

Random access protocols for channel access

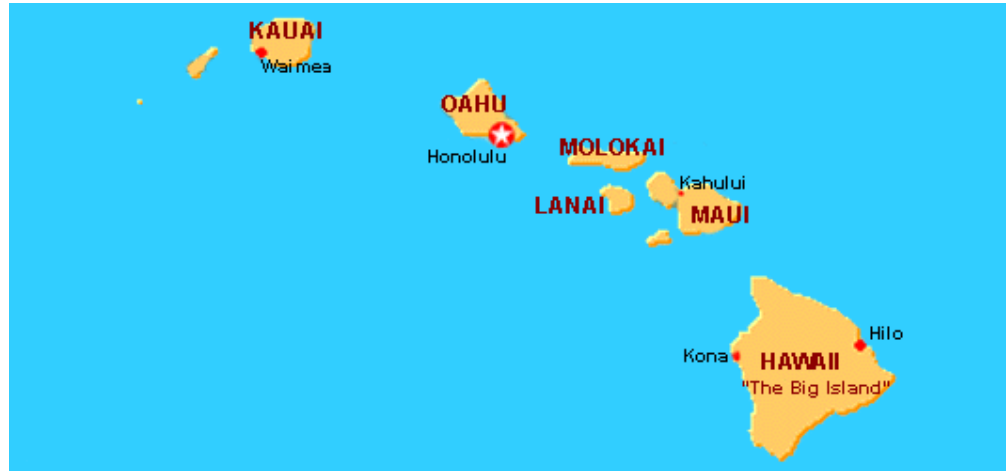
Markov chains and their stability

Laurent Massoulié

laurent.massoulie@inria.fr

Aloha: the first random access protocol for channel access

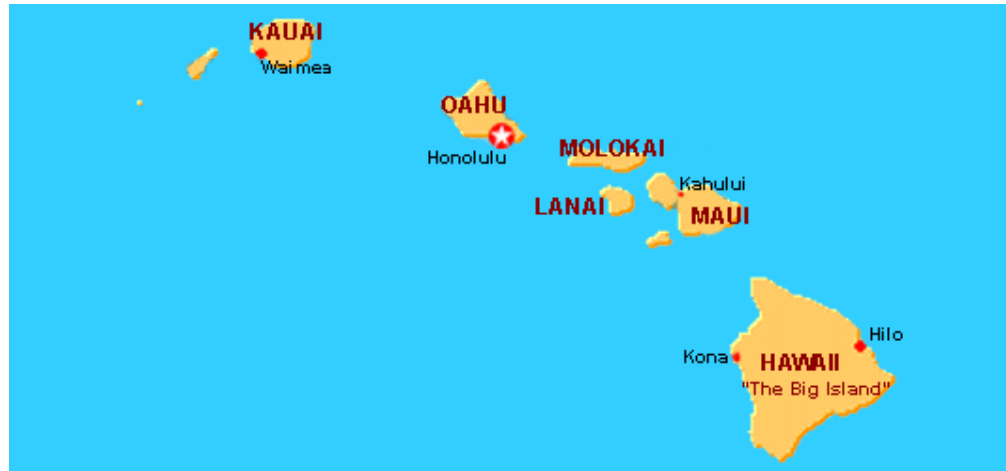
[Abramson, Hawaii 70]



- Goal: allow machines on remote islands to transmit by radio to « master machine » without heavy coordination between them

Aloha: the first random access protocol for channel access

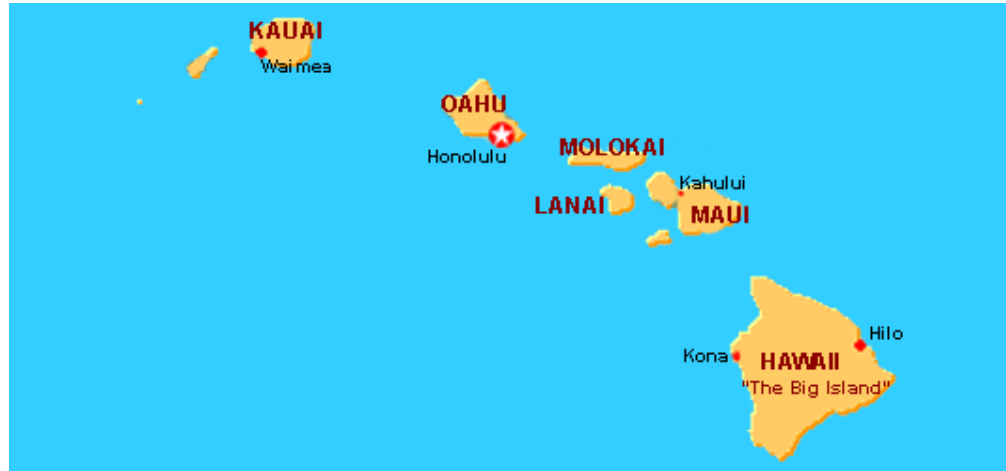
[Abramson, Hawaii 70]



