Introduction to Markov Models Henry Glick • Introduction to Markov models For the Markov Models

Henry Glick

Epi 550

March April 1, 2020

March April 1, 2020
 Example Markov models

• Introduction to Markov models

• Steps for developing Markov models

• Constructing model

– Roll back an For the Markov Models

Henry Glick

Epi 550

March April 1, 2020

The Southern State of the Southern State of the Southern State of the State of the State of the State of Constructing model

∴ Analyzing model

− Roll back Introduction to Markov Models

Henry Glick

Epi 550

March April 1, 2020

March April 1, 2020

The March April 1, 2020

Outline

• Introduction to Markov models

• 5 steps for developing Markov models

• Constructing model Introduction to Markov Models

Fight S60

Epi 550

March April 1, 2020

March April 1, 2020

And Sensitivity analysis

The production to Markov models

Steps for developing Markov models

Discharturing model

Analyzing mod Introduction to Markov Models

Fig. 550

March April 1, 2020

March April 1, 2020

Outline

The production to Markov models

steps for developing Markov models

Constructing model

Constructing model

— Roll back and sensi

Epi 550

March April 1, 2020

Outline

-
-
-
- -
	-

Decision Trees and Markov Models

-
- Introduction to Markov models
• Constructing model
• Constructing model
• Constructing model
• Roll back and sensitivity analysis
• Second-order Monte Carlo
• Second-order Monte Carlo
• Second-order Monte Carlo
• Const • Introduction to Markov models
• 5 steps for developing Markov models
• Constructing model
• Analyzing model
• Follows and ensitivity analysis
• Second-order Monte Carlo
• Second-order Monte Carlo
• Second-order Monte Ca over time mtroduction to Markov models

Scheps for developing Markov models

Characterizing model

In analyzing model

In analyzing model

In action of Carlo Carlo

In action of Carlo

In action of Carlo Carlo

Characterizing amount oduction to Markov models
tages for developing Markov models
alyzing model
Roll back and sensitivity analysis
Second-order Monte Carlo

Cancer Monte Carlo
Becombe Markov Models
The Colection Trees and Markov Models
The Col • Steps for developing Markov models
• Constructing model
• Roll back and sensitivity analysis
• Second-order Monte Carto
• Second-order Monte Carto
• Second-order Monte Carto
• Cecision Trees and Markov Models
• Markov mo • Constructing model
• Arallyzing model
• Field back and sensitivity analysis
• Second-order Monte Carlo
• Second-order Monte Carlo
• Second-order Monte Carlo
• Construction of the median conduction that have events that o
	-
-
- usually less explicitly accounted for in decision trees

State Transition or Markov Models

- series of states
	- with five or six health states
		- HF): HF subdivided into New York Heart Association (NYHA) classes I through 4, and death (either from heart failure or other causes)
- disease): No disease, HF subdivided into New York Heart Association (NYHA) classes I through 4, and death (either from heart failure or other causes) • State Transition or Markov Models
• Develop description of disease by simplifying it into a
• e.g., models of heart failure (HF) might be constructed
with five or six health states.
• Five state model (If everyone in mo • Develop description of metallom the set of the set of steads by simplifying it into a

series of states

• e.g., modes of heart failure (HF) might be constructed

with five or six health states

• Five state model (if ev

Progression in Model

- of transitions among states in periods, often of fixed duration (e.g., months, years, etc.)
- transition probabilities

Outcomes of Model

- Assess outcomes of Model
• Assess outcomes such as resource use, cost, and
AALYs based on resource use, cost, and QALY weights
• experienced:
• Method 1: by making transition from one state to
• e.g., average cost amon QALYs based on resource use, cost, and QALY weights experienced: Cutcomes of Model

Making Season University of Model

Making the same of the state of

- Method 1: by making transition from one state to

anot Outcomes of Model

ess outcomes such as resource use, cost, and

Ys based on resource use, cost, and QALY weights

reinced:

telthod 1: by making transition from one state to
 \bullet e.g., average cost among patients who beg Outcomes of Model

Seses outcomes such as resource use, cost, and

NALYs based on resource use, cost, and QALY weights

experienced:

another

a endother

e.g., average cost among patients who begin a

period in NYHA class Outcomes of Model

Susses outcomes such as resource use, cost, and

the theod of the resource use, cost, and QALY weights

reinched

telhod 1: by making transition from one state to

e.g., average cost among patients who b • Dutcomes of Model

• Assess outcomes such as resource use, cost, and QALY weights

experienced:

• Method : by making transition from one state to

another

• e.g., average cost among patents who begin a

• period in N Outcomes of Model

Maxies assess outcomes such as resource use, cost, and QALY weights

xperienced:

The Model: by making transition from one state to

another

another

another

application probability and all begin nex ess outcomes such as resource use, cost, and

Ys based on resource use, cost, and QALY weights

terhical 1: by making transition from one state to

reduce the cost among patients who begin a

period in NYHA class 1 and be
	- another
	- period in NYHA class 1 and begin next period in NYHA class 2 OR Subcomes Such as resolute use, cost, and QALY weights
poperienced:
The Hothod : by making tansition from one state to
mother the disconnection of the states of an equivalent sum of the state of
a period in NYHA class 2 QR
 enhoned:

	e.e., average cost among paraistion from one state to

	e.e., average cost among patients who begin a

	period in NYHA class 1 and begin next period in

	EMPIA class 2 OR

	e.g., average cost of being in NYHA class 1
	- year

Modeling an Intervention

- intervention as a change in:
	-
	-
	- - 1 \$500 less than without intervention

Systemic Lupus Erythematosus (SLE) (I)

- SLE *
- - 58 of whom were treated with steroids
	- followed at least yearly until death or study termination
	-
	-

SLE (II)

- -
- Systemic Lupus Erythematosus (SLE) (I)

 Markov model used for illustration predicts prognosis in

 Study sample for natural history probabilities

 98 patients followed from 1950-1966 (steroid period),

 All patients Systemic Lupus Erythematosus (SLE) (I)

Markov model used for illustration predicts prognosis in

SLEY

SLEY

Substitute of interactive from the stress of derival properties

- 98 patients followed from 1950-1966 (steroid Systemic Lupus Erythematosus (SLE) (I)

Markov model used for illustration predicts prognosis in

SLE *

SLE of patients followed from 1950-1966 (steriod period),

- 98 patients followed from 1950-1966 (steriod period),
 with greater than 2+ proteinuria on two or more successive visits)
	-
	-
- criteria for SLE
- Compare for natural history probabilities

 98 patients followed from 1950-1966 (steroid period),

 Six of whom were treated with steroids

 All patients were seen more than once and were

followed at least yearly of d Studies and the United Harmonic Studies and Studies and Studies and Studies and Studies and Studies and the Studies and the Studies and the United Studies and the United Studies and the United Studies and the United Studie • So content solution the transfer of the matrice of the matrix and the followed at least yearly until death or study

