Probabilistic Model Checking

Marta Kwiatkowska Gethin Norman Dave Parker



University of Oxford

Part 5 - Continuous-Time Markov Chains

Overview

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probabilities, steady-state, transient, ...
- Properties of CTMCs: The logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards

Exponential distribution

• Continuous random variable X is exponential with parameter $\lambda > 0$ if the density function is given by

$$f_{\chi}(t) = \begin{cases} \lambda \cdot e^{-\lambda \cdot t} & \text{if } t > 0 \\ 0 & \text{otherwise} \end{cases}$$

• Cumulative distribution function (P[X \le t]) of X: $F_X(t) = \int_0^t \lambda \cdot e^{-\lambda \cdot x} dx = [-e^{-\lambda \cdot x}]_0^t = 1 - e^{-\lambda \cdot t}$

$$-P[X > t] = e^{-\lambda \cdot x}$$

- expectation E[X] = $\int_0^\infty x \cdot \lambda \cdot e^{-\lambda \cdot x} dx = \frac{1}{\lambda}$
- variance Var[X] = $\frac{1}{\lambda^2}$

Exponential distribution – Examples



- The more λ increases, the faster the c.d.f. approaches 1

Exponential distribution

- Adequate for modelling many real-life phenomena
 - failure rates
 - inter-arrival times
 - continuous process to change state
- Can approximate general distributions arbitrarily closely
- Maximal entropy if just the mean is known
 - i.e. best approximation when only mean is known

Exponential distribution - Memoryless

- Memoryless property: $P[X > t_1 + t_2 | X > t_1] = P[X > t_2]$
- Exponential distribution is the only continuous distribution which is memoryless
- $P[X > t_1 + t_2 | X > t_1] = P[X > t_1 + t_2 \land X > t_1] / P[X > t_1]$ $= P[X > t_1 + t_2] / P[X > t_1]$ $= e^{-\lambda \cdot (t1 + t2)} / e^{-\lambda \cdot t1}$ $= (e^{-\lambda \cdot t1} \cdot e^{-\lambda \cdot t2}) / e^{-\lambda \cdot t1}$ $= e^{-\lambda \cdot t2}$ $= P[X > t_2]$

recall $P[X>t] = e^{-\lambda \cdot t}$

Exponential distribution - Properties

• Minimum of two independent exponential distributions is an exponential distribution (parameter is sum)

 $P[min(X_1, X_2) \le t] = 1 - P[min(X_1, X_2) > t]$

$$= 1 - P[X_1 > t \land X_2 > t]$$

$$= 1 - P[X_1 > t] \cdot P[X_2 > t]$$

$$= 1 - e^{-\lambda_1 \cdot t} \cdot e^{-\lambda_2 \cdot t}$$

$$= 1 - e^{-(\lambda_1 + \lambda_2) \cdot t}$$

$$= 1 - P[Y > t] = P[Y \le t]$$

- recall $P[X>t] = e^{-\lambda \cdot t}$

Overview

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probabilities, steady-state, transient, ...
- Properties of CTMCs: The logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards

- Continuous-time Markov chains (CTMCs)
 - labelled transition systems augmented with rates
 - discrete states
 - continuous time-steps
 - delays exponentially distributed

Suited to modelling:

- reliability models
- control systems
- queueing networks
- biological pathways
- chemical reactions

- Formally, a CTMC C is a tuple (S,s_{init},R,L) where:
 - S is a finite set of states ("state space")
 - $\boldsymbol{s}_{init} \in \boldsymbol{S}$ is the initial state
 - $\mathbf{R} : \mathbf{S} \times \mathbf{S} \rightarrow \mathbb{R}_{\geq 0}$ is the transition rate matrix
 - L : S \rightarrow 2^{AP} is a labelling with atomic propositions

Transition rate matrix assigns rates to each pair of states

- used as a parameter to the exponential distribution
- transition between s and s' when R(s,s')>0
- probability triggered before t time units $1 e^{-R(s,s') \cdot t}$

- What happens when there exists multiple s' with R(s,s')>0?
 - first transition triggered determines the next state
 - called the race condition
- Time spent in a state before a transition:
 - minimum of exponential distributions
 - exponential with parameter given by summation:

$$\mathsf{E}(\mathsf{s}) = \sum_{\mathsf{s}' \in \mathsf{S}} \mathsf{R}(\mathsf{s},\mathsf{s}')$$

- E(s) is the exit rate of state s
- state absorbing if E(s)=0 (no outgoing transitions)
- probability of leaving a state s within [0,t] equals $1-e^{-E(s)\cdot t}$

Embedded DTMC

- Can determine the probability of each transition occurring
 - independent of the time at which it occurs
- Embedded DTMC: emb(C)=(S,s_{init},P^{emb(C)},L)
 - state space, initial state and labelling as the CTMC
 - for any s,s' \in S

$$\mathbf{P}^{emb(C)}(s,s') = \begin{cases} R(s,s')/E(s) & \text{if } E(s) > 0 \\ 1 & \text{if } E(s) = 0 \text{ and } s = s' \\ 0 & \text{otherwise} \end{cases}$$

- Alternative characterisation of the behaviour:
 - remain in s for delay exponentially distributed with rate E(s)
 - probability next state is s' is given by P^{emb(C)}(s,s')

Infinitesimal generator matrix

$$Q(s,s') = \begin{cases} R(s,s') & s \neq s' \\ -\sum_{s\neq s'} R(s,s') & otherwise \end{cases}$$

Alternative definition: a CTMC is:

- a family of random variables { X(t) $| t \in \mathbb{R}_{\geq 0}$ }
- X(t) are observations made at time instant t
- i.e. X(t) is the state of the system at time instant t
- which satisifies...