- ❑ Goal: allow machines on remote islands to transmit by radio to « master machine » without heavy coordination between them
- ❑ Key idea: use randomization for scheduling transmissions to avoid collisions between transmitters

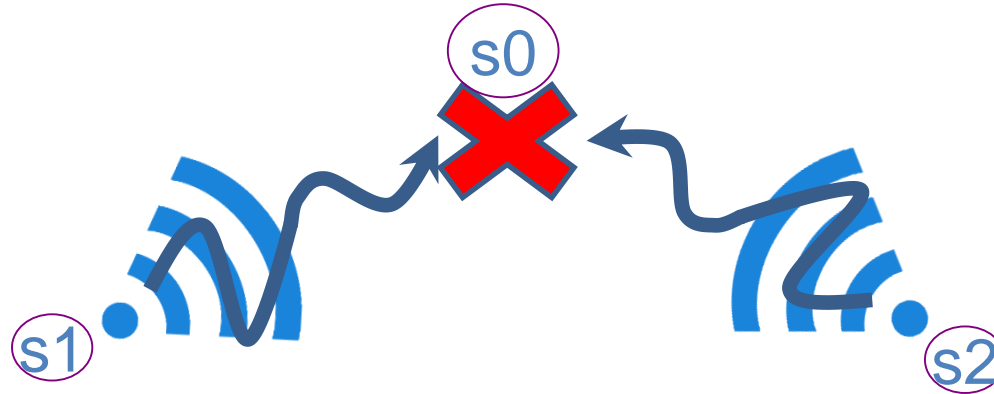
Aloha: the first random access protocol for channel access

[Abramson, Hawaii 70]



- ❑ Goal: allow machines on remote islands to transmit by radio to « master machine » without heavy coordination between them
 - ❑ Key idea: use randomization for scheduling transmissions to avoid collisions between transmitters
- A randomized, distributed algorithm

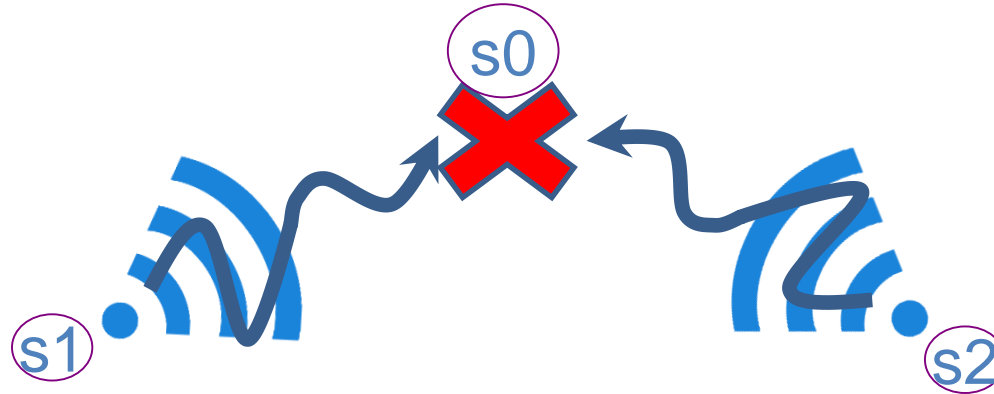
Aloha's principle



Slotted time: fixed transmission intervals

Station with message to send: emits it with probability p

Aloha's principle



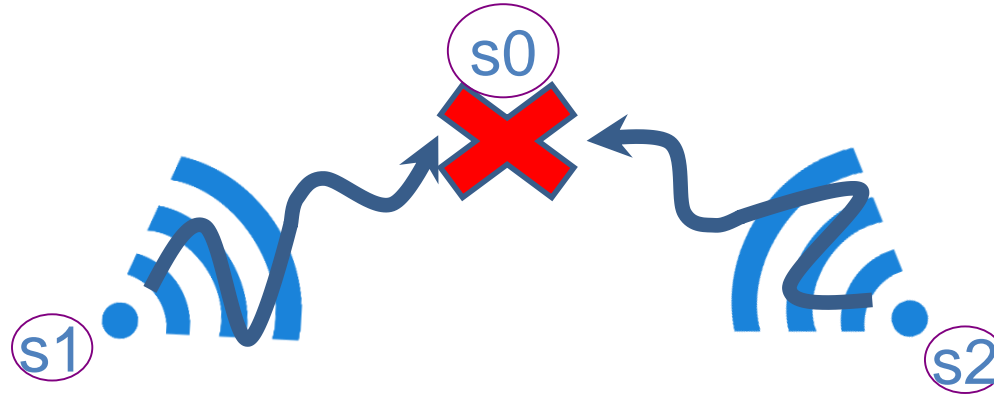
Slotted time: fixed transmission intervals