• All patients were seen more than one and were

termination

• All patient was lost to follow-up

– T • A set of 11 clinical findings and 9 laboratory values were

termination

termination

between the set of 11 clinical filters in the set of 12 clinical fields and the set of 12 clinical

statements were not all the set o A set of 11 clinical findings and 9 laboratory values were
used to classify patients' disease into four severity grades, 1 through 4

Diagnosing SLE, 2012

- Diagnosing SLE, 2012
• Criteria have changed twice since publication of source
data
– 1997 revision of 1982 criteria cited in paper
– 2012 revision of criteria
• In 2012, 17 Systemic Lupus International Coordinating
Cli data and a state of the state of Diagnosing SLE, 2012

Criteria have changed twice since publication of source

Itata

- 1997 revision of 1982 criteria cited in paper

- 2012 revision of criteria

- 2012 revision of criteria

- Increased weight of rash/ph Diagnosing SLE, 2012

Diagnosing SLE, 2012

The property of 1982 criteria cited in paper

- 1997 revision of 1982 criteria cited in paper

- 2012, 17 Systemic Lupus International Coordinating

- Reduced weight of nash/
	-
	-
- Clinics (SLICC) categories
-
-
-
- Diagnosing SLE, 2012

 Criteria have changed twice since publication of source

data

− 1997 revision of 1982 criteria cited in paper

− 2012 revision of criteria

 In 2012, 17 Systemic Lupus International Coordinatin Diagnosing SLE, 2012

Criteria have changed wice since publication of source

Itata

- 1997 revision of 1982 criteria cited in paper

- 2012 revision of ratrice

- 2012, 17 Systemic Lupus International Coordinating

Clinic Diagnosing SLE, 2012

Citieria have changed wice since publication of source

Lata

Lata

2012 revision of 1982 criteria cited in paper

2012 revision of retiral

2012, 17 Systemic Lupus International Coordinating

2012, 1 Diagnosing SLE, 2012

Triteria have changed wice since publication of source

1997 revision of 1982 criteria cited in paper

– 2012 revision of criteria

– 2012, 17 Systemic Lupus International Coordinating

– Increased we • Criteria have changed twice since publication of source

data

• 1997 revision of 1982 criteria cited in paper

– 2012 revision of criteria

• In 2012, 17 Systemic Lupus International Coordinating

Clinics (SLICC) cate at least one clinical and one immunologic criterion OR biopsy-proven lupus nephritis in presence of antinucle**ary and the contract of the contract of the contract of** antibodies or anti-double-stranded DNA antibodies. Diagnosing SLE, 2012

Criteria have changed wive since publication of source

data

-1997 revision of criteria cited in paper

-1021 revision of criteria cited in paper

Clinic (SLICC) categories

Clinic (SLICC) categorie

2012 SLICC Criteria for Classification of SLE

Leukopenia or lymphopenia Criteria have been genuined year, 2012

Christian and chronic cuteria cited in paper
 -2012 revision of criteria
 -1997 revision of criteria

Chronic criteria cited in paper

Chronic cutations weight of remotology

Ch • Criteria have changed twice since publication of source

-1997 revision of criteria cited in paper

-2012 revision of criteria cited in paper

- have alternative to real presentativity

- Record weight of rastylentoses data

- 1997 revision of 1982 criteria cited in paper

- 2012 revision of orthos

- Lind 2012, 17 Systemic Lupus International Coordinating

Clinics (SLICC) categories

- Reduced weight of rankyhetocensitivity

- Increased - 1997 revision of 1992 criteria cited in paper

- 2012 revision of criteria Lunch and Dordinating

Clinics (SLICC) categories letrantional Coordinating

Clinics (SLICC) categories intermuloogy

- Increased weight of hemot - 2012 restoro of orterina

- in 2012, 17 Systemic Lupus International Coordinating

Clinics (SLICC) categories

- Reduced weight of ranklyhotosensitivity

- Increased weight of finantional

- threesaed weight of finantion Find 2012 SUCC criterial conditions and the complete complete the charge of the ch Lenton Control r Classification of SLE

Leukopenia or lymphopenia

Thrombookydenia

Ami-disDNA

Ani-disDNA

Ani-disDNA

Ani-disDNA

Ani-disDNA

Leukopenient

Direct Coombs' test

Therefore Coombs' test

The Cooline of the Cooline

The Co

conditions
 $- p=0.24$

But Does 349/690 Represent Correct Prevalence?

-
- 2700-5056/100,000
-

† p value, 41 vs 349 sample: p<0.0000

Step 1: Imagine model, draw "tree" Step 1: Imagine model, draw "tree"

Example 2014

Figure 1.4 Enumerate States

Markov models made up of states

• Markov models made up of states

• In standard Markov models, states are all inclusive and

mutually exclus Step 1: Imagine model, draw "tree"

• The control of the control control control of the Step 1: Imagine model, draw "tree"

Examples a Clearly defined to standard Markov models made up of states

• Markov models made up of states

• Markov models made up of states

• In standard Markov models, states are all Step 1: Imagine model, draw "tree"

• The control of their prognosis, transition probab Step 1: Imagine model, draw "tree"

• Step 1.A Enumerate States

• Markov models made up of states

• In standard Markov models, states are all inclusive and

mutually exclusive (all patients must be in one and only

one s **EXECUTE:**
 EXECU

Step 1.A Enumerate States

-
- In standard Markov models, states are all inclusive and mutually exclusive (all patients must be in one and only one state at all times in model)
- based notions of disease
- or payoffs
- or literature
- etc.)

6

States for Modeling Systemic Lupus (II)

- disease activity during year, even if severity was only present during a portion of year
	- grade 4 during any visit in a calendar year were considered to have a flare year
- per year and all patients were seen at least once a year States for Modelling Systemic Lupus (II)

• Each patent year was classified by greatest severity of

disease activity during year, over if severity was only

present during a portion of year

– e.g., patients whose disease States for Modeling Systemic Lupus (II)

Fach patient year was classified by greatest severity of

disease activity during vary, went if severity was only

present during a portion of year
 $-e$ on calibrative whose disease

Step 1.B Define Allowable State Transitions

-
- (e.g., death)

Tree-Like Markov Construction

- understandable to audience
- state, there are several pathways to one transition state
- Free-Like Markov Construction
• Potentially makes path through model more
• Also can simplify model equations if, from same initial
• Also can simplify model equations if, from same initial
• E.g., there may be less traum Tree-Like Markov Construction
• Potentially makes path through model more
understandable to audience
• Also can simplify model equations if, from same initial
state, there are several pathways to one transitions state
– E. Tree-Like Markov Construction

otentially makes path through model more

understandable to audience

slabso can simplify model equations if, from same initial

slabso can simplify model equations to one transition state

– (with lower costs and higher QALYs) and more traumatic transitions to death (with higher costs and lower QALYs Free-Like Markov Construction

trially makes path through model more

transition to audience

the model equations if, from same initial
 \therefore , there me several pathways to one transition state

with lower costs and highe Tree-Like Markov Construction

entially makes path through model more

can simplify model equations if, from same initial

can simplify model equations if, from same initial

.g., there are several pathways to one transiti
	- accruing a weighted average of 2 QALY estimates and of 2 cost estimates
	- transitioning to death (no need for weighted avg)