Memoryless (Markov property)

 $\mathsf{P}[\mathsf{X}(\mathsf{t}_k) = \mathsf{s}_k \mid \mathsf{X}(\mathsf{t}_{k-1}) = \mathsf{s}_{k-1}, \dots, \mathsf{X}(\mathsf{t}_0) = \mathsf{s}_0] = \mathsf{P}[\mathsf{X}(\mathsf{t}_k) = \mathsf{s}_k \mid \mathsf{X}(\mathsf{t}_{k-1}) = \mathsf{s}_{k-1}]$

Simple CTMC example

- Modelling a queue of jobs
 - initially the queue is empty
 - jobs arrive with rate 3/2
 - jobs are served with rate 3
 - maximum size of the queue is 3



Simple CTMC example

 $C = (S, S_{init}, R, L)$ $S = \{S_0, S_1, S_2, S_3\}$ $S_{init} = S_0$



AP = {empty, full} L(s₀)={empty} L(s₁)=L(s₂)= \emptyset and L(s₃)={full}



Paths of a CTMC

- Infinite path ω is a sequence $s_0t_0s_1t_1s_2t_2...$ such that
 - $\ \textbf{R}(s_i,s_{i+1}) > 0 \ \text{and} \ t_i \in \mathbb{R}_{>0} \ \text{ for all } i \in \mathbb{N}$
 - amount of time spent in the jth state: time(ω ,j)=t_i
 - state occupied at time t: $\omega @t=s_j$ where j smallest index such that $\sum_{i \le j} t_i \ge t$
- Finite path is a sequence $s_0t_0s_1t_1s_2t_2...t_{k-1}s_k$ such that
 - $R(s_i,s_{i+1}) > 0$ and $t_i \in \mathbb{R}_{>0}~$ for all $i{<}k$
 - $-s_k$ is absorbing (R(s,s') = 0 for all s' \in S)
 - amount of time spent in the ith state only defined for $j \le k$: time(ω ,j)=t_i if j < k and time(ω ,j)= ∞ if j=k
 - state occupied at time t: if $t \le \sum_{i \le k} t_j$ then $\omega@t$ as above otherwise $t > \sum_{i \le k} t_j$ then $\omega@t = s_k$

Probability space

- Sample space: Path(s) (set of all paths from a state s)
- Events: sets of infinite paths
- Basic events: sets of paths with common finite prefix
 - probability of a single finite path is zero
 - include time intervals in cylinders
- Cylinder is a sequence $s_0, I_0, s_1, I_1, ..., I_{n-1}, s_n$
 - $s_0, s_1, s_2, \dots, s_n$ sequence of states where $R(s_i, s_{i+1}) > 0$ for i < n
 - $-I_0,I_1,I_2,\ldots,I_{n-1}$ sequence of of nonempty intervals of $\mathbb{R}_{\geq 0}$
- $C(s_0, I_0, s_1, I_1, ..., I_{n-1}, s_n)$ set of (infinite and finite paths): - $\omega(i) = s_i$ for all $i \le n$ and time(ω, i) $\in I_i$ for all i < n

Probability space

Define measure over cylinders by induction

$$- Pr_s(C(s)) = 1$$

-
$$Pr_s(C(s,I,s_1,I_1,\ldots,I_{n-1},s_n,I',s'))$$
 equals



Probability space

- Probability space (Path(s), $\Sigma_{Path(s)}$, Pr_s)
- Sample space Ω = Path(s) (infinite and finite paths)
- Event set $\Sigma_{Path(s)}$
 - least $\sigma\text{-algebra}$ on Path(s) containing all cylinders starting in s
- Probability measure Pr_s
 - Pr_s extends uniquely from probability defined over cylinders
- See [BHHK03] for further details

Probability space – Example

- Cylinder $C(s_0, [0, 2], s_1)$
- $Pr(C(s_0, [0, 2], s_1)) = Pr(C(s_0)) \cdot P^{emb(C)}(s_0, s_1) \cdot (e^{-E(s_0) \cdot 0} e^{-E(s_0) \cdot 2})$ = $1 \cdot 1 \cdot (e^{-3/2 \cdot 0} - e^{-3/2 \cdot 2})$ = $1 - e^{-3}$ ≈ 0.95021
- Probability of leaving the initial state s_0 and moving to state s_1 within the first 2 time units of operation



Transient and steady-state behaviour

Transient behaviour

- state of the model at a particular time instant
- $\underline{\pi}^{c}_{s,t}(s')$ is probability of, having started in state s, being in state s' at time t
- $\ \underline{\pi}^{c}_{s,t}(s') = Pr_{s} \{ \ \omega \in Path^{c}(s) \mid \omega @t=s' \ \}$

Steady-state behaviour

- state of the model in the long-run
- $\underline{\pi}^{c}_{s}(s')$ is probability of, having started in state s, being in state s' in the long run
- $\underline{\pi}^{C}{}_{s}(s') = \lim_{t \to \infty} \underline{\pi}^{C}{}_{s,t}(s')$
- the percentage of time, in long run, spent in each state

