

Distributed Computing

Nitin Vaidya

Distributed computing in Nature

What is distributed computing?

A distributed system is one in which the failure of a computer you didn't even know existed can render your own computer unusable.

Leslie Lamport

What is distributed computing?

Parallel computing versus *distributed* computing

Example:

To add N numbers where N very large
use 4 processors, each adding up $N/4$,
then add the 4 partial sums

Parallel or distributed ?

What is distributed computing?

- *Parallel* computing versus *distributed* computing
- Role of uncertainty in distributed systems
 - Clock drift
 - Network delays
 - Network losses
 - Asynchrony
 - Failures

Clocks

- Notion of *time* very useful in real life, and so it is in distributed systems
- Example ...

Submit programming assignment
by e-mail by **11:59 pm Monday**

Clocks

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- Example ...

Submit programming assignment
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By which clock ?

Clocks

- Notion of *time* very useful in real life, and so it is in distributed systems
- Example ...

Submit programming assignment
by e-mail by **11:59 pm Monday**

If it reaches at 12:01, how do we
know it was sent by 11:59 pm?

How to synchronize clocks?

How to synchronize clocks?

Role of delay uncertainty

Ordering of Events

- If we can't have “perfectly” synchronized clocks, can we still accurately determine *what happened first?*

Distribute Storage

How to improve system availability?

- Potentially large network delays ... network partition
- Failures

Replication is a common approach

- If data stored only in one place, far away user will incur significant access delay

➔ Store data in multiple replicas,

Clients prefer to access “closest” replica

Replicated Storage

- How to keep replicas “consistent” ?
- What does “consistent” really mean?

Consistency Model

- Since shared memory may be accessed by different processes concurrently, we need to define how the updates are observed by the processes
- *Consistency model* captures these requirements

Consistency #1

Alice: My cat was hit by a car.

Alice: But luckily she is fine.

Bob: That's great!

What should Calvin observe?

Consistency #1

Alice: My cat was hit by a car.

Alice: But luckily she is fine.

Bob: That's great!

What should Calvin observe?

Consistency #2

Alice: My cat was hit by a car.

Alice: But luckily she is fine.

Bob: That's terrible!

What should Calvin observe?

Agreement

- Where to meet for dinner?

Agreement with Failure

- Non-faulty nodes must agree

Agreement with Crash Failure & Asynchrony

What if nodes misbehave?

- Crash failures are benign
- Other extreme ... Byzantine failures

“Local” Algorithms

Consensus

- Each node has an input (scalar or vector)

Consensus

- Each node has an input (scalar or vector)
- Consensus: **Output in *convex hull* of the inputs**