Station with message to send: emits it with probability p

By end of interval: learns whether msg successfully received, or not (due to collision or other interference)

Repeat until no message left to be sent

Aloha's principle



Slotted time: fixed transmission intervals

Station with message to send: emits it with probability p

By end of interval: learns whether msg successfully received, or not (due to collision or other interference)

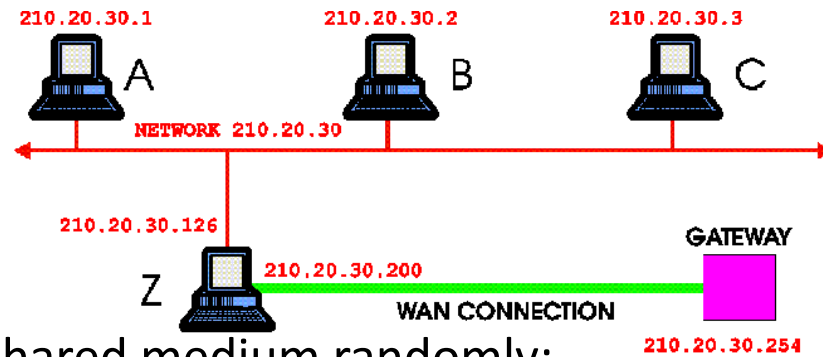
Repeat until no message left to be sent

→ Minimal feedback (only listen for ack after having emitted)

→ implicit coordination by receiver's acknowledgement

Ethernet principles

[Metcalfe, Xerox Parc 73]

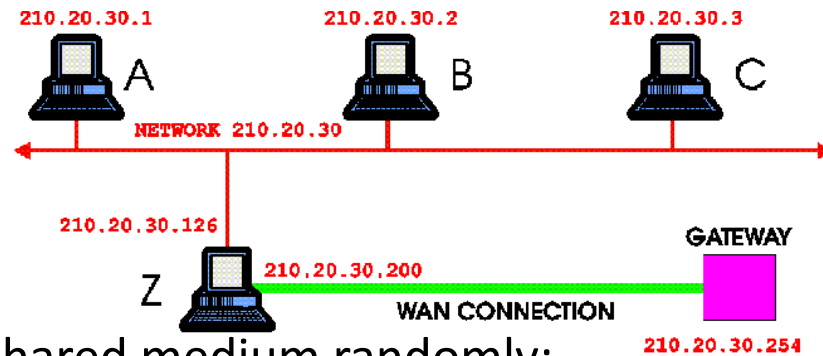


Machine emits on shared medium randomly:

After k failed attempts, waits before retransmitting for random number of slots picked uniformly from $\{1, 2, \dots, 2^k\}$ (so-called contention window)

Ethernet principles

[Metcalfe, Xerox Parc 73]



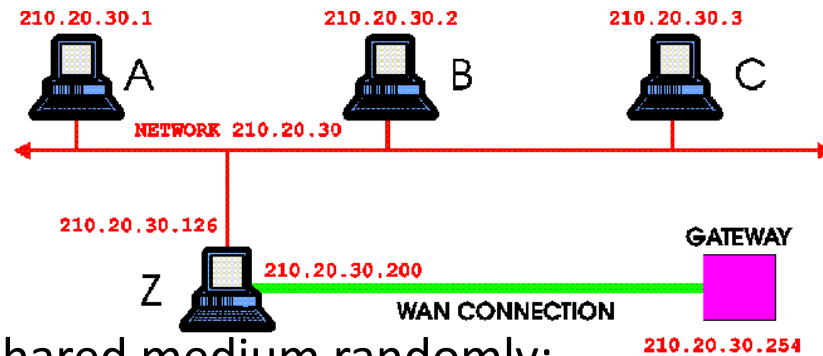
Machine emits on shared medium randomly:

After k failed attempts, waits before retransmitting for random number of slots picked uniformly from $\{1, 2, \dots, 2^k\}$ (so-called contention window)

→ The exponential backoff method, a refinement over Aloha

Ethernet principles

[Metcalfe, Xerox Parc 73]



Machine emits on shared medium randomly:

After k failed attempts, waits before retransmitting for random number of slots picked uniformly from $\{1, 2, \dots, 2^k\}$ (so-called contention window)

→ The exponential backoff method, a refinement over Aloha

Other refinement: sense channel before transmitting (allows to compete by random access only during small fraction of total time)

Principles underly 802.11x (Wi-Fi) protocols

Goals

Understand performance of random access protocols

→ for given traffic, or demand, or workload offered to system (=process of message request arrivals),

Does system transmit them all?

Does it reach some steady state behaviour?

How long do transmissions take?