Computing transient probabilities

- Π_t matrix of transient probabilities
 - $\Pi_{t}(s,s') = \underline{\pi}_{s,t}(s')$
- Π_t solution of the differential equation: $\Pi_t' = \Pi_t \cdot Q$
 - **Q** infinitesimal generator matrix
- Can be expressed as a matrix exponential and therefore evaluated as a power series

$$\boldsymbol{\Pi}_t = e^{\boldsymbol{Q}\cdot\boldsymbol{t}} = \sum\nolimits_{i=0}^\infty \left(\boldsymbol{Q}\cdot\boldsymbol{t}\right)^i / i\,!$$

- computation potentially unstable
- probabilities instead computed using the uniformised DTMC

- Uniformised DTMC unif(C)=(S,s_{init}, P^{unif(C)}, L) of C=(S,s_{init}, R, L)
 - set of states, initial state and labelling the same as C
 - $\mathbf{P}^{unif(C)} = \mathbf{I} + \mathbf{Q}/\mathbf{q}$
 - $q \ge max{E(s) | s \in S}$ is the uniformisation rate

- Each time step (epoch) of uniformised DTMC corresponds to one exponentially distributed delay with rate q
 - if E(s)=q transitions the same as embedded DTMC (residence time has the same distribution as one epoch)
 - if E(s)<q add self loop with probability 1-E(s)/q (residence time longer than 1/q so one epoch may not be 'long enough')

 Using the uniformised DTMC the transient probabilities can be expressed by:



$$\boldsymbol{\Pi}_t = \sum\nolimits_{i=0}^{\infty} \boldsymbol{\gamma}_{q \cdot t,i} \cdot \left(\, \boldsymbol{P}^{unif(C)} \, \right)^i$$

- (**P**^{unif(C)})ⁱ is probability of jumping between each pair of states in i steps
- + $\gamma_{q \cdot t,i}$ is the ith Poisson probability with parameter q-t
 - the probability of i steps occurring in time t, given each has delay exponentially distributed with rate q
- Can truncate the summation using the techniques of Fox and Glynn [FG88], which allow efficient computation of the Poisson probabilities

- Computing $\underline{\pi}_{s,t}$ for a fixed state s and time t
 - can be computed efficiently using matrix-vector operations
 - pre-multiply the matrix Π_t by the initial distribution
 - in this $\underline{\pi}_{s,0}$ where $\underline{\pi}_{s,0}(s')$ equals 1 if s=s' and 0 otherwise

$$\begin{split} \underline{\boldsymbol{\pi}}_{s,t} &= \underline{\boldsymbol{\pi}}_{s,0} \cdot \boldsymbol{\Pi}_{t} \; = \; \underline{\boldsymbol{\pi}}_{s,0} \cdot \sum_{i=0}^{\infty} \boldsymbol{\gamma}_{q\cdot t,i} \cdot \left(\boldsymbol{P}^{\text{unif}(C)} \right)^{i} \\ &= \; \sum_{i=0}^{\infty} \boldsymbol{\gamma}_{q\cdot t,i} \cdot \underline{\boldsymbol{\pi}}_{s,0} \cdot \left(\boldsymbol{P}^{\text{unif}(C)} \right)^{i} \end{split}$$

- compute iteratively to avoid the computation of matrix powers

$$\left(\underline{\pi}_{s,t} \cdot \mathbf{P}^{\mathsf{unif}(C)} \right)^{i+1} = \left(\underline{\pi}_{s,t} \cdot \mathbf{P}^{\mathsf{unif}(C)} \right)^{i} \cdot \mathbf{P}^{\mathsf{unif}(C)}$$

Overview

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probabilities, steady-state, transient, ...
- Properties of CTMCs: The logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards

- Temporal logic for describing properties of CTMCs
 - CSL = Continuous Stochastic Logic [ASSB00,BHHK03]
 - extension of (non-probabilistic) temporal logic CTL
- Key additions:
 - probabilistic operator P (like PCTL)
 - steady state operator S
- Example: down $\rightarrow P_{>0.75}$ [\neg fail U^{\leq [1,2]} up]
 - when a shutdown occurs, the probability of a system recovery being completed between 1 and 2 hours without further failure is greater than 0.75
- Example: S_{<0.1}[insufficient_routers]
 - in the long run, the chance that an inadequate number of routers are operational is less than 0.1



- where a is an atomic proposition, I interval of $\mathbb{R}_{\geq 0}$ and $p\in[0,1],~ {\bf \sim}\in\{<,>,\leq,\geq\}$
- A CSL formula is always a state formula
 - path formulas only occur inside the P operator

CSL semantics for CTMCs

- CSL formulas interpreted over states of a CTMC
 s ⊨ φ denotes φ is "true in state s" or "satisfied in state s"
- Semantics of state formulas:
 - for a state s of the CTMC (S, s_{init}, R, L):



