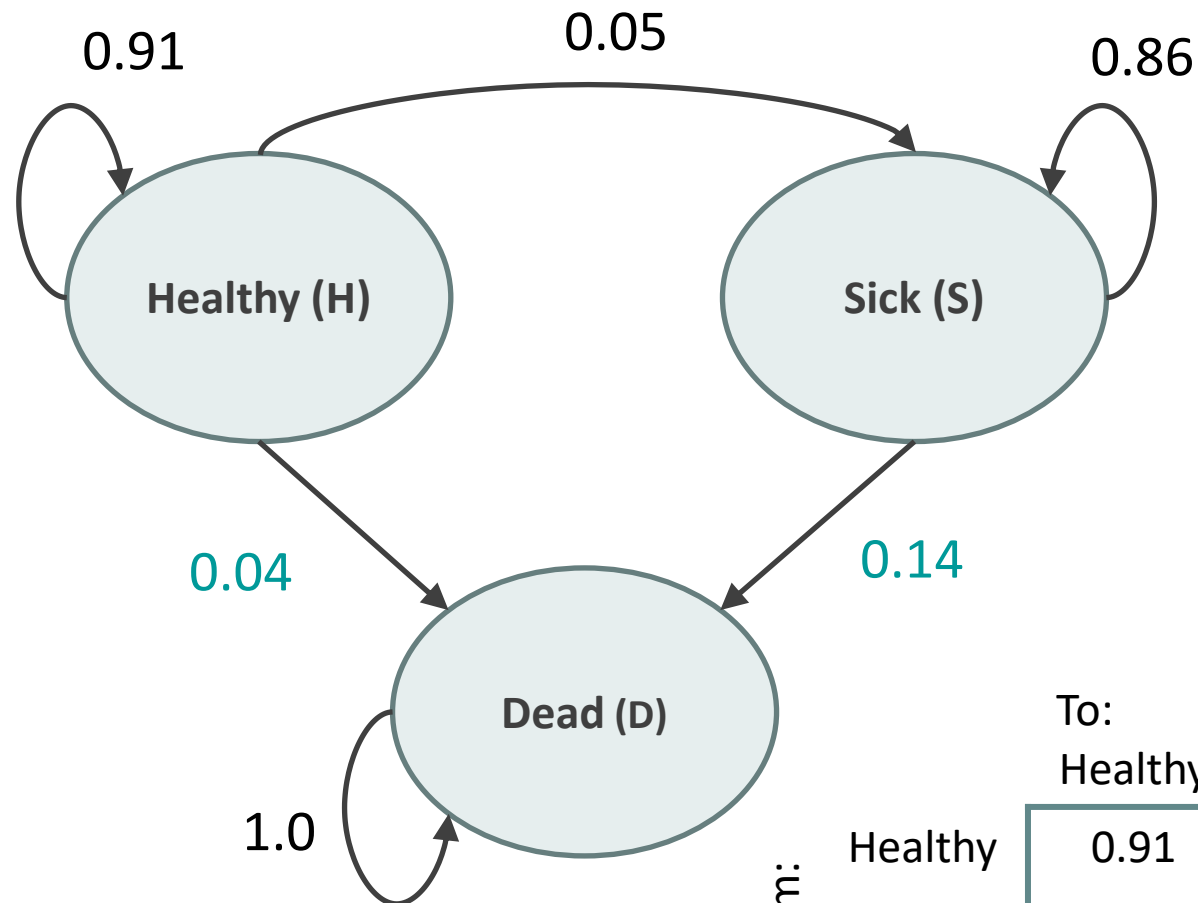
# Three-State Model



$t = 1$

From:	To:		
	Healthy	Sick	Dead
Healthy	0.92	0.05	0.03
Sick	0	0.88	0.12
Dead	0	0	1.0

# Three-State Model



$t = 2$

	To:		
	Healthy	Sick	Dead
From: Healthy	0.91	0.05	0.04
Sick	0	0.86	0.14
Dead	0	0	1.0