Step 2: Identify probabilities

Step 2.a Associate Probabilities with Transitions

- Step 2: Identify probabilities

 Step 2. a Associate Probabilities with Transitions

 Suppose you had data from a lupus registry that was

 Suppose you had data from a lupus registry that was

 Observations were mad following 98 patients Step 2: Identify probabilities

(Controller Step 2.a. Associate Probabilities with Transitions

suppose you had data from a lupus registry that was

suppose you had data from a lupus registry that was

belowing 98 patients Step 2: Identify probabilities

(a) The Step 2.a Associate Probabilities with Transitions

suppose you had data from a lupus registry that was

suppose you had data from a lupus registry that was

plowing 98 patients

excl Step 2: Identify probabilities

(accounting across year and data from a lupus registry that was

suppose you had data from a lupus registry that was

collowing 89 patents

each year

each year

each year

each year

each y Step 2: Identify probabilities

• 100 patients

• 100 patients

• 100 patients

• 100 patients

and year and data from a lupus registry that was

pose-values were made at beginning and end of

nach year of observation, you **Example 1998**
 1938
 1938
 1939
 1939
 1939
 1939 patients were made at beginning and end of

whing 98 patients were made at beginning and end of

Such years of observation, you had 1117 patient

clocoling acr **1.80** and the Machinese of Machinese State Probabilities with Transitions

pose you had data from a lupus registry that was

where the subservations were made at beginning and end of

achi year

the multiplemod of observa
	- each year
	- years of observation
	- -
		-
		-

Remission Transition Probabilities

- Remission Transition Probabilities
• Suppose that among 100 classified as having spent a
• year in remission
• 59 classified as having spent following year in
• 41 classified as having spent following year with
• None cl year in remission Framission Transition Probabilities
Suppose that among 100 classified as having spent a
rear in remission
remission
remission
 -59 classified as having spent following year with
active disease
- None classified as having Framission Transition Probabilities
Suppose that among 100 classified as having spent a
ear in remission
— 59 classified as having spent following year in
— 41 classified as having spent following year with
— None classifi Framission Transition Probabilities

Suppose that among 100 classified as having spent a

near in remission

remission

remission as having spent following year with

active disease

at classified as having spent following **Examples 12**
 Examples that arrong 100 classified as having spent a

year in remission

- 59 classified as having spent following year in

remission

- 41 classified as having spent following year with

active disease
 • Remission Transition Probabilities
• Suppose that among 100 classified as having spent a
• F57 classified as having spent following year in
• articlassified as having spent following year with
• active disease
• Nota d Remission Transition Probabilities

Suppose that memission

and in femission

centerations of the start following year in

the mission

centeration assistified as having spent following year with

active disease

There cas suppose that among 100 classified as having spent a

rear in remission

rear in emission

and classified as having spent following year with

active disease

active disease

-None classified as having spent following year
	- remission
	- active disease
	- flare or dead – 50 classified as having spent following year in

	remission

	active disease

	active disease

	– None classified as having spent following year with

	there or dead

	Mhate are annual transition probabilities?

	

	Mater are an remision

	remision dassified as having spent following year with

	active disease

	Nhat are annual transition probabilities?

	There or dead

	Mhat are annual transition probabilities?

	

	Active Transition Probabilities?

	

	A
-

Active Transition Probabilities

- year with active disease + 41 classified as having spent following year with

active disease

– None classified as having spent following year with

1 what are a mual transition probabilities?

• What are a mual transition Probabilities

• Supp • Active Transition Probabilities
• Suppose that among 937 classified as having spent a

– 66 classified as having spent following year in

— 66 classified as having spent following year with

— soft classified as having Active Transition Probabilities

anyongs that among 937 classified as having spent a

cervent with active disease

cervent inclusion

- 60 classified as having spent following year with

active disease

- 9 classified as h suppose that among 937 classified as having spent a
rear with active disease
— 66 classified as having spent following year with
— 20 classified as having spent following year with
— 56 classified as having spent following
	- remission
	- active disease
	-
	-
-

Flare Transition Probabilities

- year with flare – 66 classified as having spent following year in

- remission

- conclassified as having spent following year with flare

active disease

– 96 classified as having spent following year with flare

– Pobabillities?

– Tare remission

– 806 classified as having spent following year with

active disease

– 5 diessified as having spent following year with flare

– 9 died

– Orbabilities?

– Chassified as having spent following year in

– Chassi – BUS classified as having spent following year with

active disease

– 56 classified as having spent following year with flare

– 9 died

• Probabilities?

• Probabilities?

• Suppose that among 80 classified as having
	- remission
	- active disease
	-
	-
-

?? Rule of Thumb When No Transitions Observed ??

- remission to death, and flare to remission
- transition
	-
	-
	-
	-
	-
	-

12

Rule of Thumb When No Transitions Observed (2)

- - approximately 27% of upper limit of Wilson CI for 0 successes among 104 tries (0.0356214)
- **Rule of Thumb When No Transitions Observed (2)**
• Why add 1 (and not 0.5 or 1.5)?
– For remission, 0.01 (0.009569) represents
approximately 27% of upper limit of Wilson CI for 0
successes among 104 tries (0.0356214)
– For le of Thumb When No Transitions Observed (2)

Why add 1 (and not 0.5 or 1.5)?

— For remission, 0.01 (0.009569) represents

approximately 27% of upper limit of Wilson CI for 0

successes among 104 tries (0.0356214)

— For For France of Thumb When No Transitions Observed (2)

Mhy add 1 (and not 0.5 or 1.5)?

- For remission, 0.01 (0.009569) represents

approximately 27% of uper limit of Wilson Cl for 0

successes among 104 tries (0.0356214)
 27% of upper limit of Wilson CI for 0 successes among 84 tries (0.0437317) **Rule of Thumb When No Transitions Observed (2)**

• Why add 1 (and not 0.5 or 1.5)?

– For remission, 0.01 (0.009569) represents

approximately 27% of upper limit of Wilson Cl for 0
 27% of upper limit of Wilson Cl for **Rule of Thumb When No Transitions Observed (2)**

• Why add 1 (and not 0.5 or 1.5)?

– For memsion, 0.01 (0.009569) represents

approximately 27% of upper limit of Wilson Cl for 0

successes among 104 tries (0.0437317)

– For Thumb When No Transitions Observed (2)

Why add 1 (and not 0.5 or 1.5)?

— For remission, 0.01 (0.003689) represents

approximately 27% of upper limit of Wilson Cl for 0

successes arrong 04 thes (0.0347317)

arrong 8 Why add 1 (and not 0.5 or 1.5)?