Outline

- ❑ Introduction to Markov chain theory
 - ❑ Fundamental notions (recurrence, irreducibility, ergodicity, transience)
 - ❑ Criteria for ergodicity or transience

- ❑ Performance of Random Access Protocols
 - ❑ Aloha with finitely many stations
 - ❑ Aloha with an infinite number of stations
 - ❑ Results for Ethernet and other variants

Markov chains

- E a countable set (e.g., \mathbb{N} or $[n] = \{1, \dots, n\}$)

Markov chains

- E a countable set (e.g., \mathbb{N} or $[n] = \{1, \dots, n\}$)
- Definition: $\{X_n\}_{n \in \mathbb{N}}$ Markov chain with transition matrix P iff
 $\forall n > 0, \forall x_0^n = \{x_0, \dots, x_n\} \in E^{n+1}$,
$$\mathbb{P}(X_n = x_n | X_0^{n-1} = x_0^{n-1}) = \mathbb{P}(X_n = x_n | X_{n-1} = x_{n-1}) = p_{x_n x_{n-1}}$$
where $\forall x, y \in E, p_{xy} \geq 0$ and $\sum_{z \in E} p_{xz} = 1$
(i.e. P is a *stochastic matrix*)

- E a countable set (e.g., \mathbb{N} or $[n] = \{1, \dots, n\}$)
- Definition: $\{X_n\}_{n \in \mathbb{N}}$ Markov chain with transition matrix P iff
 $\forall n > 0, \forall x_0^n = \{x_0, \dots, x_n\} \in E^{n+1}$,
 $\mathbb{P}(X_n = x_n | X_0^{n-1} = x_0^{n-1}) = \mathbb{P}(X_n = x_n | X_{n-1} = x_{n-1}) = p_{x_n x_{n-1}}$
where $\forall x, y \in E, p_{xy} \geq 0$ and $\sum_{z \in E} p_{xz} = 1$
(i.e. P is a *stochastic matrix*)
- Canonical example
 X_0 independent of $\{Y_n\}_{n \geq 0}$ an i.i.d. sequence, $Y_n \in E'$
For some function $f : E \times E' \rightarrow E$,

$$\forall n \geq 0, X_{n+1} = f(X_n, Y_n)$$

- E a countable set (e.g., \mathbb{N} or $[n] = \{1, \dots, n\}$)
- Definition: $\{X_n\}_{n \in \mathbb{N}}$ Markov chain with transition matrix P iff
 $\forall n > 0, \forall x_0^n = \{x_0, \dots, x_n\} \in E^{n+1}$,
 $\mathbb{P}(X_n = x_n | X_0^{n-1} = x_0^{n-1}) = \mathbb{P}(X_n = x_n | X_{n-1} = x_{n-1}) = p_{x_n x_{n-1}}$
where $\forall x, y \in E, p_{xy} \geq 0$ and $\sum_{z \in E} p_{xz} = 1$
(i.e. P is a *stochastic matrix*)

- Canonical example
 X_0 independent of $\{Y_n\}_{n \geq 0}$ an i.i.d. sequence, $Y_n \in E'$
For some function $f : E \times E' \rightarrow E$,

$$\forall n \geq 0, X_{n+1} = f(X_n, Y_n)$$

- Illustration: reflected Random Walk on
 $\mathbb{N} : X_{n+1} = \max(0, X_n + Y_n)$

Basic properties

- By induction $\mathbb{P}(X_n^{n+m} = x_n^{n+m}) = \mathbb{P}(X_n = x_n) \prod_{i=n+1}^{n+m} p_{x_{i-1}x_i}$

$$\Rightarrow \mathbb{P}(X_0^{n+m} = x_0^{n+m} | X_n = x_n) = \mathbb{P}(X_0^{n-1} = x_0^{n-1} | X_n = x_n) \times \cdots \\ \cdots \times \mathbb{P}(X_{n+1}^{n+m} = x_{n+1}^{n+m} | X_n = x_n)$$

(past and future independent conditionally on present)

Basic properties

- By induction $\mathbb{P}(X_n^{n+m} = x_n^{n+m}) = \mathbb{P}(X_n = x_n) \prod_{i=n+1}^{n+m} p_{x_{i-1}x_i}$

$$\Rightarrow \mathbb{P}(X_0^{n+m} = x_0^{n+m} | X_n = x_n) = \mathbb{P}(X_0^{n-1} = x_0^{n-1} | X_n = x_n) \times \cdots \\ \cdots \times \mathbb{P}(X_{n+1}^{n+m} = x_{n+1}^{n+m} | X_n = x_n)$$

(past and future independent conditionally on present)