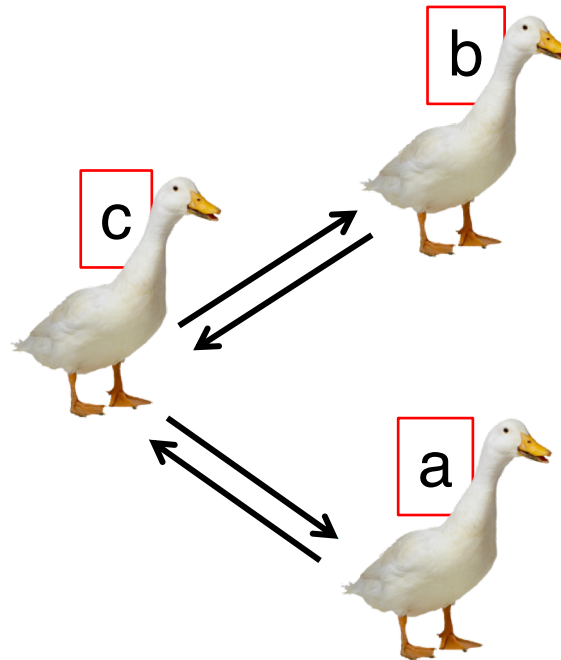
Consensus



Consensus

Initially, state = input

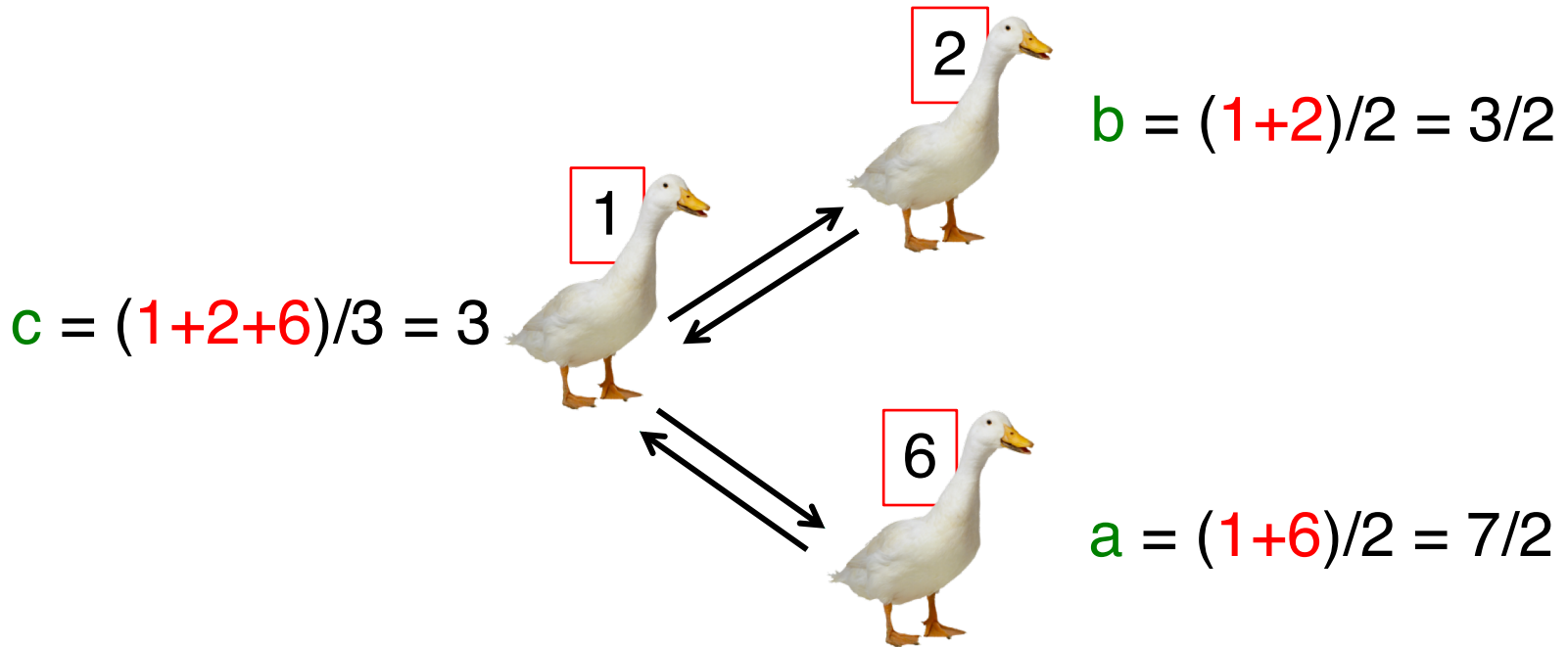
$$c = (a+b+c)/3$$



$$b = (b+c)/2$$