- For remission, 0.01 (0.009569) represents

successes among 104 tries (0.0036214)
 $-$ For flare, 0.01 (0.0191968) represents approximately
 27% of upper limit of Wison Cl for 0 succes
-

Rates vs Probabilities

- probabilities
	-
	- failure rates) per unit of time $(R_{\text{ij}[t]})$, can be translated into probabilities as follows:

$$
P_{ij}(t) = 1 - e^{-R_{ij}t}
$$

Fram the unit published (meaning from state)
 $270\text{ of upper limit of MMS1 (B) at the 200\% of the 200$ beginning of period t to state j at beginning of period t+1;
Rij equals instantaneous hazard rate per period (e.g., among 84 fires (U.933/317)

What is basis for adopting -27% of upper limit?

Rates vs Probabilities

Large number of methods exist for estimating transition

probabilities

Large number of methods assuggested in Lyupus ex per year); and t equals length of period **Fraction Controllering accepts**

• Current probabilities

• Simple methods exist for estimating transition

• If wouldn'be data are hazard rates (i.e., instantaneous

failure rates) per unit of time (R_{pl}), can be trans Rates vs Probabilities

arge number of methods exist for estimating transition

— Simple methods as suggested in Lupus example

— fivaliable data are hazard rates (i.e., instantaneous

failure rates) per unit of time (R_R arge number of methods exist for estimating transition
 \sim Emiple methods as suggested in Lupus example
 \sim Emialable data are hazard rates (i.e., instantaneous

failure rates) per unit of time (F_{q_l} i), can be tran – If available data are hazard rates (i.e., instantaneous

failure rates) per unit of time (R_{HI}), can be translated

into probabilities as follows:
 $P_q(t) = 1 - e^{-R_q t}$

where $P_l(t)$ equals are based in the

primary of failure rates) per unit of time (R_PL), can be translated

into probabilities as follows:
 $P_1(1) = 1 \cdot e^{-t_1 t}$

where $P_2(1)$ quality prevailing of motions (a) and teap and teap and teap of pairs of

Equipmination stat

Step 2.B Identify a Cycle Length and Number of Cycles (Markov Termination)

- - follow-up
	- study question or available data; ignore differences that don't make a difference
-
-

determine what will happen to patients who begin in remission, make probability of being in remission 1.0)

Step 3. Identify Outcome Values

- different states
- - $-$ Costs of making a transition from one state to another state or of being in a state
	- adjusted life expectancy)

Outcomes for Transitions

- Outcomes for Transitions
• For current analysis, outcomes are modeled as a
function of making a transition from one state to another
– Number of hospitalizations, cost, and QALYs
experienced by patients who at beginning of function of making a transition from one state to another Culticomes for Transitions

For current analysis, outcomes are modeled as a

munction of making a transition from one state to another

– Number of hospitalizations, cost, and QALYs

are in state i and at beginning of tim experienced by patients who at beginning of time t Outcomes for Transitions

current analysis, outcomes are modeled as a

ction of making a transition from one state to another

experienced by patients who at beginning of time t

are in state i and at beginning of time t+1 Outcomes for Transitions

current analysis, outcomes are modeled as a

dion of making a transition from one state to another

tumber of hospitalizations, cost, and QALYs

xperienced by patients who at beginning of time t
 • For current analysis, outcomes are modeled as a

timction of making a transition from one state to another

– Number of hospitalizations, cost, and QALYs

experienced by patients who at beginning of time H + are in st Contract many is contract and the matter of the matter of the matter of the contract method of matter as the contract of the matter of th Outcomes for Transitions

current amayles, outcomes are modeled as a

tulon of making a transition from one state to another

specifienced by patients who at beginning of time t

re in state i and at beginning of time the For current analysis, outcomes are modeled as a

— Number of hospitalizations from one state to another

experienced by patients who at beginning of time that are

are in state i and a beginning of time that are in state i
	-
	-

Lupus Outcome Variables

- -
	-
	- from observation of subjects for a year
- when the of hospitalizations, cost, and QALYs

recorded by patients who at beginning of time it is are in state j

re city, transition from remission to active disease

recorded to a status and the disease

the cost beginn end of year and measured number of times they were hospitalized during year Lupus Outcome Variables

• e.g., transition from remission to active disease

• e.g., transition from remission to active disease

Hypothetical Cost Data

• Costs model as # of hospitalizations \times

• C-thesp assumed to Lupus Outcome Variables

Lupus Outcome Variables

contential cost Data

Costs modeled as # of hospitalization \times \$

c-frelop assumed to equal 10,000

Suppose that our hospitalization data were derived

the recorded thei
	- number of hospitalizations for those who begin in

* Krishnan, Hospitalization and mortality of patients with systemic lupus erthematosus. J Rheumatol. 2006;33:1770-4.

Numbers of Hospitalizations

remission will have 0.05 hospitalizations during year; those who begin with active disease and develop a flare will have 1 hospitalization during year

Hypothetical QALY Data (I)

- Hypothetical QALY Data (I)
• Suppose you found a study that reported preference
weights from cross sectional observation of subjects
(i.e., authors assessed preference for current health
among cohorts of patients who we weights from cross sectional observation of subjects (i.e., authors assessed preference for current health among cohorts of patients who were in remission, active disease or flare)
- (NYHA class weights provided for reference):

Hypothetical QALY Data (II)

- - we know that people in remission experience 0.9 QALYs and those in active disease experience 0.7
	- active disease occurs at mid-interval, mean QALYs among those who begin period in remission and end it in active disease are:

 $(0.5 \times 0.9) + (0.5 \times 0.7)$

Other Outcomes

-
- Other Outcomes

 Years of life

 1 for every transition other than transition to death

 0.5 for every transition to death

 Discounted years of life

 Years of life rewards that include discounting

 Number of disco Other Outcomes

Years of life

- 1 for every transition other than transition to death

- 0.5 for every transition to death

- Years of life rewards that include discounting

- Years of life rewards that include discountin Other Outcomes

Vears of life
 $-$ 1 for every transition other than transition to death
 $-$ 0.5 for every transition to death

Discounted years of life
 $-$ Years of life rewards that include discounting
 $-$ Years of l Other Outcomes