CSL semantics for CTMCs

- Prob(s, $\psi)$ is the probability, starting in state s, of satisfying the path formula ψ
 - $\operatorname{Prob}(s, \psi) = \operatorname{Pr}_s \{ \omega \in \operatorname{Path}_s \mid \omega \vDash \psi \}$
- Semantics of path formulas: - for a path ω of the CTMC: - $\omega \models X \varphi \quad \Leftrightarrow \quad \omega(1)$ is defined and $\omega(1) \models \varphi$ - $\omega \models \varphi_1 \cup^{I} \varphi_2 \quad \Leftrightarrow \quad \exists t \in I. \ (\ \omega @t \models \varphi_2 \land \forall t' < t. \ \omega @t' \models \varphi_1)$ there exists a time instant in the interval I where φ_2 is true and φ_1 is true at all preceding time instants

if $\omega(0)$ is absorbing

CSL derived operators

- (As for PCTL) can derive basic logical equivalences:
 - false $\equiv \neg true$ (false)- $\phi_1 \lor \phi_2 \equiv \neg (\neg \phi_1 \land \neg \phi_2)$ (disjunction)- $\phi_1 \rightarrow \phi_2 \equiv \neg \phi_1 \lor \phi_2$ (implication)
- The "eventually" operator (path formula)
 - $F \varphi \equiv true U \varphi$ (F = "future")
 - sometimes written as $\diamond \phi$ ("diamond")
 - "φ is eventually true"
 - timed version: $F^{I} \varphi \equiv true \ U^{I} \varphi$
 - "¢ becomes true in the interval I"

(F = "future") ("diamond")

More on CSL

Negation and probabilities

$$\begin{aligned} &- \neg \mathsf{P}_{>p} \left[\begin{array}{c} \varphi_1 \ \mathsf{U}^{\scriptscriptstyle \mathsf{I}} \ \varphi_2 \end{array} \right] \equiv \mathsf{P}_{\leq p} \left[\begin{array}{c} \varphi_1 \ \mathsf{U}^{\scriptscriptstyle \mathsf{I}} \ \varphi_2 \end{array} \right] \\ &- \neg \mathsf{S}_{>p} \left[\begin{array}{c} \varphi \end{array} \right] \equiv \mathsf{S}_{\leq p} \left[\begin{array}{c} \varphi \end{array} \right] \end{aligned}$$

- The "always" operator (path formula)
 - $G \phi \equiv \neg(F \neg \phi) \equiv \neg(true \cup \neg \phi)$ (G = "globally")

("box")

- sometimes written as $\Box \phi$
- "φ is always true"
- bounded version: $G^{I} \phi \equiv \neg (F^{I} \neg \phi)$
- " ϕ holds throughout the interval I"
- strictly speaking, G ϕ cannot be derived from the CSL syntax in this way since there is no negation of path formulas
- but, as for PCTL, we can derive P_{-p} [G ϕ] directly...

Derivation of $P_{\sim p}$ [G φ]

$$s \vDash P_{>p} [G \varphi] \Leftrightarrow Prob(s, G \varphi) > p$$

$$\Leftrightarrow Prob(s, \neg(F \neg \varphi)) > p$$

$$\Leftrightarrow 1 - Prob(s, F \neg \varphi) > p$$

$$\Leftrightarrow Prob(s, F \neg \varphi) < 1 - p$$

$$\Leftrightarrow s \vDash P_{<1-p} [F \neg \varphi]$$

• Other equivalences:

Quantitative properties

- Consider CSL formulae P_{-p} [ψ] and S_{-p} [ϕ]
 - if the probability is unknown, how to choose the bound p?
- When the outermost operator of a CSL formula is P or S
 - allow bounds of the form $P_{=?}$ [ψ] and S $_{=?}$ [φ]
 - what is the probability that path formula ψ is true?
 - what is the long-run probability that ϕ holds?
- Model checking is no harder: compute the values anyway
- As we have seen, useful for spotting patterns and trends

CSL example - Workstation cluster

- Case study: Cluster of workstations [HHK00]
 - two sub-clusters (N workstations in each cluster)
 - star topology with a central switch
 - components can break down, single repair unit
 - minimum QoS: at least ¾ of the workstations operational and connected via switches
 - premium QoS: all workstations operational and connected via switches



CSL example - Workstation cluster

- $P_{=?}$ [true U^[0,t] ¬minimum]
 - the chance that the QoS drops below minimum within t hours
- \neg minimum $\rightarrow P_{<0.1}[F^{[0,t]} \neg$ minimum]
 - when facing insufficient QoS, the probability of facing the same problem after t hours is less than 0.1
- S_{=?}[minimum]
 - the probability in the long run of having minimum QoS
- minimum $\rightarrow P_{>0.8}$ [minimum U^[0,t] premium]
 - the probability of going from minimum to premium QoS within t hours without violating minimum QoS is at least 0.8
- $P_{=?}[\neg minimum U^{[t,\infty)} minimum]$
 - the chance it takes more than t time units to recover from insufficient QoS

Overview

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probabilities, steady-state, transient, ...
- Properties of CTMCs: The logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards

CSL model checking for CTMCs

- Algorithm for CSL model checking [BHHK03]
 - inputs: CTMC C=(S,s_{init},R,L), CSL formula ϕ
 - output: $Sat(\varphi) = \{ s \in S \mid s \models \varphi \}$, the set of states satisfying φ
- What does it mean for a CTMC C to satisfy a formula $\varphi?$
 - check that $s \vDash \varphi$ for all states $s \in S,$ i.e. Sat($\varphi) = S$
 - know if $s_{init} \models \varphi$, i.e. if $s_{init} \in Sat(\varphi)$
- Sometimes, focus on quantitative results
 - e.g. compute result of P=? [true $U^{[0,13.5]}$ minimum]
 - e.g. compute result of P=? [true $U^{[0,t]}$ minimum] for $0 \le t \le 100$

CSL model checking for CTMCs

• Basic algorithm proceeds by induction on parse tree of ϕ - example: $\phi = S_{<0,1}[\neg fail] \rightarrow P_{>0.95}[\neg fail U^{I} succ]$