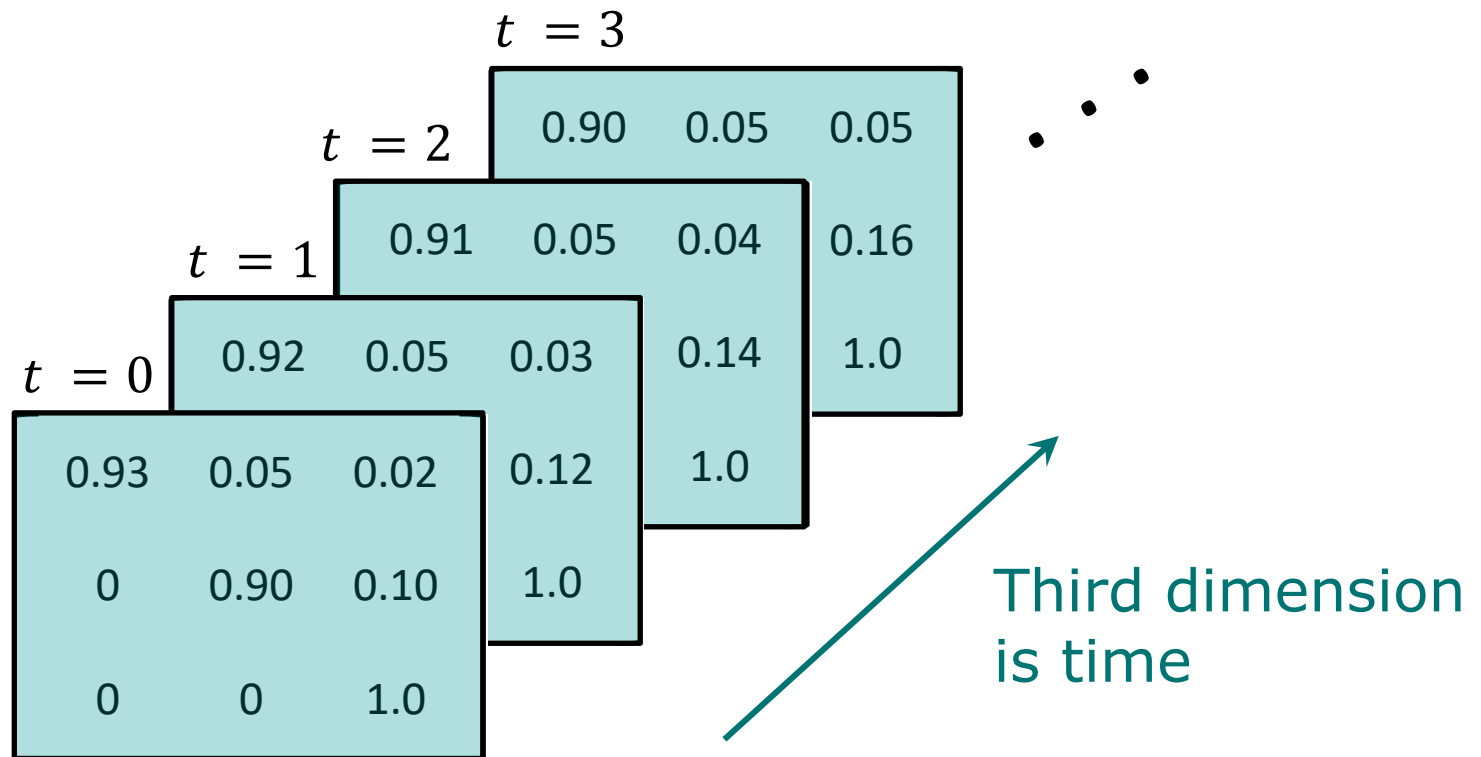
# Simulating Cohort with Time-Varying Probabilities

- Cohort distribution at next time step is still calculated through matrix multiplication, but ***matrix changes over time***

$$\left[ \text{---} x_{t+1} \text{---} \right] = \left[ \text{---} x_t \text{---} \right] \left[ \begin{array}{c} \text{Transition} \\ \text{Probability} \\ \text{Matrix} \\ P_t \end{array} \right]$$