• Years of life

– 1 for every transition other than transition to death

– 0.5 for every transition to death

– Discounted years of life

– Years of life rewards that include discounting

• Number of disc Other Outcomes

Years of life

- 1 for every transition other than transition to death

- 0.5 for every transition to death

- Calcounted years of life

- Years of life rewards that include discounting

Jumber of discounte Other Outcomes

• Years of life

– 1 for every transition other than transition to death

– 0.5 for every transition to death

• Discounted years of life

– Years of life rewards that include discounting

– Number of disc Other Outcomes

- I for every transition of the film transition to death

- 0.5 for every transition to death

Discounted years of life

- Years of Ilfe rewards that include discounting

ulturber of discounted hospitaliza
-
-
-
-

Discounting

- Years of life

 1 for every transition other than transition to death

 0.5 for every transition to death

 Discounted years of life

 Number of discounted the originalizations

 Calculated by setting chosp = 1

 discounted
- Old Methods
	- - -
- Fears of life

 1 for every transition of the than transition to death

 0.5 for every transition to death

 Years of life rewards that include discounting

 Years of life rewards that include discounting

 Calculated is of the eyery transition of
the revery transition to death
 $\frac{5}{2}$ for every transition of death

counted years of life

exacts the rewards that include discounting

and discounting chicage = 1

and discounting

and d y transition our train transition to death

eyer transition to death

life rewards that include discounting

liscounted hospitalizations

by setting chosp = 1

Discounting

Discounting

Discounting

exercised to the must • where y anaskant to be
and of the rewards that include discounting
there of discounted hospitalizations
disculated by setting chosp = 1
and calculated by setting chosp = 1
EXEMPLE COUNTEMPLATE COUNTER AND COUNTER COU the velocity of the include discounting
are of discounted hospitalizations
coulated by setting chosp = 1
total counter of discounting
trees experienced over time, and thus must be
the
discounting equation as part of reward - Years of life ewards that include discounting

ulumber of discounted hospitalizations

- Calculated by setting chosp = 1

-

Rewards experienced over time, and thus must be

slicounted

- Write our discounting equation examples are the specific of the specific specifical control of the specific specification of the specific specification of the specific of the specific specific specific specific specific specific specific specific specif
	-
	- Discount(payoff; rate; time) = payoff / $((1 + rate)^{time})$

Hypothetical Intervention

- by everyone in all states for life, but affects only transition from remission to active disease
	- - R to A: 0.8537 * 0.41
		-
		- residual of changed probability goes to correct state **the contract of the con**
- mg/day; 2014 FSS, 3.69/mg, 365*25*3.69 = 34K

Construct Intervention Subtree

-
-
- Construct Intervention Subtree
• Change "Intervention" node to a Markov node
• Place curso on "Usual Care" node
• \Subtre\Select Subtree OR Right click: Select Subtree
• \Edit\Copy
• Place cursor on intervention node
• \E Construct Intervention Subtree
• Change "Intervention" node to a Markov node
• Place cursor on "Usual Care" node
• SubtreelSelect Subtree OR Right click: Select Subtree
• Editory – Care cursor on intervention node
• L'elit • Change "Intervention" node to a Markov node
• Change "Intervention" node to a Markov node
• Riace cursor on "Usual Care" node
• Natificapy
• Riace cursor on intervention node
• Nadit or Right click \ Paste Construct Intervention Subtree
• Change "Intervention" node to a Markov node
• Place cursor on "Usual Care" node
• \Subtree/Select Subtree OR Right click: Select Subtree
• \Edit\Copy
• Place cursor on intervention node
• \ Construct Intervention Subtree
• Change "Intervention" node to a Markov node
• Place cursor on "Usual Care" node
• \ Subtree\Select Subtree OR Right click: Select Subtree
• \ Edit\Copy
• Place cursor on intervention node
• Construct Intervention Subtree
• Change "Intervention" node to a Markov node
• Place cursor on "Usual Care" node
• \Edit(Copy
• Edit(Copy)
• Place cursor on intervention node
• \Edit(or Right click \ Paste
• \Edit(or Rig
-
-
-

Construct Intervention Subtree (2)

- termination condition
	- changed "Intervention" node to a Markov node
- Change "Intervention" node to a Markov node
• Place curso con "Usual Care" node
• StudtreelSeled Subtree OR Right click: Select Subtree
• LeititCopy
• Everything should have copied EXCEPT Markov
• Construct Intervention Construct Intervention Subtree

Plange "Intervention" node to a Markov node

Subtree/Select Subtree OR Right click: Select Subtree

EditCopy

Place cursor on intervention node

Editi or Right click \ Paste

Construct Inter • Change "intervention" node to a Markov node
• Piace cursor on "Usual Care" node
• Yestbrees Salest Subtree
• Neith Copy
• Piace cursor on intervention node
• Celt or Right click Y Piate
• Celt or Right click Y Piate
• Co Place cursor on "Usual Care" node

Subtree/Select Subtree OR Right click: Select Subtree

EditiCopy

Place cursor on intervention node

Edit or Right click \ Paste

Construct Intervention condition

Construct Intervention • ReditCopy

• Refide Copy and the Copy of State Copy and the Copy and the Copy and the Copy and the Copy of State Copy and the Copy of State Co • Edit or Right click \ Paste

• Place cursor on intervention node

• YEdit or Right click \ Paste

• Construct Intervention Subtree (2)

• Construct Intervention Subtree (2)

• Corypting should have copied EXCEPT Markov

-
-

Calculate Expected Values

- -
	-
	-

Iterate Model

- to estimate distribution of patients in later periods (e.g., years) of model
-

Remission: 0.10; Active: 0.85; Flare: 0.05

Transition to Remission

beginning of model is 0.1, 0.85, and 0.05, what is probability a patient will be in remission next year?

(i.e., multiply initial distribution times first column of transition matrix)

- and number of hospitalizations per transition/period to estimate expected number of hospitalizations in each $\overline{}$ period of model
-

Expected QALYs

• Use initial distribution, transition probabilities, and QALY
weights to estimate expected QALYS / period

-
-

 $0.1007 + 0.5526 + 0.03635 + 0.009225 = 0.698875$

Distribution for Probabilities If More than 2 Branches?

- Problem: Using separate beta distributions for each
• Problem: Using separate beta distributions for each
• Problem: Using separate beta distributions for each
• For probabilistic sensitivity analysis, separate draws fr branch (or n-1 distributions plus #) should work for point estimate **For probabilities if More than 2 Branches?**

• Problem: Using separate beta distributions for each

branch (or n-1 distributions plus #) should work for point

estimate

• For probabilistic sensitivity analysis, separate vertical of the Probabilities for More than 2 Branches?

• Problem: Using separate beta distributions for each

thanch (or n-1 distributions plus #) should work for point

• For probabilistic sensitivity analysis, separate tribution for Probabilities If More than 2 Branches?
Problem: Using separate beta distributions for each
branch (or n-1 distributions plus #) should work for point
estimate
T-or probabilistic sensitivity analysis, separate **•** Problem: Using eeparate beta distributions for each

• Problem: Using separate beta distributions for each

testimate

• Ero probabilities censitivity analysis, separate draws from

• The probabilities multinomial (mo istribution for Probabilities If More than 2 Branches?