- For the non-probabilistic operators:
 - Sat(true) = S
 - $Sat(a) = \{ s \in S \mid a \in L(s) \}$
 - $\ Sat(\neg \varphi) = S \ \setminus \ Sat(\varphi)$
 - $\ Sat(\varphi_1 \, \wedge \, \varphi_2) = Sat(\varphi_1) \, \cap \, Sat(\varphi_2)$

Untimed properties

- Untimed properties can be verified on the embedded DTMC
 - properties of the form: $P_{-p} [X \varphi]$ or $P_{-p} [\varphi_1 U^{[0,\infty)} \varphi_2]$
 - use algorithms for checking PCTL against DTMCs
- Certain qualitative time-bounded until formulae can also be verified on the embedded DTMC

- for any (non-empty) interval I

 $s \models P_{\sim 0} \ [\phi_1 \cup \phi_2 \] \text{ if and only if } s \models P_{\sim 0} \ [\phi_1 \cup \phi_2 \]$

- can use pre-computation algorithm Prob0

Untimed properties

- $s \models P_{\sim 1} [\phi_1 U^{[0,\infty)} \phi_2]$ does not imply $s \models P_{\sim 1} [\phi_1 U^{I} \phi_2]$
- Consider the following example
 - with probability 1 eventually reach state s_1
 - $\boldsymbol{s}_{0} \vDash \boldsymbol{P}_{\geq 1} \; [\boldsymbol{\varphi}_{1} \; \boldsymbol{U}^{[0,\infty)} \; \boldsymbol{\varphi}_{2} \;]$
 - probability of remaining in state s₀ until time-bound t is greater than zero for any t



Model checking – Time-bounded until

- Compute Prob(s, $\phi_1 \cup \phi_2$) for all states where I is an arbitrary interval of the non-negative real numbers
 - Prob(s, $\phi_1 U^{I} \phi_2$) = Prob(s, $\phi_1 U^{cI(I)} \phi_2$) where cl(I) closure of the interval I
 - Prob(s, $\phi_1 U^{[0,\infty)} \phi_2$) = Prob^{emb(C)}(s, $\phi_1 U \phi_2$) where emb(C) is the embedded DTMC
- Therefore, remains to consider the cases when
 - I = [0,t] for some t $\in \mathbb{R}_{\geq 0}$
 - I = [t,t'] for some t,t' $\in \mathbb{R}_{\geq 0}$ such that t \leq t'
 - I = [t, ∞) for some t $\in \mathbb{R}_{\geq 0}$

Model checking – $P_{\sim p}[\phi_1 U^{[0,t]} \phi_2]$

• Computing the probabilities reduces to determining the least solution of the following set of integral equations:



Model checking – $P_{\sim p}[\phi_1 \ U^{[0,t]} \phi_2]$

- Construct CTMC $C[\phi_2][\neg \phi_1 \land \neg \phi_2]$
 - where for CTMC C=(S,s_{init},R,L), let C[θ]=(S,s_{init},R[θ],L) where R[θ](s,s')=R(s,s') if s \notin Sat(θ) and 0 otherwise
- Make all ϕ_2 states absorbing
 - in such a state $\phi_1 U^{[0,x]} \phi_2$ holds with probability 1
- Make all $\neg \varphi_1 \land \neg \varphi_2$ states absorbing
 - in such a state $\phi_1 U^{[0,x]} \phi_2$ holds with probability 0
- Problem then reduces to calculating transient probabilities of the CTMC $C[\phi_2][\neg \phi_1 \land \neg \phi_2]$:

$$Prob(s, \varphi_1 U^{[0,t]} \varphi_2) = \sum_{s' \in Sat(\varphi_2)} \underline{\pi}_{s,t}^{C[\varphi_2][\neg \varphi_1 \land \neg \varphi_2]}(s')$$

transient probability: starting in state the probability of being in state s' at time t

Model checking – $P_{-p}[\phi_1 U^{[0,t]} \phi_2]$

- Can now adapt uniformisation to computing the vector of probabilities Prob($\phi_1 U^{[0,t]} \phi_2$)
 - recall Π_t is matrix of transient probabilities $\Pi_t(s,s') = \underline{\pi}_{s,t}(s')$
 - computed via uniformisation: $\Pi_t = \sum_{i=0}^{\infty} \gamma_{q\cdot t,i} \cdot (P^{\text{unif}(C)})^i$
- Combining with: Prob(s, $\varphi_1 U^{[0,t]} \varphi_2$) = $\sum_{s' \in Sat(\varphi_2)} \underline{\pi}_{s,t}^{C[\varphi_2][\neg \varphi_1 \land \neg \varphi_2]}(s')$

$$\underline{\operatorname{Prob}}(\Phi_{1} \ U^{[0,t]} \ \Phi_{2}) = \Pi_{t}^{C[\Phi_{2}][\neg \Phi_{1} \land \neg \Phi_{2}]} \cdot \underline{\Phi_{2}}$$

$$= \left(\sum_{i=0}^{\infty} \gamma_{q \cdot t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\Phi_{2}][\neg \Phi_{1} \land \neg \Phi_{2}])} \right)^{i} \right) \cdot \underline{\Phi_{2}}$$

$$= \sum_{i=0}^{\infty} \left(\gamma_{q \cdot t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\Phi_{2}][\neg \Phi_{1} \land \neg \Phi_{2}])} \right)^{i} \cdot \underline{\Phi_{2}} \right)$$