- Noting $p_{x,y}^n = \mathbb{P}(X_n = y | X_0 = x)$, semi-group property:

$$p_{xy}^{n+m} = \sum_{z \in E} p_{xz}^n p_{zy}^m$$

Basic properties

- By induction $\mathbb{P}(X_n^{n+m} = x_n^{n+m}) = \mathbb{P}(X_n = x_n) \prod_{i=n+1}^{n+m} p_{x_{i-1}x_i}$

$$\Rightarrow \mathbb{P}(X_0^{n+m} = x_0^{n+m} | X_n = x_n) = \mathbb{P}(X_0^{n-1} = x_0^{n-1} | X_n = x_n) \times \cdots \\ \cdots \times \mathbb{P}(X_{n+1}^{n+m} = x_{n+1}^{n+m} | X_n = x_n)$$

(past and future independent conditionally on present)

- Noting $p_{x,y}^n = \mathbb{P}(X_n = y | X_0 = x)$, semi-group property:

$$p_{xy}^{n+m} = \sum_{z \in E} p_{xz}^n p_{zy}^m$$

- Linear algebra interpretation

For finite E (e.g. $E = [k]$), Matrix $p^n = n$ -th power of P

Further properties

- Denote $\mathbb{P}_x(\cdot) = \mathbb{P}(\cdot | X_0 = x)$ distribution of chain started at 0

Further properties

- Denote $\mathbb{P}_x(\cdot) = \mathbb{P}(\cdot | X_0 = x)$ distribution of chain started at 0
- Def: $T \in \mathbb{N} \cup \{+\infty\}$ **stopping time** iff
 $\forall n \in \mathbb{N}$, $\{T = n\}$ is $\sigma(X_0^n)$ -measurable, i.e.
 $\exists \phi_n : E^{n+1} \rightarrow \{0, 1\}$ such that $\mathbb{I}_{T=n} = \phi_n(X_0^n)$
- Key example $T_x := \inf\{n > 0 : X_n = x\}$

- Denote $\mathbb{P}_x(\cdot) = \mathbb{P}(\cdot | X_0 = x)$ distribution of chain started at 0
- Def: $T \in \mathbb{N} \cup \{+\infty\}$ **stopping time** iff
 $\forall n \in \mathbb{N}$, $\{T = n\}$ is $\sigma(X_0^n)$ -measurable, i.e.
 $\exists \phi_n : E^{n+1} \rightarrow \{0, 1\}$ such that $\mathbb{I}_{T=n} = \phi_n(X_0^n)$
- Key example $T_x := \inf\{n > 0 : X_n = x\}$
- **Strong Markov property**
Markov chain X_0^∞ with transition matrix P , stopping time T
Then conditionally on $T < +\infty$ and $X_T = x$,
 X_0^T and X_T^∞ independent with $X_T^\infty \sim \mathbb{P}_x$

State x is

- **recurrent** if $\mathbb{P}_x(T_x < +\infty) = 1$
- **positive recurrent** if $\mathbb{E}_x(T_x) < +\infty$
- **null recurrent** if $\mathbb{P}_x(T_x < +\infty) = 1$ & $\mathbb{E}_x(T_x) = +\infty$
- **transient** if not recurrent, i.e. $\mathbb{P}_x(T_x < +\infty) < 1$
- **d -periodic** if $d = \text{GCD}(n \geq 0 : p_{xx}^n > 0)$

State x is

- **recurrent** if $\mathbb{P}_x(T_x < +\infty) = 1$
- **positive recurrent** if $\mathbb{E}_x(T_x) < +\infty$
- **null recurrent** if $\mathbb{P}_x(T_x < +\infty) = 1$ & $\mathbb{E}_x(T_x) = +\infty$
- **transient** if not recurrent, i.e. $\mathbb{P}_x(T_x < +\infty) < 1$
- **d -periodic** if $d = \text{GCD}(n \geq 0 : p_{xx}^n > 0)$

ILLUSTRATION: reflected random walk on \mathbb{N} ,
 $S_{n+1} = \max(0, S_n + Y_n)$

State 0 is

- **positive recurrent** if $\mathbb{E}(Y_n) < 0$
- **transient** if $\mathbb{E}(Y_n) > 0$
- **null recurrent** if $\mathbb{E}(Y_n) = 0$ & $0 < \text{Var}(Y_n) < +\infty$

Decomposition in cycles of recurrent chains

Fix a state x that is recurrent ($\mathbb{P}_x(T_x < +\infty) = 1$),

Let $T_{x,k}$ = instant of k -th visit to state x

\Rightarrow Trajectory X_1^∞ : concatenation of cycles

$$C_k := \{X_n\}_{T_{x,k} < n \leq T_{x,k+1}}$$

Strong Markov property \Rightarrow cycles C_k are i.i.d.