• Froblem: Using separate beta distributions for each

testimate

• For probabilities ensitivity analysis, separate draws from

• The distributions resel or sum to l Problem: Using separate beta distributions for each

starting the starting of the T-1 distributions plus #) should work for point

starting for probabilistic sensitivity analysis, separate draws from

Hed distributions rel
- n-1 of the distributions need not sum to less than 1 manch of the transition spins with single and the point of the sistence of the state of the concentration and the ded distribution that ensures that probabilities for the examples sum to 1

Examples sum to 1

Dirichlet Di
- e.g., For transitions from Flare (fFlare)

e.g., For the distribution that ensures that probabilities for the

manchs sum to 1

Dirichlet Distribution

Dirichlet Distribution

Dirichlet Distribution

Dirichlet Distribu

Dirichlet Distribution

- categories) extension of binomial Beta distribution Dirichlet Distribution

Dirichlet Distribution

Dirichlet Distribution

Dirichlet Distribution

Dirichlet Distribution

Defined by counts for each of outcomes
 $-e.g., For transitions from Renmission (Remiss)$

List(5,9.90 DR. List(5,906,55.9)

List(6,8.9 Dirichlet Distribution

• Dirichlet Distribution is multimonial (Inter than 2

• calenda by counts for each of cultoness

• - a., 6-r transitions from Remission (IRemiss)

• List(59.41:0.0) OR List(59.41:0) OR Beta distri Dirichlet Distribution

• Dirichlet Distribution is multinomial (more than 2

• Defined by causts for each of outcomes

• Desp. For transitions from Reminsion (Klemies)

• List(59.41,0) OR List(59.41) OR Beta distribution • Dirichlet Distribution is multinomial (more than 2

• Defined by counts for each of outcomes

• $P = e, g$, For transitions from Remission (Remiss)

List(69:410:00 R. List(59:306:56:9)

• e.g., For transitions from Refine
- - List(59;41;0;0) OR List(59;41) OR Beta distribution
	- - List(66;806;56;9)
	-
	- List(0;22;18;40) OR List(22;18;40)
	-

Assigning Dirichlet Distribution to Nodes

-
- second element is A to A,….
- -
	-
	-
	-
- Union User to Music the Music Controller and the Care of each of Distribution

Defined by coaling to Active (Martins)

List(59,41): CD, Client(59,41) OR Beta distribution

List(59,205, For transitions from Active (Mative) experience of particular and and and an interesting of the mission (Remarks of the state of material of mathematic method (Active)

List(59.41:0,0) OR List(59.41:0) OR Beta distribution
 $-\mathbf{e}$, For transitions from Fina – e.g., For transitions for Relations (Remiss)

List(59,41; 0,0) OR List(2;54;1) OR Beta distintion

List(0,22;18,40) OR List(2;5.80,569)

– e.g., For transitions from Active (McNive)

– e.g., For transitions from Rine – u_2 , For drainstorial room resumes of the Cliential Control (Victime)

List(59.41:0,0) OR List(59.80:56:9)

– e.g., For transitions from Frare (Flare)

– e.g., For initial distribution

– e.g., For initial distributio **Lexival Propose the first element are in a different order (Rack are in a distribution** List(66:306:56:9)
 Lest(0:22:18:40) OR List(22:18:40)
 Lest(0:22:18:40) OR List(22:18:40)
 Lest(100:937:80) (Don't include coun to A), need to change number after semicolon (e.g., (2;1) rather than (2;2)

Log Relative Risk

 $ln(RR) = ln(a) + ln(b+d) - ln(b) - ln(a+c)$

$$
se[ln(RR)] = \sqrt{\frac{1}{a} + \frac{1}{b} - \frac{1}{a+c} - \frac{1}{b+d}}
$$

 $((1/35)+(1/41)-((1/100)+(1/100))$ ⁻.5 = .1816

similar to point estimate for RR (0.8537)

Cost Distributions

-
- Log Relative Risk

 Log(RR) and SE Log(RR)
 $ln(RR) = ln(a) + ln(b+d) ln(a+c)$
 $selfln(RR) = \sqrt{\frac{1}{a} + \frac{1}{b} \frac{1}{a+c} \frac{1}{b+d}}$

 RR distributed log normal (2) parameters)

 μ (in RR): $ln(35)+ln(100) + (ln(41)+ln(100)) = .1582$
 $= signa$ ((1/35)+ – Single parameter Poisson distributions (lambda = – Single parameter Poisson distributions (lambda =
point estimate); separate distribution for each possible transition $ln(RR) = ln(a) + ln(b+d) - ln(a+c)$
 $selfln(RR) \equiv \sqrt{\frac{1}{a} + \frac{1}{b} - \frac{1}{a+c} - \frac{1}{b+d}}$

• RR distributed log normal (2) parameters)

– μ (in RR): $ln(35) + ln(100) + (ln(41) + ln(100)) = .1582$
 $= signa$ (gen h(RR):
 $(135) + (144) + ((1100) + (1100)) + .5 = .1816$
 se[In(RR)] = $\sqrt{\frac{1}{a} + \frac{1}{b} \cdot \frac{1}{a+c} \cdot \frac{1}{b+d}}$

RR distributed log normal (2 parameters)

+ (in RRS): In(36)-in(100)-(ln(41)-in(100))) = -1582

(i) (R35)-(144)-(14(176)(1)(11/00))) = 5 -1816

(OTE: Mean of distribut se[In(RR)] = $\sqrt{\frac{1}{4} + \frac{1}{10} \cdot \frac{1}{4t}}$ = $\frac{1}{4t}$ of Ristributed log normal (2 parameters)
 $- \mu$ (In RR): In(35)+In(100)-(In(41)+in(100)) = -1582
 $=$ sigma (8 te In(RR): $\ln(35) + \ln(100) - (\ln(41) + \ln(100)))^2 = -1582$
 • Relativity a $\sqrt{a^2 + b^2} = \frac{a^2b^2}{b^2 + 2ab}$
 $- \mu \ln RR$; $ln(R3) \ln(30) + ln(100) + ln(100) = -1582$
 $- \sin \ln \left(8 \ln (100) + (100) + (100)) \right)$, 5 = .1816

(1/35) +(1/41) (1/100) +(1/100))), 5 = .1816

NOTE: Mean of distribution (0.867 RR distributed log normal (2 parameters)
 -1 (in RRS): Inn(35)-in(100)-[In(41)-in(100))) = -1582
 $-$ sigma (se ln(RR)):

((17.85)+(1/41)-(1/11/00)()) + 5 - 1816

(OTE: Mean of distribution (0.8679) is reasonably

imilar – μ (In RR): In(35)+In(100)-(In(41)+In(100)) = -1582

= sigma (se in RR): (1/35)+(1/41)-((1/100)+(In(41)+In(100)))^x = -15813

((1/35)+(1/41)-((1/100)+(1/100))^x 5 = -1816

((1/35)+(1/41)-((1/100)+(1/100))^x 5 = -18
	- e.g., hdAtoA, poisson, 0.2; hdAtoF, poisson 1.0
- -
	-
-
-
-

-
- Gamma Cost Distributions

 Cost per hospitalization

 α = 10,000 / 100² = 10,000

 A = 10,000 / 100² = 1

 Cost of intervention

 α = 365² / 50² = 53.29

 λ = 365 / 50² = 0.146 Gamma Cost Distributions

Cost per hospitalization
 $-\alpha = 10,000^2 / 100^2 = 10,000$
 $-\lambda = 10,000 / 100^2 = 1$