# Transition Probability Array

- Stack cycle-specific transition probability matrices together to form a **transition probability array**



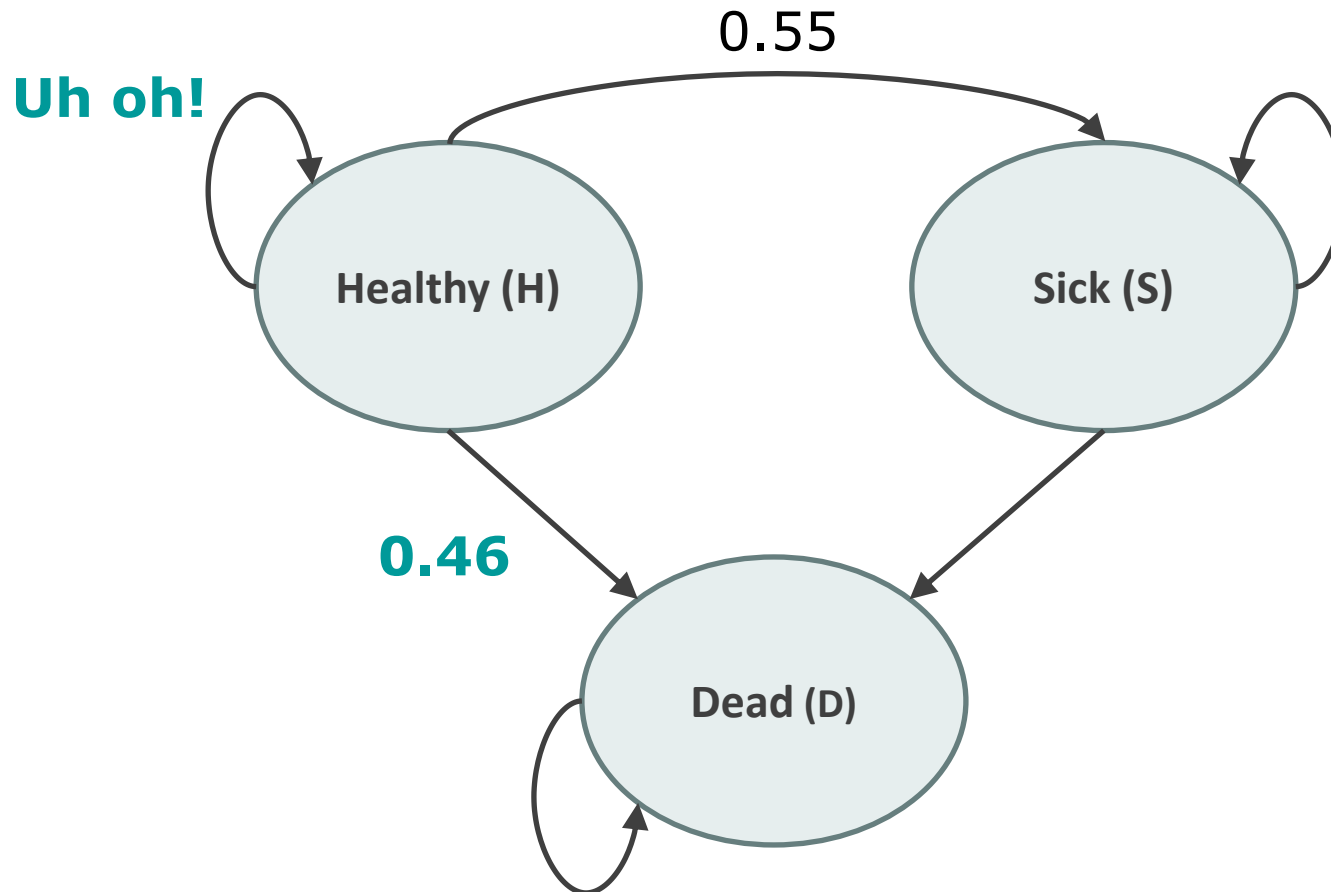


# Conditional Transitions

- Always need to ensure that rows of the transition probability matrix sum to 1
- When modeling aging cohorts over a lifetime, oldest ages have high probabilities of mortality
  - The sum of age-specific mortality with other possible events, if defined as independent, can exceed 1
- Defining transitions as conditional is one approach to avoiding this problem