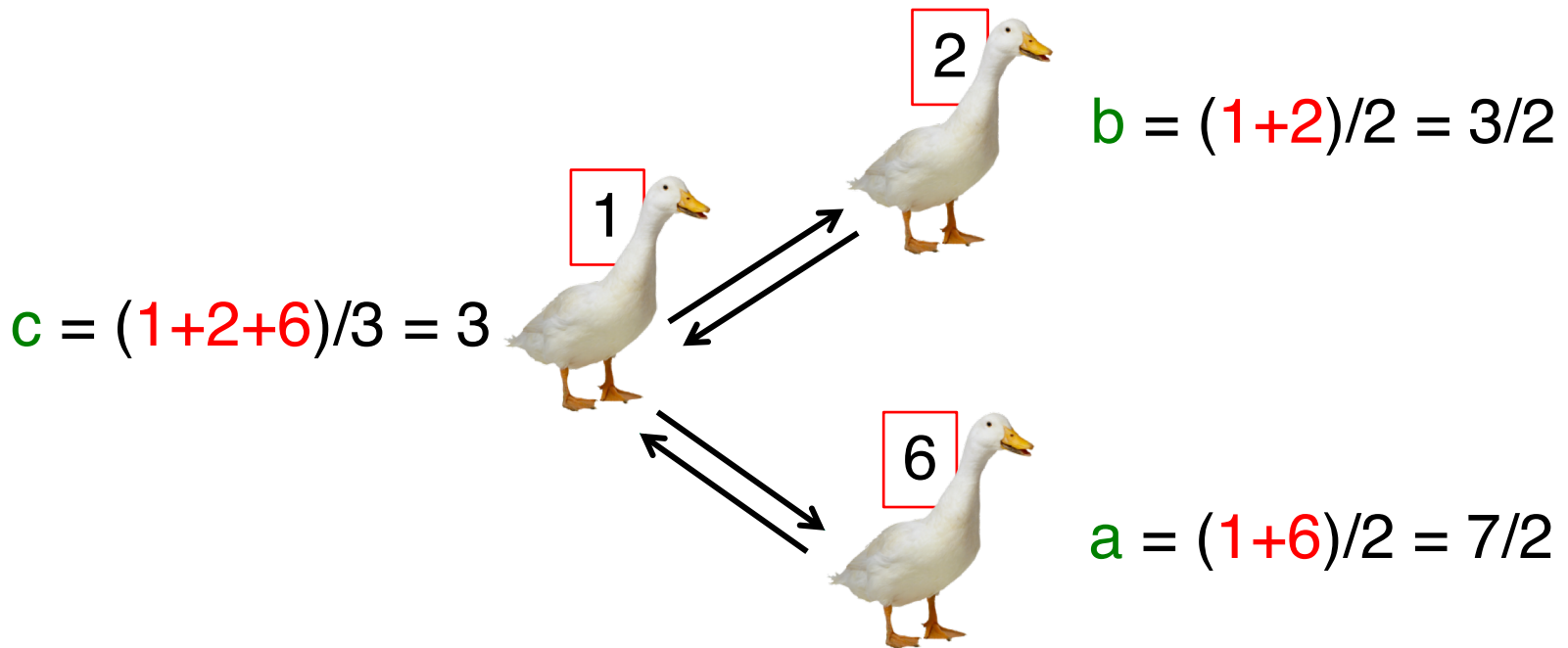
$$a = (a+c)/2$$

Consensus



Consensus

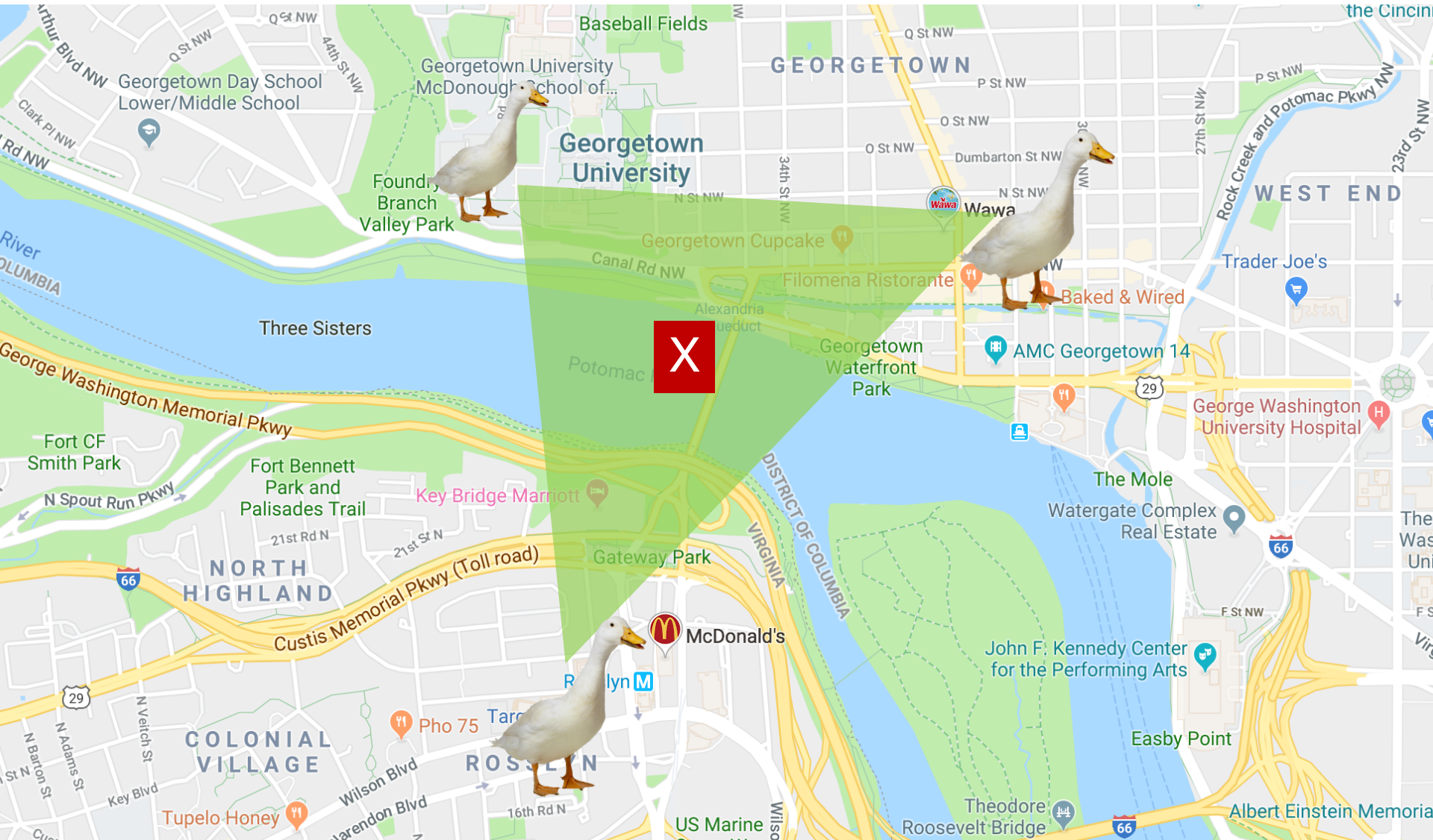
As time $\rightarrow \infty$, values become identical