Irreducibility

Markov chain is **irreducible** iff $\forall x, y \in E$,
 $\exists n \in \mathbb{N}, x_0^n \in E^{n+1} \mid x_0 = x, x_n = y \ \& \ \prod_{i=1}^n p_{x_{i-1}x_i} > 0$

i.e., graph on E with directed edge (x, y) iff $p_{xy} > 0$ **strongly connected**

Markov chain is **irreducible** iff $\forall x, y \in E$,
 $\exists n \in \mathbb{N}, x_0^n \in E^{n+1} \mid x_0 = x, x_n = y \ \& \ \prod_{i=1}^n p_{x_{i-1}x_i} > 0$

i.e., graph on E with directed edge (x, y) iff $p_{xy} > 0$ **strongly connected**

EXAMPLE

Standard random walk on graph G irreducible iff G connected

Irreducibility

Markov chain is **irreducible** iff $\forall x, y \in E$,
 $\exists n \in \mathbb{N}, x_0^n \in E^{n+1} \mid x_0 = x, x_n = y \ \& \ \prod_{i=1}^n p_{x_{i-1}x_i} > 0$

i.e., graph on E with directed edge (x, y) iff $p_{xy} > 0$ **strongly connected**

EXAMPLE

Standard random walk on graph G irreducible iff G connected

Proposition

For irreducible chain, if one state x is transient (resp. null recurrent, positive recurrent, d -periodic) then all are

Non-negative measure π on E is **stationary** for P iff

$$\forall x \in E, \pi_x = \sum_{y \in E} \pi_y p_{yx}$$

Non-negative measure π on E is **stationary** for P iff

$$\forall x \in E, \pi_x = \sum_{y \in E} \pi_y p_{yx}$$

Notation: $\mathbb{P}_\nu := \sum_{x \in E} \nu_x \mathbb{P}_x$ chain's distribution when $X_0 \sim \nu$

\Rightarrow For stationary probability distribution π ,

$$\forall n > 0, \mathbb{P}_\pi(X_n^\infty \in \cdot) = \mathbb{P}_\pi(X_0^\infty \in \cdot)$$

Recurrence and stationary measures

Irreducible recurrent chain admits a stationary measure, unique up

to multiplicative factor $\forall y \in E, \pi_y = \mathbb{E}_x \sum_{n=1}^{T_x} \mathbb{I}_{X_n=y}$

Irreducible chain admits a stationary probability distribution iff it is positive recurrent

Limit theorems 1

Recurrence and stationary measures

Irreducible recurrent chain admits a stationary measure, unique up

to multiplicative factor $\forall y \in E, \pi_y = \mathbb{E}_x \sum_{n=1}^{T_x} \mathbb{I}_{X_n=y}$

Irreducible chain admits a stationary probability distribution iff it is positive recurrent

Ergodic theorem

Irreducible, positive recurrent chain satisfies almost sure convergence

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n f(X_k) = \sum_{x \in E} \pi_x f(x)$$

for all π -integrable f , where $\pi =$ unique stationary distribution

Limit theorems 1

Recurrence and stationary measures

Irreducible recurrent chain admits a stationary measure, unique up

to multiplicative factor $\forall y \in E, \pi_y = \mathbb{E}_x \sum_{n=1}^{T_x} \mathbb{I}_{X_n=y}$

Irreducible chain admits a stationary probability distribution iff it is positive recurrent

Ergodic theorem

Irreducible, positive recurrent chain satisfies almost sure convergence

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n f(X_k) = \sum_{x \in E} \pi_x f(x)$$

for all π -integrable f , where $\pi =$ unique stationary distribution

Such chains are called ergodic

Convergence in distribution

Ergodic, aperiodic chain satisfies $\forall x \in E, \lim_{n \rightarrow \infty} \mathbb{P}(X_n = x) = \pi_x$
where π : unique stationary distribution

Convergence in distribution

Ergodic, aperiodic chain satisfies $\forall x \in E, \lim_{n \rightarrow \infty} \mathbb{P}(X_n = x) = \pi_x$
where π : unique stationary distribution

“Converse”

Irreducible, non-ergodic chain satisfies
 $\forall x \in E, \lim_{n \rightarrow \infty} \mathbb{P}(X_n = x) = 0$

Theorem

An irreducible chain such that there exist $V : E \rightarrow \mathbb{R}_+$, a finite set $K \subset E$ and $\epsilon, b > 0$ satisfying

$$\mathbb{E}(V(X_{n+1}) - V(X_n) | X_n = x) \leq \begin{cases} -\epsilon, & x \notin K, \\ b - \epsilon, & x \in K, \end{cases}$$

is then ergodic.