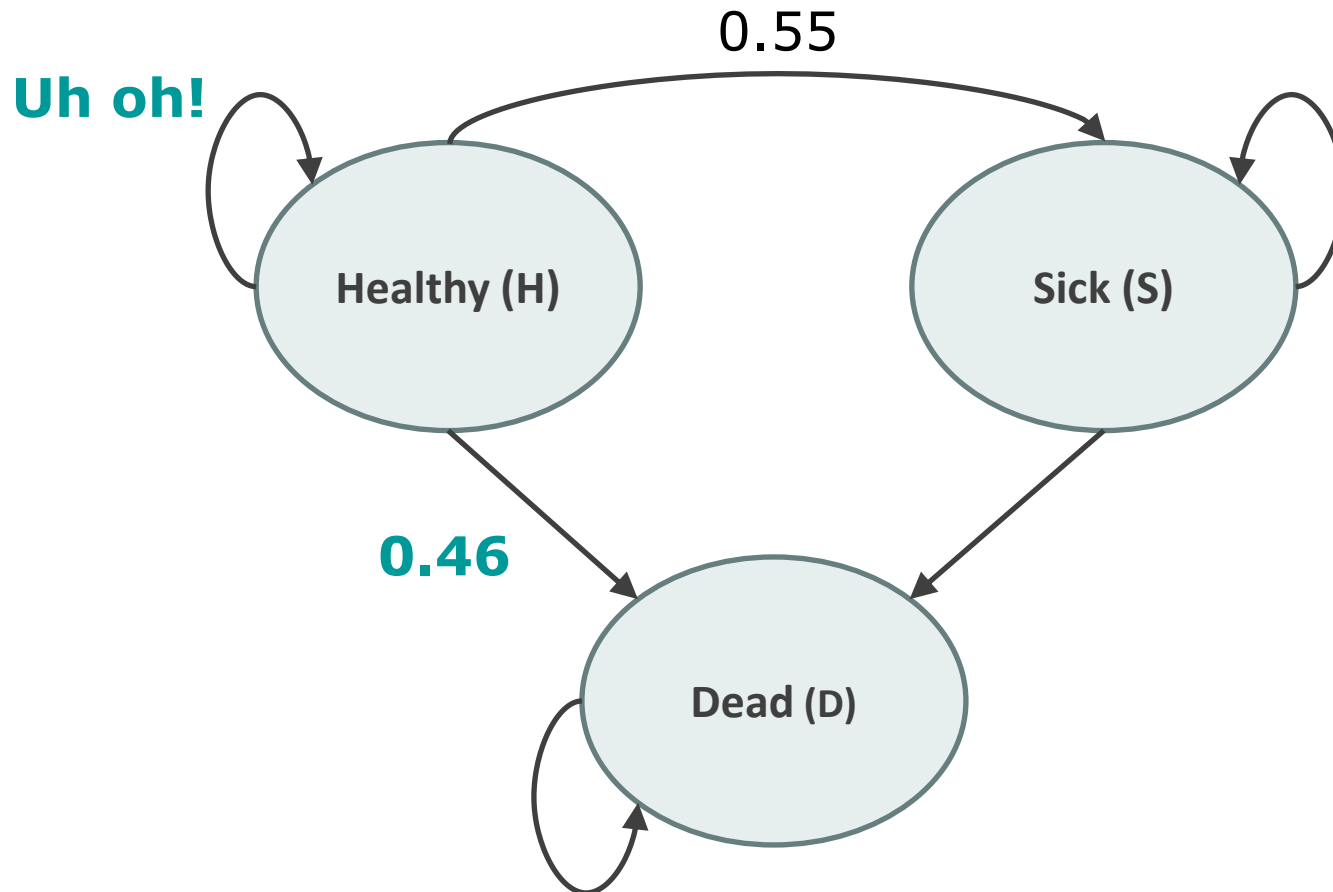
# Conditional Transitions

- Problem: Sum of transition probabilities can exceed 1 over time



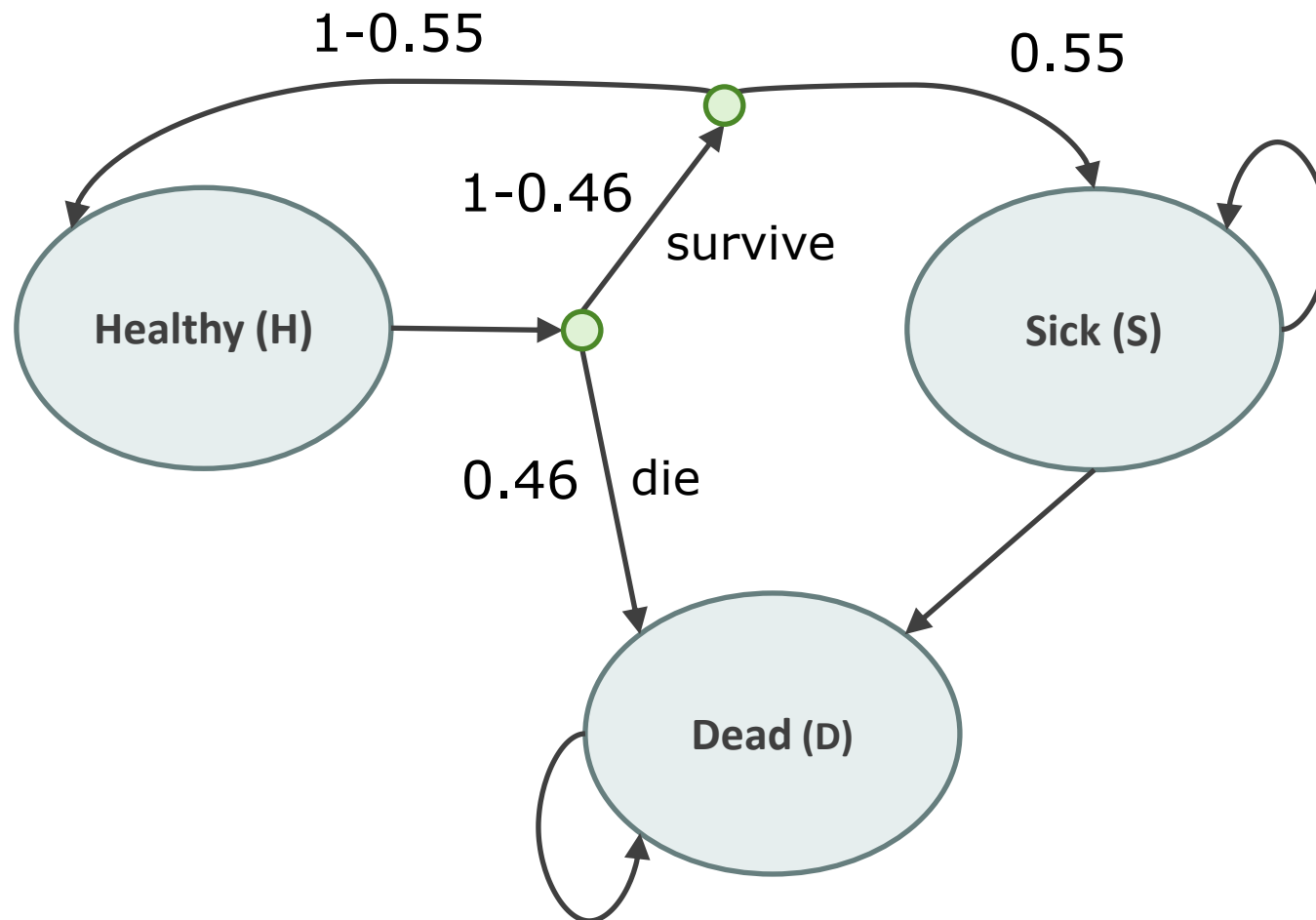
# Conditional Transitions

- Solution: Condition other events on survival



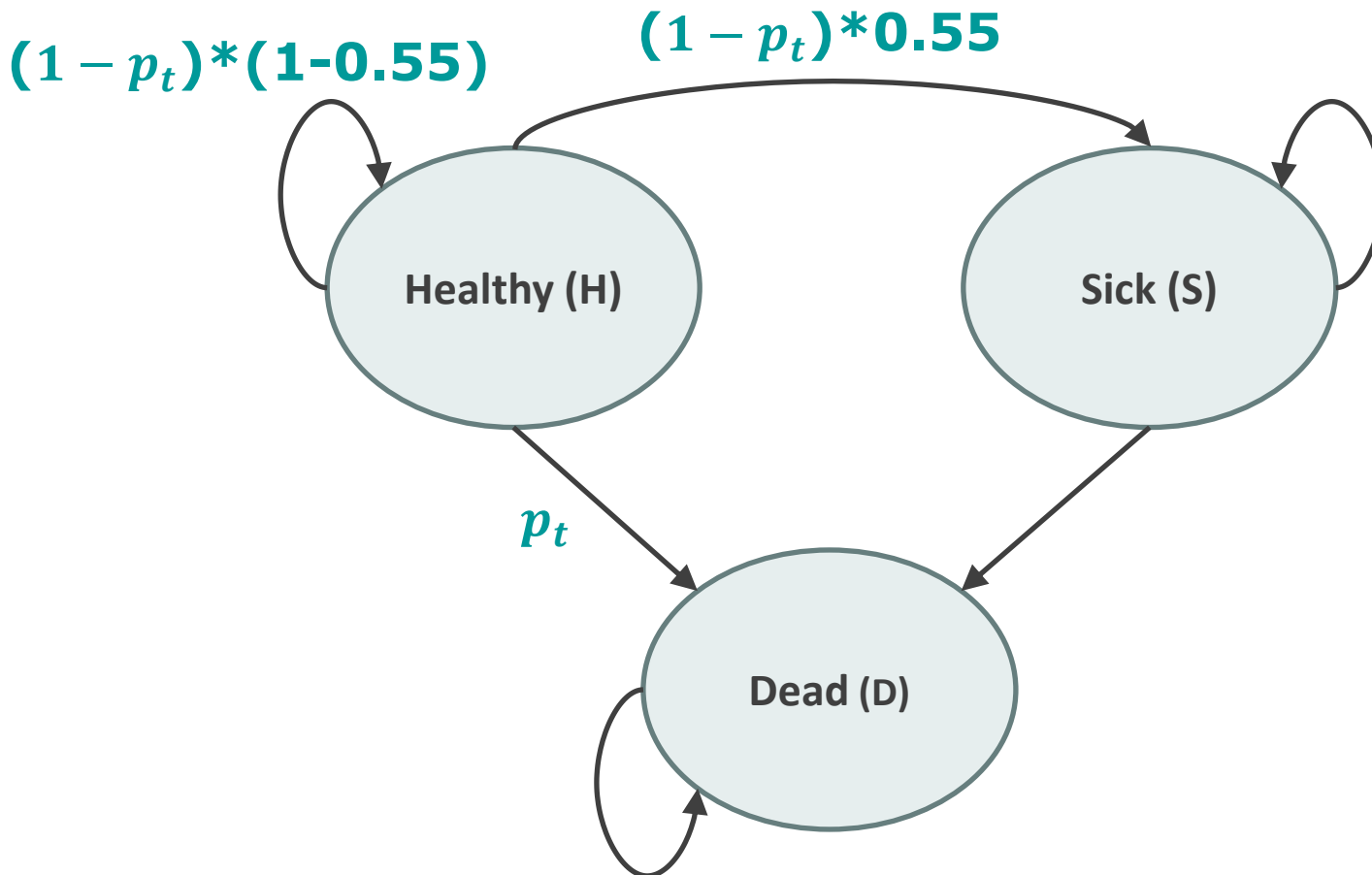