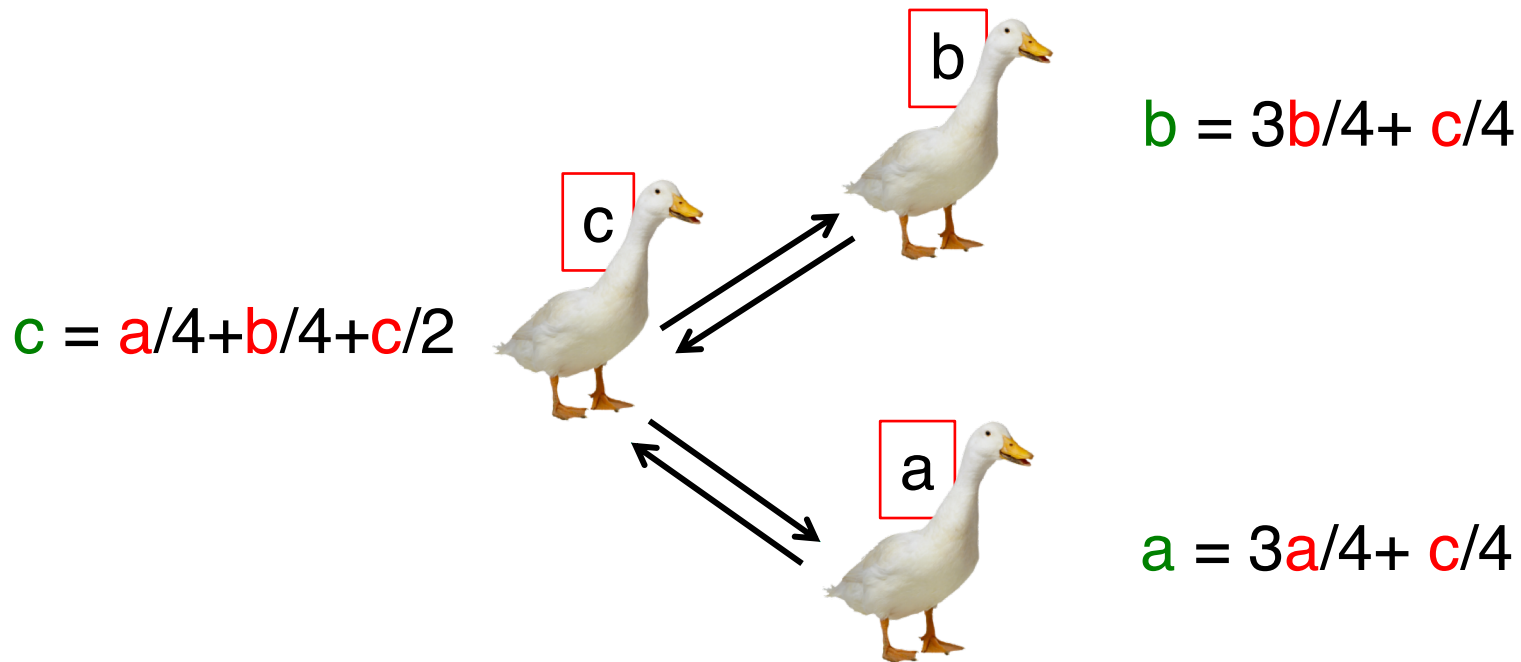
Average Consensus

- Each node has an input (scalar or vector)
- Average consensus: **Output = average of inputs**