Aloha with finitely many stations

Stations $s \in \mathcal{S}$, $|\mathcal{S}| < \infty$

- New arrivals at station s in slot n : $A_{n,s} \in \mathbb{N}$, $\{A_{n,s}\}_{n \geq 0}$ i.i.d.
- Probability of transmission by s if message in queue: p_s
- Source of randomness: $\{B_{n,s}\}_{n \geq 0}$ i.i.d., Bernoulli(p_s)
- Transmits iff $B'_{n,s} = 0$ where $B'_{n,s} = B_{n,s} \mathbb{I}_{L_{n,s} > 0}$

Aloha with finitely many stations

Stations $s \in \mathcal{S}$, $|\mathcal{S}| < \infty$

- New arrivals at station s in slot n : $A_{n,s} \in \mathbb{N}$, $\{A_{n,s}\}_{n \geq 0}$ i.i.d.
- Probability of transmission by s if message in queue: p_s
- Source of randomness: $\{B_{n,s}\}_{n \geq 0}$ i.i.d., Bernoulli(p_s)
- Transmits iff $B'_{n,s} = 0$ where $B'_{n,s} = B_{n,s} \mathbb{I}_{L_{n,s} > 0}$

Queue dynamics

$$L_{n+1,s} = L_{n,s} + A_{n,s} - B'_{n,s} \prod_{s' \neq s} (1 - B'_{n,s'})$$

Aloha with finitely many stations

Assume $\forall s, 0 < \mathbb{P}(A_{n,s} = 0) < 1$

Then chain is irreducible and aperiodic

Sufficient condition for ergodicity

$$\forall s, \lambda_s := \mathbb{E}(A_{n,s}) < p_s \prod_{s' \neq s} (1 - p_{s'})$$

Sufficient condition for transience

$$\forall s, \lambda_s > p_s \prod_{s' \neq s} (1 - p_{s'})$$

Aloha with finitely many stations

Symmetric case $\lambda_s = \lambda/|\mathcal{S}|$, $p_s \equiv p$:

Recurrence if $\lambda < |\mathcal{S}|p(1-p)^{|\mathcal{S}|-1}$

Transience if $\lambda > |\mathcal{S}|p(1-p)^{|\mathcal{S}|-1}$

\Rightarrow To achieve stability (ergodicity) for fixed λ , need $p \rightarrow 0$ as $|\mathcal{S}| \rightarrow \infty$

Impractical! (Collisions take forever to be resolved)

Aloha with infinitely many stations

Many stations, very rarely active (just one message)

- A_n new messages in interval n , $\{A_n\}_{n \geq 0}$ i.i.d.
- Source of randomness $\{B_{n,i}\}_{n,i \geq 0}$ i.i.d., Bernoulli (p)
- Queue evolution

$$L_{n+1} = L_n + A_n - \mathbb{I}_{\sum_{i=1}^{L_n} B_{n,i}=1}$$

- Assumption $0 < \mathbb{P}(A_n = 0) < 1$ ensures irreducibility (and aperiodicity)

Aloha with infinitely many stations

ABRAMSON'S HEURISTIC ARGUMENT

For $A_n \sim \text{Poisson}(\lambda)$, Nb of attempts per slot $\approx \text{Poisson}(G)$ for unknown G

Hence successful transmission with probability Ge^{-G} per slot

Solution to $\lambda = Ge^{-G}$ exists for all $\lambda < 1/e$

Hence "Aloha should be stable (ergodic) whenever $\lambda < 1/e$ "

Aloha with infinitely many stations

ABRAMSON'S HEURISTIC ARGUMENT

For $A_n \sim \text{Poisson}(\lambda)$, Nb of attempts per slot $\approx \text{Poisson}(G)$ for unknown G

Hence successful transmission with probability Ge^{-G} per slot

Solution to $\lambda = Ge^{-G}$ exists for all $\lambda < 1/e$

Hence “Aloha should be stable (ergodic) whenever $\lambda < 1/e$ ”

Theorem: Instability of Aloha

With probability 1, channel jammed forever ($\sum_{i=1}^{L_n} B_{n,i} > 1$) after finite time. Hence only finite number of messages ever transmitted.

Fixing Aloha: richer feedback

Assumption: L_n known

Backlog-dependent retransmission probability $p_n = 1/L_n$

Then system ergodic if $\lambda := \mathbb{E}(A_n) < \frac{1}{e} \approx 0.368$

Fixing Aloha: richer feedback

Assumption: L_n known

Backlog-dependent retransmission probability $p_n = 1/L_n$

Then system ergodic if $\lambda := \mathbb{E}(A_n) < \frac{1}{e} \approx 0.368$

Denote $J_n = \{0, 1, *\}$ outcome of n -th channel use
(0: no transmission. 1: single successful transmission. *: collision)

Fixing Aloha: richer feedback

Assumption: L_n known

Backlog-dependent retransmission probability $p_n = 1/L_n$

Then system ergodic if $\lambda := \mathbb{E}(A_n) < \frac{1}{e} \approx 0.368$

Denote $J_n = \{0, 1, *\}$ outcome of n -th channel use
(0: no transmission. 1: single successful transmission. *: collision)

Weaker assumption: channel state J_n heard by all stations

Backlog-dependent retransmission probability $p_n = 1/\hat{L}_n$, where estimate \hat{L}_n computed by

$$\hat{L}_{n+1} = \max(1, \hat{L}_n + \alpha \mathbb{I}_{J_n=*} - \beta \mathbb{I}_{J_n=0})$$

renders Markov chain $(L_n, \hat{L}_n)_{n \geq 0}$ ergodic for suitable $\alpha, \beta > 0$ if $\lambda := \mathbb{E}(A_n) < \frac{1}{e} \approx 0.368$

Fixing Aloha: richer feedback

With same ternary feedback $J_n = \{0, 1, *\}$, can stability hold for $\lambda > 1/e$?