# Conditional Transitions

- Solution: Condition other events on survival



# Conditional Transitions

- Solution: Condition other events on survival



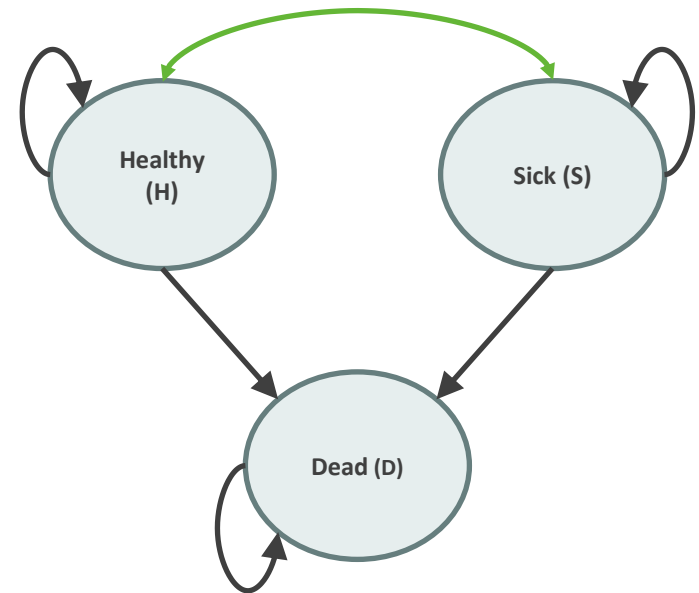
# History Dependence