Cost of intervention
 $-\alpha = 365^2 / 50^2 = 53.29$
 $-\lambda = 365 / 50^2 = 0.146$ $-\alpha$ = 10,000² / 100² = 10,000
 $-\lambda$ = 10,000 / 100² = 1 Gamma Cost Distributions

Cost per hospitalization
 $-\alpha = 10,000^2 / 100^2 = 10,000$
 $-\lambda = 10,000 / 100^2 = 1$

Cost of intervention
 $-\alpha = 365^2 / 50^2 = 53.29$
 $-\lambda = 365 / 50^2 = 0.146$ Gamma Cost Distributions

• Cost per hospitalization

– $\alpha = 10,000^2 + 10,000^2 = 10,000$

– $\lambda = 10,000^2 + 0.000^2 = 1$

• Cost of intervention

– $\alpha = 365^2 / 50^2 = 53.29$

– $\lambda = 365 / 50^2 = 0.146$ Gamma Cost Distributions

Cost per hospitalization
 $-\alpha = 10,000^2 / 100^2 = 10,000$
 $-\lambda = 10,000 / 100^2 = 1$

Cost of intervention
 $-\alpha = 365 / 50^2 = 53.29$
 $-\lambda = 365 / 50^2 = 0.146$ Cost per hospitalization

Cost per hospitalization

– α = 10,000 / 100² = 10,000

– λ = 10,000 / 100² = 11

Cost of intervention

– λ = 365 / 50² = 5.329

– λ = 365 / 50² = 0.146
-
- $\alpha = 365^2 / 50^2 = 53.29$
-

Log Normal Cost Distributions

- Cost per hospitalization

 α = 10,000/ 100² = 10,000

 λ = 10,000/ 100² = 10,000

 Cost of intervention

 α = 365 / 50² = 5.146

 λ = 365 / 50² = 0.146

 **Log Normal Cost Distributions

 μ = 9.21020037
** Gamma Cost Distributions

Cost per hospitalization
 $-\alpha = 10,000^2 / 100^2 = 10,000$
 $-\lambda = 30,00^2 / 100^2 = 1$
 $-\alpha = 365^2 / 50^2 = 53.29$
 $-\lambda = 365 / 50^2 = 0.146$
 $-\alpha = 365 / 50^2 = 0.146$

Log Normal Cost Distributions

Cost per Gamma Cost Distributions

Sost per hospitalization
 $-\alpha = 10,0007/100^2 = 10,000$
 $-\alpha = 10,0007/100^2 = 1,0000$
 $-\alpha = 365^2/50^2 = 53.29$
 $-\lambda = 365/50^2 = 0.146$
 $-\lambda = 365/50^2 = 0.148$

Log Normal Cost Distributions

Sost per • Cost per hospitalization
 $-\alpha = 10,0007/100^2 = 10,000$

• $-\lambda = 10,000/100^2 = 52.92$
 $-\lambda = 365^2/50^2 = 52.46$
 $-\lambda = 365/50^2 = 0.146$
 $-\lambda = 365/50^2 = 0.146$
 Log Normal Cost Distributions
 Log Normal Cost Distributions $\log P$ in responsibilities of the state of the response of the revention
 $-\alpha = 3667/50^2 = 53.29$
 $-\alpha = 365/50^2 = 0.146$
 $-\alpha = 365/50^2 = 0.146$
 $\log N \text{Normal Cost Distributions}$
 $\log N \text{Normal Cost Distributions}$
 $\log \text{Normal Cost Distributions}$
 $\log \text{Normal Cost Distributions}$
 $\mu = 9.21029037$
 $\$ – α = 10,000/100² = 10,000
 $-\alpha$ = 365²/50² = 53.29

Ost of intervention

ost of intervention
 $-\lambda$ = 365 / 50² = 0.146
 $-\lambda$ = 365 / 50² = 0.146
 \blacksquare

Log Normal Cost Distributions
 \therefore p = 9.21020037

	-
-

QALY Distributions

-
-
- Log Normal Cost Distributions

 Le 9.2020907

 sigma = 0.00999975

 Cost of intervention

 μ = 5.89060168

 sigma = 0.13635011

 sigma = 0.13635011

 Sasume normal distributions

 Assume normal distribution (me 70 patients in remission, active, and flare, respectively

Creating Distributions in TreeAge

- Creating Distributions in TreeAge

 Create desired distributions in Treeage distributions view

 Open distributions view and create each of

distributions receded for tree. Don't worry about

defining parameters for dist Creating Distributions in TreeAge

Create desired distributions in Treeage distributions view

— Open distributions view and create each of

distributions needed for tree. Don't worry about

defining parameters for distrib distributions needed for tree. Don't worry about Creating Distributions in TreeAge

ate desired distributions in Treeage distributions view

been distributions news and create each of

stributions needed for tree. Don't worry about
 $\overline{\text{F.g., 4}}$ Dirchelet for probabili
	- defining parameters for distribution
		-
		-
		-
		-
- Creating Distributions in TreeAge

ate desired distributions in Treeage distributions view

the desired distributions are acceled each of

istributions releade for tree. Don't vorry about

effining parameters for distribut Creating Distributions in TreeAge

the desired distributions in Treeage distributions view

the desired distributions in the reage distributions view

the finitions readed for the c. Don't worry about

finition gradenes fo Creating Distributions in TreeAge

te desired distributions in Treeage distributions view

then distributions mediate can be a cont worry about

Effining parameters for distribution

• E.g., 4 Dichelet for probabilities

• Creating Distributions in TreeAge

te desired distributions in Treeage distributions view

then distributions in view and create each of

stributions reeded for tree. Don't worry about

Finip parameters for distribution

F Creating Distributions in TreeAge

• Create desired distributions in Treeage distributions view

– Open distributions weak and create each of

distributions meeted for tree. Don't worry about

• E.g. 4 Dirchelet for probab you want to enter/edit parameter values. Click "Open in new Excel Spreadsheet" button (fifth button from right **asse** in row of icons above "Index | Type....)

Editing Distributions in Excel

- - You can edit index, type, name, description or
parameter values
- Update Distributions
-

Not sure if it is still required, but I had to install the add-in in Treeage; then I had to update the Excel Trust Center indicating it was trustworthy)

Running PCEA: Sampling

- on root node
- To analyze both therapies simultaneously, place cursor
• To analyze both therapies simultaneously, place cursor
• On root node
• Carlo Simulation\Sampling (Probabilistic
• Set number of samples
• Custributions\Sample al • To analyze both therapies simultaneously, place cursor

on root node

• Analysis\Monte Carlo Simulation\Sampling (Probabilistic

Sensitivity...)

– Set number of samples

– Ensure that you are sampling from all distrib Sensitivity...) – Running PCEA: Sampling

To analyze both therapies simultaneously, place cursor

n root node

Analysis/Monte Carlo Simulation/Sampling (Probabilistic

Pensitivity...)