Model checking –
$$P_{-p}[\phi_1 U^{[0,t]} \phi_2]$$

• Have shown that we can calculate the probabilites as:

$$\underline{\text{Prob}}(\varphi_1 \ U^{[0,t]} \ \varphi_2) = \sum_{i=0}^{\infty} \left(\gamma_{q \cdot t,i} \cdot \left(\mathbf{P}^{\text{unif}(C[\varphi_2][\neg \varphi_1 \land \neg \varphi_2])} \right)^i \cdot \underline{\varphi_2} \right)$$

- Infinite summation can be truncated using the techniques of Fox and Glynn [FG88]
- Can compute iteratively to avoid matrix powers:

$$\left(\mathbf{P}^{\text{unif}(C)} \right)^{0} \cdot \underline{\Phi}_{2} = \underline{\Phi}_{2}$$

$$\left(\mathbf{P}^{\text{unif}(C)} \right)^{i+1} \cdot \underline{\Phi}_{2} = \mathbf{P}^{\text{unif}(C)} \cdot \left(\left(\mathbf{P}^{\text{unif}(C)} \right)^{i} \cdot \underline{\Phi}_{2} \right)$$

$P_{\sim p}[\varphi_1 \ U^{[0,t]} \ \varphi_2] - Example$

- P_{>0.65}[true U^[0,7.5] full]
 - "probability of the queue becoming full within 7.5 time units"
- State s_3 satisfies full and no states satisfy $\neg true$
 - in C[full][¬true $\land \neg$ full] only state s₃ made absorbing



$P_{\sim p}[\phi_1 \ U^{[0,t]} \ \phi_2] - Example$

Computing the summation of matrix-vector multiplications

$$\underline{\text{Prob}}(\varphi_1 \ U^{[0,t]} \ \varphi_2) = \sum_{i=0}^{\infty} \left(\gamma_{q \cdot t,i} \cdot \left(\mathbf{P}^{\text{unif}(C[\varphi_2][\neg \varphi_1 \land \neg \varphi_2])} \right)^i \cdot \underline{\varphi_2} \right)$$

- yields Prob(true U^[0,7.5]full) \approx (0.6482,0.6823,0.7811,1)
- $P_{>0.65}$ [true U^[0,7.5] full] satisfied in states s₁, s₂ and s₃



Model checking – $P_{\sim p}[\phi_1 \ U^{[t,t']} \phi_2]$

- In this case the computation can be split into two parts:
- + Probability of remaining in φ_1 states until time t
 - can be computed as transient probabilities on the CTMC where are states satisfying $\neg \varphi_1$ have been made absorbing
- Probability of reaching a ϕ_2 state, while remaining in states satisfying ϕ_1 , within the time interval [0,t'-t]
 - i.e. computing $\underline{\text{Prob}}(\phi_1 \ U^{[0,t'-t]} \phi_2)$



Model checking – $P_{\sim p}[\phi_1 U^{[t,t']} \phi_2]$

• Letting $Prob_{\phi_1}(s, \phi_1 U^{[0,t]}\phi_2) = Prob(s, \phi_1 U^{[0,t]}\phi_2)$ if $s \in Sat(\phi_1)$ and 0 otherwise, from the previous slide we have:

$$\underline{\operatorname{Prob}}(\varphi_{1} \ U^{[t,t']} \ \varphi_{2}) = \Pi_{t}^{C[\neg \varphi_{1}]} \cdot \underline{\operatorname{Prob}}_{\varphi_{1}}(\varphi_{1} \ U^{[0,t'-t]} \ \varphi_{2}) \\ = \left(\sum_{i=0}^{\infty} \gamma_{q\cdot t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\neg \varphi_{1}])} \right)^{i} \right) \cdot \underline{\operatorname{Prob}}_{\varphi_{1}}(\varphi_{1} \ U^{[0,t'-t]} \ \varphi_{2}) \\ = \sum_{i=0}^{\infty} \left(\gamma_{q\cdot t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\neg \varphi_{1}])} \right)^{i} \cdot \underline{\operatorname{Prob}}_{\varphi_{1}}(\varphi_{1} \ U^{[0,t'-t]} \ \varphi_{2}) \right)$$

- summation can be truncated using Fox and Glynn [FG88]
- can compute iteratively (only scalar and matrix-vector operations)

Model checking – $P_{\sim p}[\phi_1 \ U^{[t,\infty)} \phi_2]$

- Similar to the case for $\varphi_1 ~ U^{[t,t']} ~ \varphi_2$ except second part is now unbounded, and hence the embedded DTMC can be used
- + Probability of remaining in φ_1 states until time t
- Probability of reaching a φ_2 state, while remaining in states satisfying φ_1
 - i.e. computing $\underline{\text{Prob}}(\phi_1 \ U^{[0,\infty)} \phi_2)$