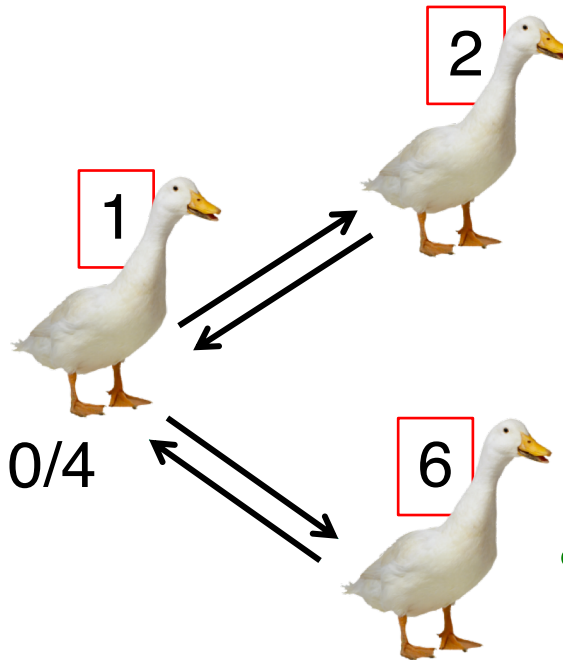
Average Consensus



Average Consensus Change of Weights



Average Consensus



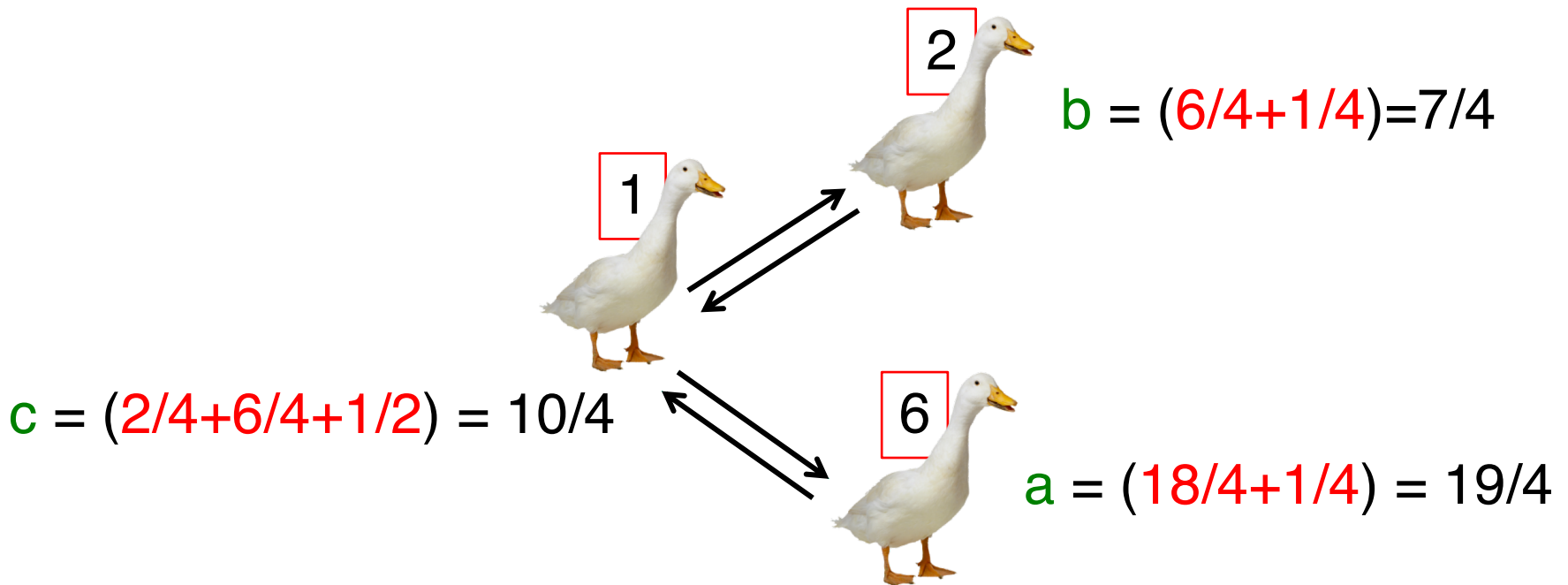
$$b = (6/4 + 1/4) = 7/4$$

$$a = (18/4 + 1/4) = 19/4$$

$$c = (2/4 + 6/4 + 1/2) = 10/4$$

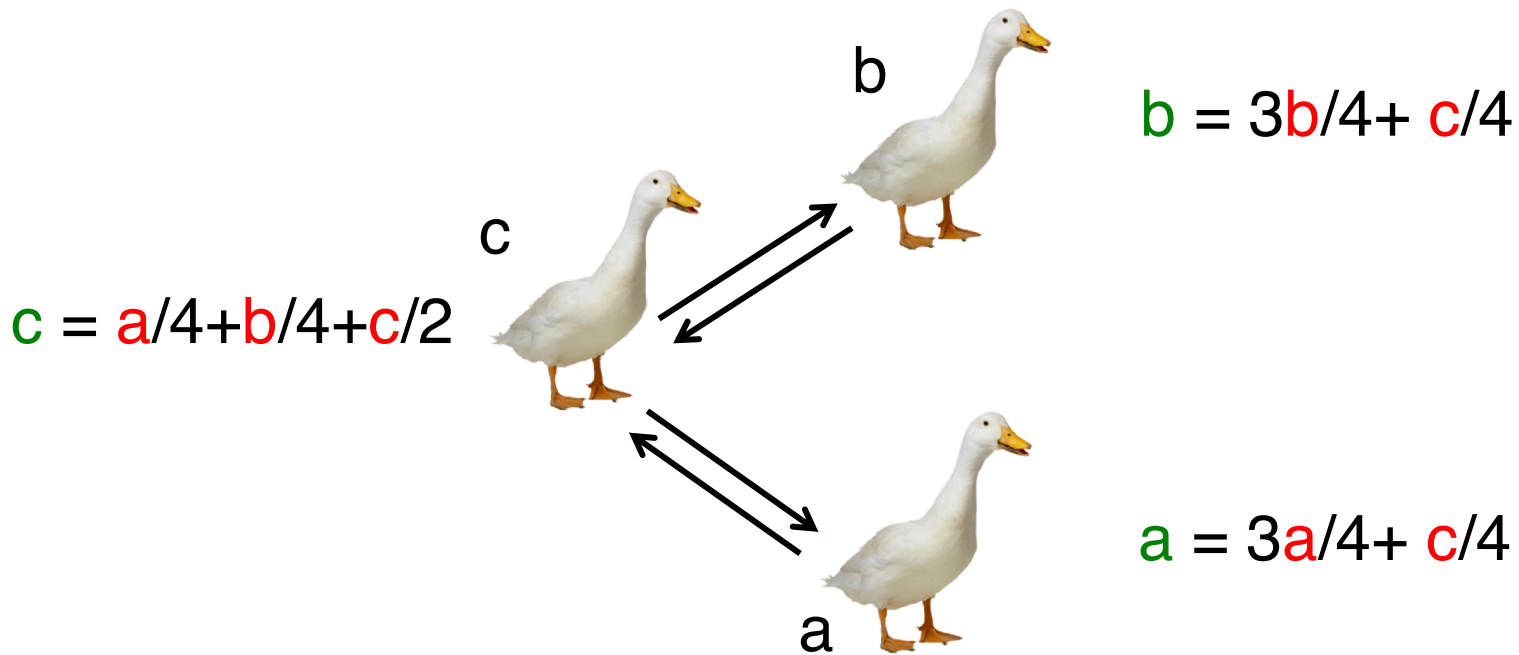
Average Consensus

As time $\rightarrow \infty$, values converge to *average* of inputs



$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := \begin{pmatrix} 3/4 & 0 & 1/4 \\ 0 & 3/4 & 1/4 \\ 1/4 & 1/4 & 1/2 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \mathbf{M} \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