– Set number of samples

– Ensure that you are sampl – Ensure that you are simultaneously, place cursor

Fo analyze both therapies simultaneously, place cursor

Analysis Monte Carlo Simulation\Sampling (Probabilistic

– Set number of samples

– Ensure that you are sampling **Example 1998**
 Example all the control of the control Running PCEA: Sampling

To analyze both therapies simultaneously, place cursor

an root node

AnalysisWonte Carlo Simulation\Sampling (Probabilistic

- Set number of samples

- Ensure that you are sampling from all distrib **Example 19 Accord Report Controllers and Second Report Controllers and Second Republishers (Probabilistic Section)**

Seeding Controllers and Simulation Sampling (Probabilistic estivity...)

et number of samples

• Ustarib Running PCEA: Sampling

To analyze both therapies simultaneously, place cursor

In root node

AnalysisWonte Carlo Simulation\Sampling (Probabilistic

Sensitivity...)

- Distributions are sampling from all distributions

-
	-
	-
	-
	-
	-
	-

‡ 2*(1-normal(5270/1647)) | 2*ttail(1100,(5270/1647))

2*(1-normal(.1959/.2397)) | 2*ttail(1100,(.1959/.2397))

Confidence Interval for Cost-Effectiveness Ratio

Confidence Interval for Cost-Effectiveness Ratio
• Given that ΔC=5270, SE_c=1647, ΔQ=0.1959,
 SE_q =0.2397 and p=0.146:
• Point estimate: 26,901 / QALY gained
• Values of WTP included in interval:
• « to -15,169 & 6274 to $SE_q = 0.2397$ and $p = 0.146$: Point estimate: 26,901 / QALY gained Values of WTP included in interval: -∞ to -15,169 & 6274 to infinity Values of WTP excluded from interval: -15,169 to 6274

 \rightarrow Can't be 95% confident of value if WTP > 6274

Concerns About Standard Error for Difference in Single Distribution Models

Problem with Reported SEs for Difference?

$$
\begin{array}{|c|c|} \hline \hline \multicolumn{3}{|c|}{\hline} \multicolumn{3}{|
$$

SEs for Difference of Correlated Variables • Simply don't see these magnitudes of covariances / correlations when we look at patient level data in observational studies or randomized trials 2 2 SE = SE + SE - 2Cov CorrDiff12 1 2 12 2 2 2 12 44,173 + 41,994 - 1647 Cov = = 1,856,018,000 2

SEs for Difference

- **SEs for Difference**

 Difference between reported and calculated SEs for

difference due to fact that use of same draw (e.g., from

chosp or from tActive) for both usual care and

intervention creates in experimential d difference due to fact that use of same draw (e.g., from SEs for Difference

Difference between reported and calculated SEs for

difference due to fact that use of same draw (e.g., from

chosp or from tActive) for both usual care and

than are ever seen in experimental data
 $-\$ intervention creates stronger correlations in model data than are ever seen in experimental data SEs for Difference

Sifference between reported and calculated SEs for

difference due to fact that use of same draw (e.g., from

the per or from tAcitye) for both usual care and

there ever seen in experimental data
 $-\rho$ SEs for Difference

en reported and calculated SEs for

fact that use of same draw (e.g., from

trive) for both usual care and

tes stronger correlations in model data

in experimental data

2. 0.9655

2. 0.9655 SEs for Difference

Sifference between reported and calculated SEs for

difference due to fact that use of same draw (e.g., from

the

characteristic proportion creates stronger correlations in model data

han are ever se SEs for Difference

en reported and calculated SEs for

fact that use of same draw (e.g., from

fact that use of same draw (e.g., from

titive) for both usual care and

in line xperimental data

in line xperimental data
 • Difference between reported and calculated SEs for

difference due to fact that use of same daw (e.g., from

chose or from tActive) for both usual care and

than are ever seen in experimental data

than are ever seen in
	- ρ for C₀ vs C₁: 0.9994 $- \rho$ for Q₀ vs Q₁: 0.9655

SEs for Difference (2)

- rates/costs/QALY scores in both Rx groups arise from same distributions, one group is sometimes above mean while other is below, or one group is sometimes a little above mean while other is more above mean; etc. difference due to fact that use of same draw (e.g., from

chose or from tActive) for both usual care and

Intervention creates in experimental data
 $- p$ for C_0 vs C_1 : 0.9994
 $- p$ for C_0 vs C_1 : 0.9655
 $- p$ f
- always exactly same distance above or same distance below mean

A Fix for SEs

• In actual data, even if underlying transition
same distributions, one group is sometimes above mean
same distributions, one group is sometimes above mean
while other is more above mean; etc.
above mean while other is m what you would observe in a trial or in observational data from 2 groups, you can generate a proxy for trial/observational data by creating 2 identical distributions, one for UC and one for intervention (e.g., tActiveu and tActivei)

Distribution of Ratios from Cost-Effect Pairs

- Distribution of Ratios from Cost-Effect Pairs

 (ALMOST) Never summarize the cost-effectiveness

ratios of the 1000 replicates

− Never report:

 Mean of ratios

 SE of ratios

 Mean + 1.96 * SE ratios of the 1000 replicates
	-
	-
	-
	-
- Distribution of Ratios from Cost-Effect Pairs

ALMOST) Never summarize the cost-effectiveness

atios of the 1000 replicates

→ Never report:

→ Mean of ratios

→ Es of ratios

→ P-value for ratios

→ Mean ± 1.96 * SE

→ C stribution of Ratios from Cost-Effect Pairs

MOST) Never summarize the cost-effectiveness

so fthe 1000 replicates

• Mean of ratios

• Mean of ratios

• Mean of ratios

• Mean 1.96 ° SE

• Prolute for ICE scatterplot are stribution of Ratios from Cost-Effect Pairs

MOST) Never summarize the cost-effectiveness

so fthe 1000 replicates

• Mean of ratios

• SE of ratios

• SE of ratios

• Fuelling of SE

• The strip of SE

• The strip of SE
 stribution of Ratios from Cost-Effect Pairs

MOST) Never summarize the cost-effectiveness

so fthe 1000 replicates

ever report:

• Mean of ratios

• P-value for ratios

• P-value for ratios

• P-value for ratios

• Mean estribution of Ratios from Cost-Effect Pairs

MOST) Never summarize the cost-effectiveness

sof the 1000 replicates

ever report:

• Mean of ratios

• SE of ratios

• SE of ratios

• Never and ratios

• SE of ratios

repli • CALMOST) Neer summarize the cost-Effect Pairs

• (ALMOST) Neer summarize the cost-effectiveness

– Never report.

• Mean of ratios

• SE of ratios

• F-value for ratios

• F-value for ratios

• F-value for ratios

• F-Y-axis, the ratios that represent the 2.5 and 97.5% percentiles represent the nonparametric CI for the ICER