Model checking –
$$P_{\sim p}[\phi_1 U^{[t,\infty)} \phi_2]$$

• Letting $Prob_{\phi_1}(s, \phi_1 U^{[0,\infty)}\phi_2) = Prob(s, \phi_1 U^{[0,\infty)}\phi_2)$ if $s \in Sat(\phi_1)$ and 0 otherwise, from the previous slide we have:

$$\underline{\operatorname{Prob}}(\Phi_{1} \ U^{[t,\infty)} \ \Phi_{2}) = \Pi_{t}^{C[\neg \Phi_{1}]} \cdot \underline{\operatorname{Prob}}_{\Phi_{1}}^{\operatorname{emb}(C)}(\Phi_{1} \ U^{[0,\infty)} \ \Phi_{2}) \\
= \left(\sum_{i=0}^{\infty} \gamma_{q,t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\neg \Phi_{1}])} \right)^{i} \right) \cdot \underline{\operatorname{Prob}}_{\Phi_{1}}^{\operatorname{emb}(C)}(\Phi_{1} \ U^{[0,\infty)} \ \Phi_{2}) \\
= \sum_{i=0}^{\infty} \left(\gamma_{q,t,i} \cdot \left(\mathbf{P}^{\operatorname{unif}(C[\neg \Phi_{1}])} \right)^{i} \cdot \underline{\operatorname{Prob}}_{\Phi_{1}}^{\operatorname{emb}(C)}(\Phi_{1} \ U^{[0,\infty)} \ \Phi_{2}) \right)$$

- summation can be truncated using Fox and Glynn [FG88]
- can compute iteratively (only scalar and matrix-vector opertions

Model Checking – $S_{\sim p}[\phi]$

- A state s satisfies the formula $S_{\sim p}[\phi]$ if $\Sigma_{s' \models \phi} \underline{\pi}^{C}_{s}(s') \sim p$
 - $\underline{\pi}{}^{\rm C}{}_{\rm s}(s')$ is probability, having started in state s, of being in state s' in the long run
- First, consider the simple case when C is irreducible
 - C is irreducible (strongly connected) if there exists a finite path from each state to every other state
 - the steady-state probabilities are independent of the starting state: denote the steady state probabilities by $\underline{\pi}^{c}(s')$
 - these probabilities can be computed as the unique solution of the linear equation system:

$$\underline{\pi}^{\mathsf{C}} \cdot \mathbf{Q} = \underline{0}$$
 and $\sum_{\mathsf{s} \in \mathsf{S}} \underline{\pi}^{\mathsf{C}}(\mathsf{s}) = 1$

Q is the infinitesimal generator matrix of C

Model Checking – $S_{\sim p}[\phi]$

- Equation system can be solved by any standard approach
 - Direct methods, such as Gaussian elimination
 - Iterative methods, such as Jacobi and Gauss-Seidel
- The satisfaction of the CSL formula
 - same for all states (steady state independent of starting state)
 - computed by summing steady state probabilities for all states satisfying $\boldsymbol{\varphi}$

Model Checking – $S_{-p}[\phi]$

- We now suppose that C is reducible
- First perform graph analysis to find set bssc(C) of bottom strongly connected components (BSCCs)
 - strongly connected components that cannot be left
- Treating each individual $B \in bscc(C)$ as an irreducible CTMC compute the steady state probabilities $\underline{\pi}^{\mathtt{B}}$
 - employ the methods described above
- Calculate the probability of reaching each individual BSCC
 - can be computed in the <code>embedded DTMC</code>
 - if a_B is an atomic proposition true only in the states of B, this probability is given by Prob^{emb(C)}(s, F a_B)

Model Checking – $S_{\sim p}[\phi]$

• For any states s and s' the steady state probability $\underline{\pi}^{c}_{s}(s')$ can then be computed as:

 $\pi_{s}^{C}(s') = \begin{cases} Prob^{emb(C)}(s, F a_{B}) \cdot \underline{\pi}^{B}(s') & \text{if } s' \in B \text{ for some } B \in bscc(C) \\ 0 & \text{otherwise} \end{cases}$

- The total work required to compute $\underline{\pi}^{C}_{s}(s')$ for all s and s'
 - solve two linear equation systems for each BSCC B
 - one to obtain the vector <u>Prob^{emb(C)}(F</u> a_B)
 - $\cdot\,$ the other to compute the steady state probabilities $\underline{\pi}^{\mathtt{B}}$
 - computation of the BSCCs requires only analysis of the underlying graph structure and can be performed using classical algorithms based on depth-first search

$S_{\sim p}[\phi] - Example$

- S_{<0.1}[full]
- CTMC is irreducible (comprises of a single BSCC)
 - steady state probabilities independent of starting state
 - can be computed by solving $\underline{\pi} \cdot \mathbf{Q} = 0$ and $\Sigma \underline{\pi}(s) = 1$

$$\mathbf{Q} = \begin{bmatrix} -3/2 & 3/2 & 0 & 0 \\ 3 & -9/2 & 3/2 & 0 \\ 0 & 3 & -9/2 & 3/2 \\ 0 & 0 & 3 & -3 \end{bmatrix}$$



 $S_{\sim p}[\phi] - Example$

$$\begin{array}{rcl} -3/2 \cdot \underline{\pi}(s_0) &+& 3 \cdot \underline{\pi}(s_1) &=& 0\\ 3/2 \cdot \underline{\pi}(s_0) &-& 9/2 \cdot \underline{\pi}(s_1) &+& 3 \cdot \underline{\pi}(s_2) &=& 0\\ && & 3/2 \cdot \underline{\pi}(s_1) &-& 9/2 \cdot \underline{\pi}(s_2) &+& 3 \cdot \underline{\pi}(s_3) &=& 0\\ && & & & 3/2 \cdot \underline{\pi}(s_2) &-& 3 \cdot \underline{\pi}(s_3) &=& 0 \end{array}$$

 $\underline{\pi}(s_0) + \underline{\pi}(s_1) + \underline{\pi}(s_2) + \underline{\pi}(s_3) = 1$

- solution: $\underline{\pi} = (8/15, 4/15, 2/15, 1/15)$



Overview

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probabilities, steady-state, transient, ...
- Properties of CTMCs: The logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards

Costs and rewards

- We augment CTMCs with rewards
 - real-valued quantities assigned to states and/or transitions
 - these can have a wide range of possible interpretations
 - allows a wide range of quantitative measures of the system
 - basic notion: expected value of rewards
 - formal property specifications in an extension of CSL

• For a CTMC (S,s_{init},R,L), a reward structure is a pair (ρ , ι)

- $\underline{\rho} : S \rightarrow \mathbb{R}_{\geq 0}$ is a vector of state rewards
- $-\iota: S \times S \rightarrow \mathbb{R}_{\geq 0}$ is a matrix of transition rewards
- continuous time: reward $t \cdot \underline{\rho}(s)$ acquired if the CTMC remains in state s for $t \in \mathbb{R}_{\geq 0}$ time units

Reward structures - Example

• Example: "number of requests served"

$$\rho = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad \text{and} \quad \iota = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

- Example: "size of message queue"
 - $\underline{\rho}(s_i) = i$ and $\iota(s_i, s_j) = 0$ for all states s_i and s_j



CSL and rewards

- Extend CSL to incorporate reward-based properties
 - add R operator similar to the one in PCTL



- where r,t $\in \mathbb{R}_{\geq 0}$, ~ $\in \{<,>,\leq,\geq\}$
- R_{r} [] means "the expected value of satisfies r"

Types of reward formulas

- Instantaneous: R_{-r} [$I^{=t}$]
 - the expected value of the reward at time-instant t is \sim r
 - "the expected queue size after 6.7 seconds is at most 2"
- Cumulative: R_{-r} [$C^{\leq t}$]
 - the expected reward cumulated up to time-instant t is ~r
 - "the expected requests served within the first 4.5 seconds of operation is less than 10"
- Reachability: R_{-r} [F φ]
 - the expected reward cumulated before reaching φ is ~r
 - "the expected requests served before the queue becomes full"
- Steady-state R_{r} [S]
 - the long-run average expected reward is ~r
 - "expected long-run queue size is at least 1.2"

Reward formula semantics

- Formal semantics of the four reward operators:
 - $s \models R_{r} [I^{=t}] \iff Exp(s, X_{i=t}) \sim r$
 - $s \models R_{r} [C^{\leq t}] \iff Exp(s, X_{C \leq t}) \sim r$
 - $s \models R_{\sim r} [F \Phi] \iff Exp(s, X_{F\Phi}) \sim r$
 - $s \vDash R_{r} [S] \qquad \Leftrightarrow \qquad \lim_{t \to \infty} (1/t \cdot Exp(s, X_{C \le t})) \sim r$
- where:
 - Exp(s, X) denotes the expectation of the random variable X : Path(s) $\rightarrow \mathbb{R}_{\geq 0}$ with respect to the probability measure Pr_s

Reward formula semantics



$$X_{F\varphi}(\omega) = \begin{cases} \infty & \text{if } s_i \notin Sat(\varphi) \text{ for all } i \ge 0 \\ \sum_{i=0}^{k_{\varphi}-1} t_i \cdot \underline{\rho}(s_i) + \iota(s_i, s_{i+1}) & \text{otherwise} \end{cases}$$

- where $j_t = min\{ j \mid \Sigma_{i \le j} t_i \ge t \}$ and $k_{\varphi} = min\{ i \mid s_i \vDash \varphi \}$

Model checking reward formulas

- Instantaneous: R_{-r} [$I^{=t}$]
 - reduces to transient analysis (state of the CTMC at time t)
 - use uniformisation
- Cumulative: R_{r} [$C^{\leq t}$]
 - extends approach for time-bounded until [KNP06]
 - based on uniformisation
- Reachability: R_{r} [F ϕ]
 - can be computed on the embedded $\ensuremath{\mathsf{DTMC}}$
 - reduces to solving a system of linear equation
- Steady-state: R_{r} [S]
 - similar to steady state formulae $S_{\sim r}$ [φ]
 - graph based analysis (compute BSCCs)
 - solve systems of linear equations (compute steady state probabilities of each BSCC)

Model checking complexity

- For model checking of a CTMC complexity:
 - linear in $|\Phi|$ and polynomial in |S|
 - linear in $q \cdot t_{max}$ (t_{max} is maximum finite bound in intervals)
- $P_{\sim p}[\Phi_1 \ U^{[0,\infty)} \ \Phi_2]$, $S_{\sim p}[\Phi]$, $R_{\sim r} \ [F \ \Phi]$ and $R_{\sim r} \ [S]$
 - require solution of linear equation system of size |S|
 - can be solved with Gaussian elimination: cubic in |S|
 - precomputation algorithms (max |S| steps)
- + $P_{\sim p}[\Phi_1 \ U^{I} \ \Phi_2]$, $R_{\sim r} \ [C^{\leq t}]$ and $R_{\sim r} \ [I^{=t}]$
 - at most two iterative sequences of matrix-vector product
 - operation is quadratic in the size of the matrix, i.e. |S|
 - total number of iterations bounded by Fox and Glynn
 - the bound is linear in the size of $q \cdot t$ (q uniformisation rate)

Summing up...

- Exponential distributions
- Continuous-time Markov chains (CTMCs)
 - definition, paths, probability measure, ...
- Properties of CTMCs: the logic CSL
 - syntax, semantics, equivalences, ...
- CSL model checking
 - algorithm, examples, ...
- Costs and rewards