Yes: rather intricate protocols have been invented and shown to achieve stability up to $\lambda = 0.487$

Largest λ for which some protocol based on this feedback is stable? Unknown (only bounds)

Ethernet and variants

Return to Acknowledgement-based feedback (only listen channel's state after transmission)

Variant of exponential backoff: transmit with probability 2^{-k} after k collisions

Assume $A_n \sim \text{Poisson}(\lambda)$

Ethernet and variants

Return to Acknowledgement-based feedback (only listen channel's state after transmission)

Variant of exponential backoff: transmit with probability 2^{-k} after k collisions

Assume $A_n \sim \text{Poisson}(\lambda)$

Theorem: instability of Ethernet's variant

For any $\lambda > 0$, (modification of) Ethernet is transient.

Ethernet and variants

Return to Acknowledgement-based feedback (only listen channel's state after transmission)

Variant of exponential backoff: transmit with probability 2^{-k} after k collisions

Assume $A_n \sim \text{Poisson}(\lambda)$

Theorem: instability of Ethernet's variant

For any $\lambda > 0$, (modification of) Ethernet is transient.

Weaker performance guarantees

Ethernet and its modification are such that with probability 1:

For $\lambda < \ln(2) \approx 0.693$, infinite number of messages is transmitted

For $\lambda > \ln(2)$, only finitely many messages are transmitted

Ethernet and variants

Return to Acknowledgement-based feedback (only listen channel's state after transmission)

Variant of exponential backoff: transmit with probability 2^{-k} after k collisions

Assume $A_n \sim \text{Poisson}(\lambda)$

Theorem: instability of Ethernet's variant

For any $\lambda > 0$, (modification of) Ethernet is transient.

Weaker performance guarantees

Ethernet and its modification are such that with probability 1:

For $\lambda < \ln(2) \approx 0.693$, infinite number of messages is transmitted

For $\lambda > \ln(2)$, only finitely many messages are transmitted

Unsolved conjecture

No acknowledgement-based scheme can induce a stable (ergodic) system for any $\lambda > 0$.

Conclusions on Random Access Protocols

Mostly negative results in theory, both for Aloha and Ethernet, yet...

...In practice, Ethernet and Wi-Fi's 802.11x protocols perform well

Conclusions on Random Access Protocols

Mostly negative results in theory, both for Aloha and Ethernet, yet...

...In practice, Ethernet and Wi-Fi's 802.11x protocols perform well

- Finite number of stations helps
- Time to instability could be huge (“metastable” behavior)
- Only small fraction of channel time used for random access collision resolution:
Once station “wins” channel access, others wait till its transmission is over

Conclusions on Random Access Protocols

Mostly negative results in theory, both for Aloha and Ethernet, yet...

...In practice, Ethernet and Wi-Fi's 802.11x protocols perform well

- Finite number of stations helps
- Time to instability could be huge (“metastable” behavior)
- Only small fraction of channel time used for random access collision resolution:
Once station “wins” channel access, others wait till its transmission is over

→ Alternative protocols based on ternary feedback have not been used

Takeaway messages

- Markov chain theory: framework for system and algorithm performance analysis

Takeaway messages

- Markov chain theory: framework for system and algorithm performance analysis
- Ergodicity (stability) analysis:
 - Determines for what demands system stabilizes into steady state
 - A “first order” performance index (know when delays remain stable, not their magnitude)

Takeaway messages

- Markov chain theory: framework for system and algorithm performance analysis
- Ergodicity (stability) analysis:
 - Determines for what demands system stabilizes into steady state
 - A “first order” performance index (know when delays remain stable, not their magnitude)
- Foster-Lyapunov criteria to prove ergodicity

Takeaway messages

- Markov chain theory: framework for system and algorithm performance analysis
- Ergodicity (stability) analysis:
 - Determines for what demands system stabilizes into steady state
 - A “first order” performance index (know when delays remain stable, not their magnitude)
- Foster-Lyapunov criteria to prove ergodicity
- Simple questions on performance of Random Access yet unsolved, and results more negative than positive

Takeaway messages

- Markov chain theory: framework for system and algorithm performance analysis
- Ergodicity (stability) analysis:
 - Determines for what demands system stabilizes into steady state
 - A “first order” performance index (know when delays remain stable, not their magnitude)
- Foster-Lyapunov criteria to prove ergodicity
- Simple questions on performance of Random Access yet unsolved, and results more negative than positive
- Still, analysis of Aloha has led to new insights and new designs such as Ethernet