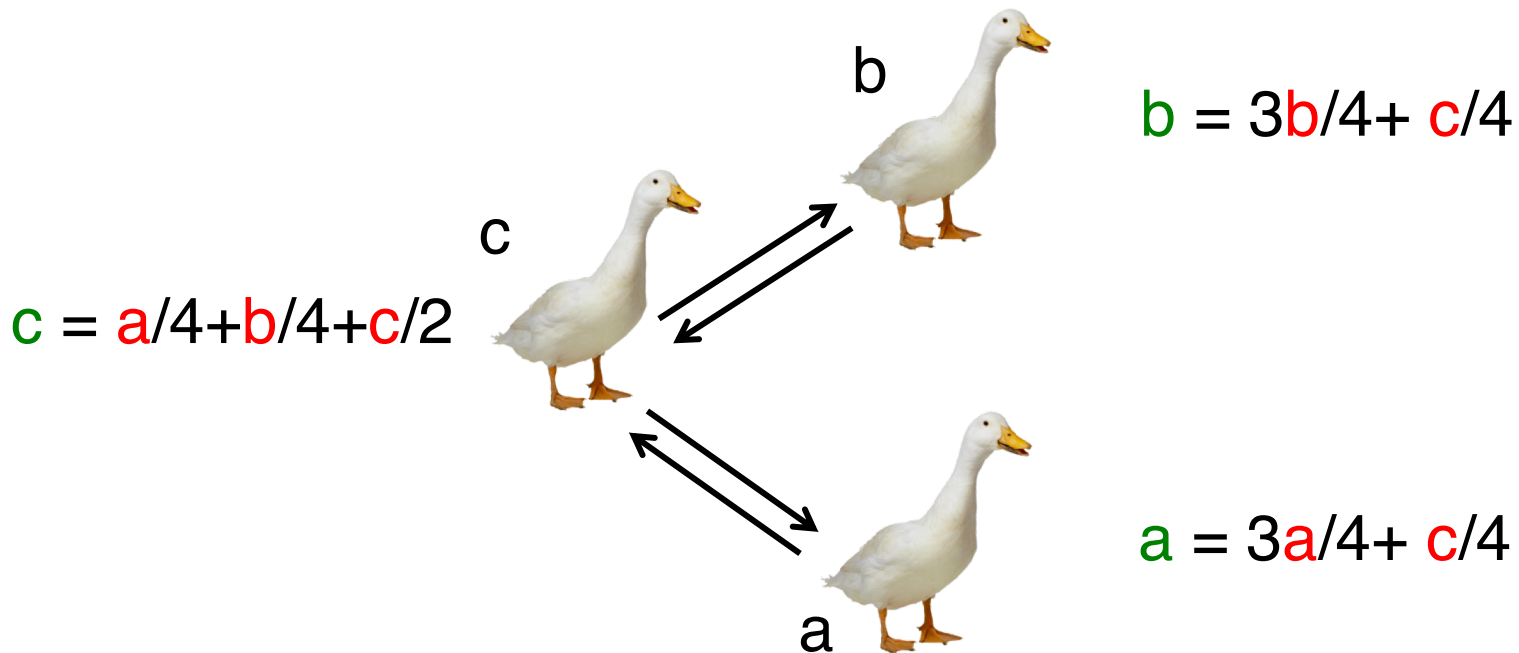
M



after 2 iterations

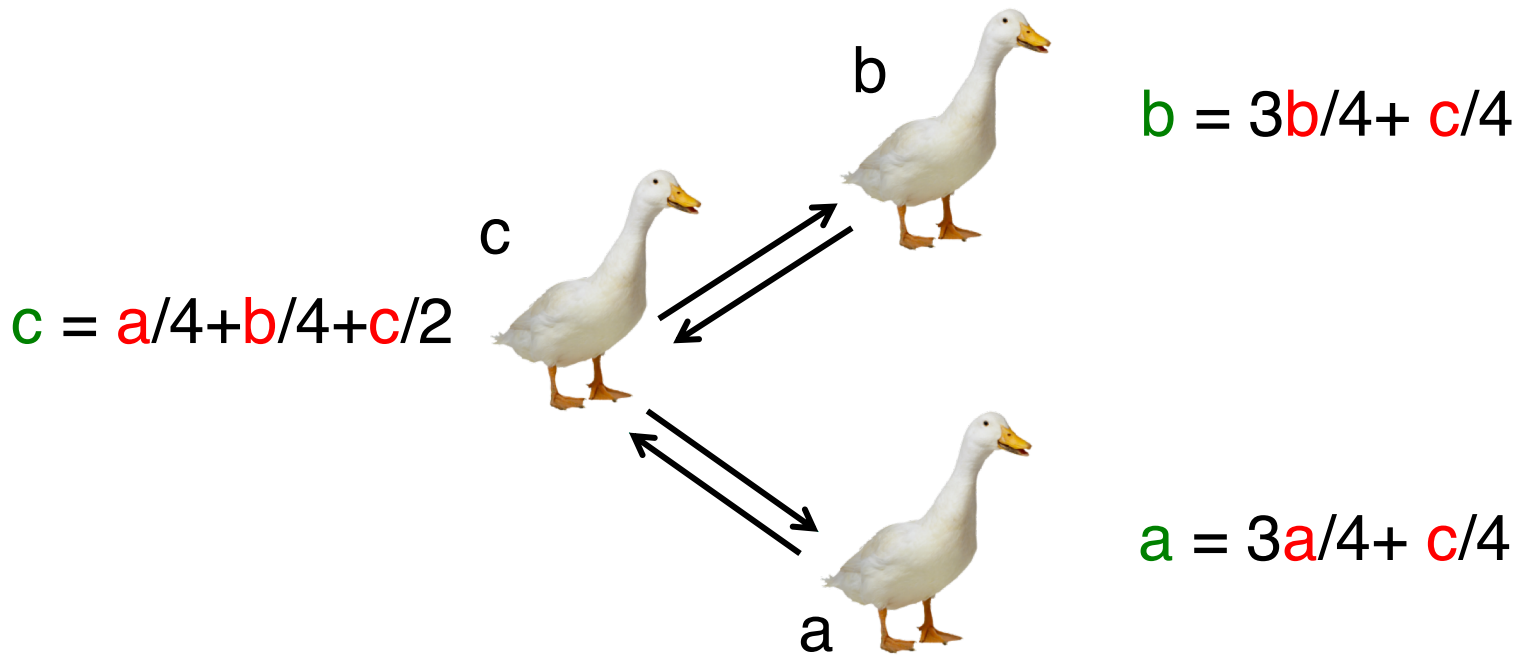
after 1 iteration

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M \left[M \begin{pmatrix} a \\ b \\ c \end{pmatrix} \right] = M^2 \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$



after k iterations

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M^k \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$