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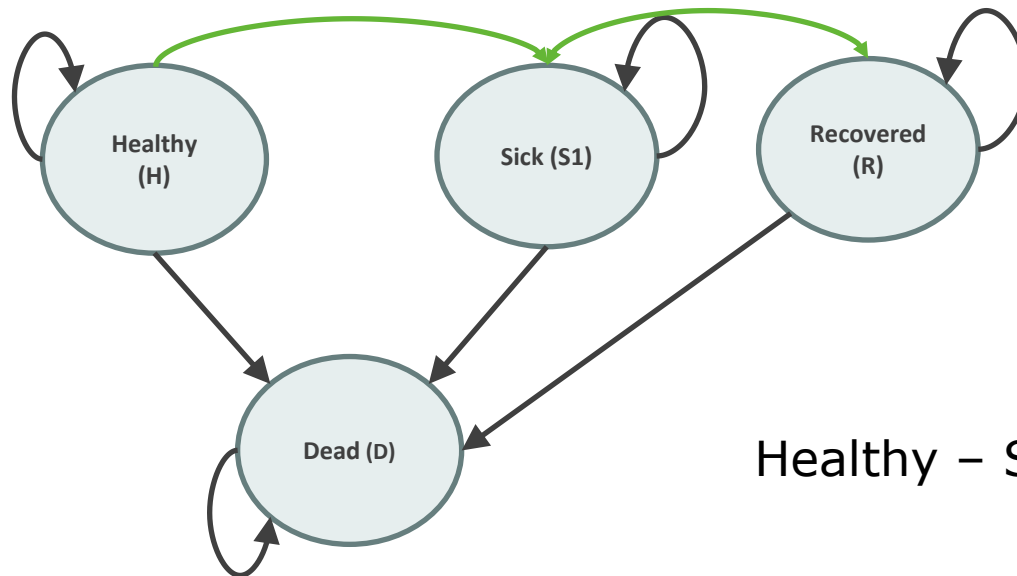
- “Memoryless” property of state transition models is a BIG assumption
  - Transition probabilities only depend on the current state and not on past states
- Many transition probabilities depend on model history, not just time since model start
  - Risk of myocardial infarction (MI) greater for persons with prior MI
  - Effectiveness of a drug used as first-line therapy may be better than if used as second-line therapy

# When history matters, create more states...

Healthy – Sick – Dead:



Once recovered, the risk of getting sick again or dying increases

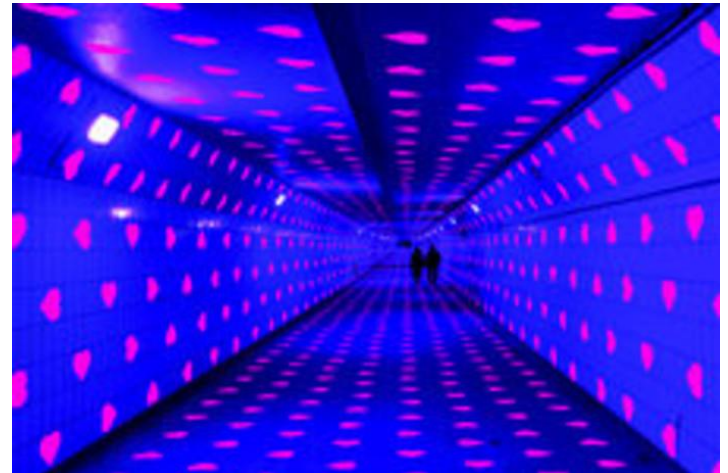


Healthy – Sick – Recovered – Dead

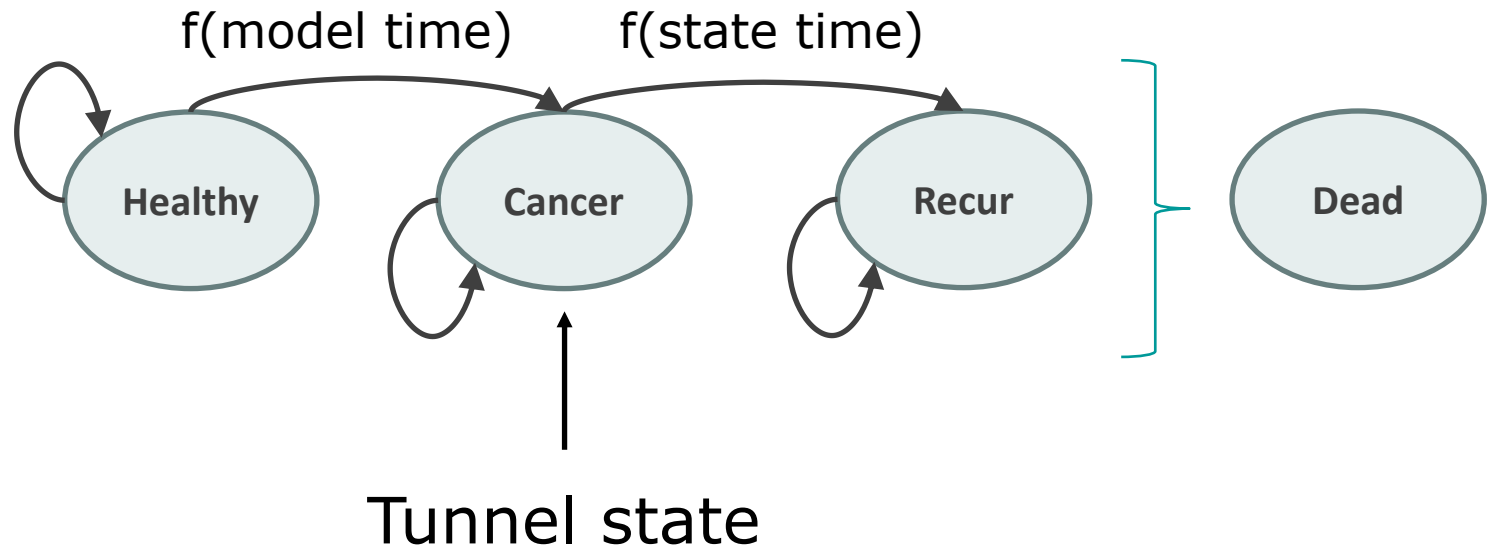


# Tunnel states

- Sometimes, transition probabilities depend on the time since an event in the model
  - E.g., Cohort of healthy patients at risk for cancer, but once cancer is diagnosed the risk of recurrence depends on time since diagnosis
- Replacing  $P$  with  $P_t$  does not work, because it's not since model start
- Solution?
  - Create "tunnel" states



# State Time



## Tunnel States