Connected Undirected Graphs

after k iterations

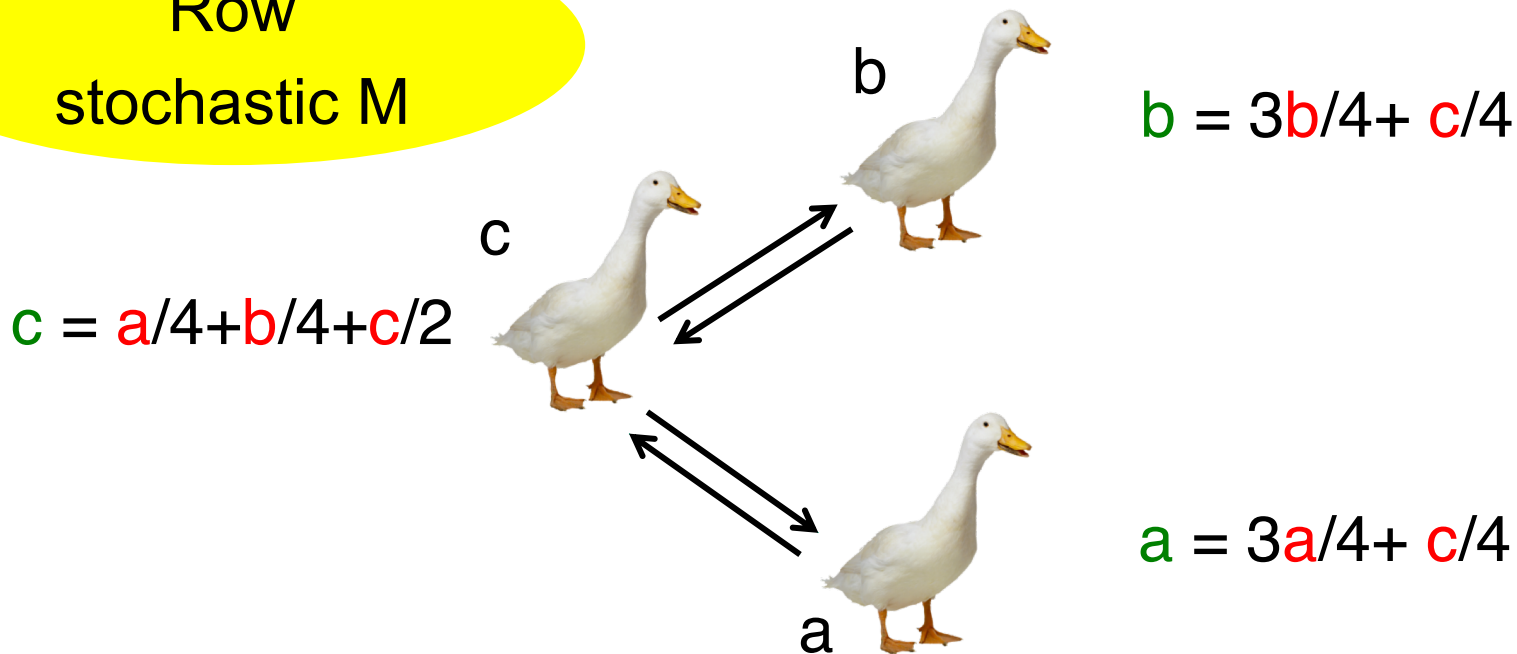
$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M^k \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

■ Consensus if M row stochastic

- Matrix elements in $[0,1]$
- M_{ij} non-zero if link (i,j) exists
- Each row adds to 1

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M^k \begin{pmatrix} a \\ b \\ c \end{pmatrix} \rightarrow \begin{pmatrix} p & q & r \\ p & q & r \\ p & q & r \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

Row
stochastic M



Row
stochastic M

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

Due to stochastic rows,
each new state
in convex hull
of old states

Connected Undirected Graphs

after k iterations

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M^k \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

■ *Average consensus*

if M doubly stochastic

- Matrix elements in $[0,1]$
- M_{ij} non-zero if link (i,j) exists
- Each **row** & each **column** adds to 1

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := \begin{pmatrix} 3/4 & 0 & 1/4 \\ 0 & 3/4 & 1/4 \\ 1/4 & 1/4 & 1/2 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \mathbf{M} \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

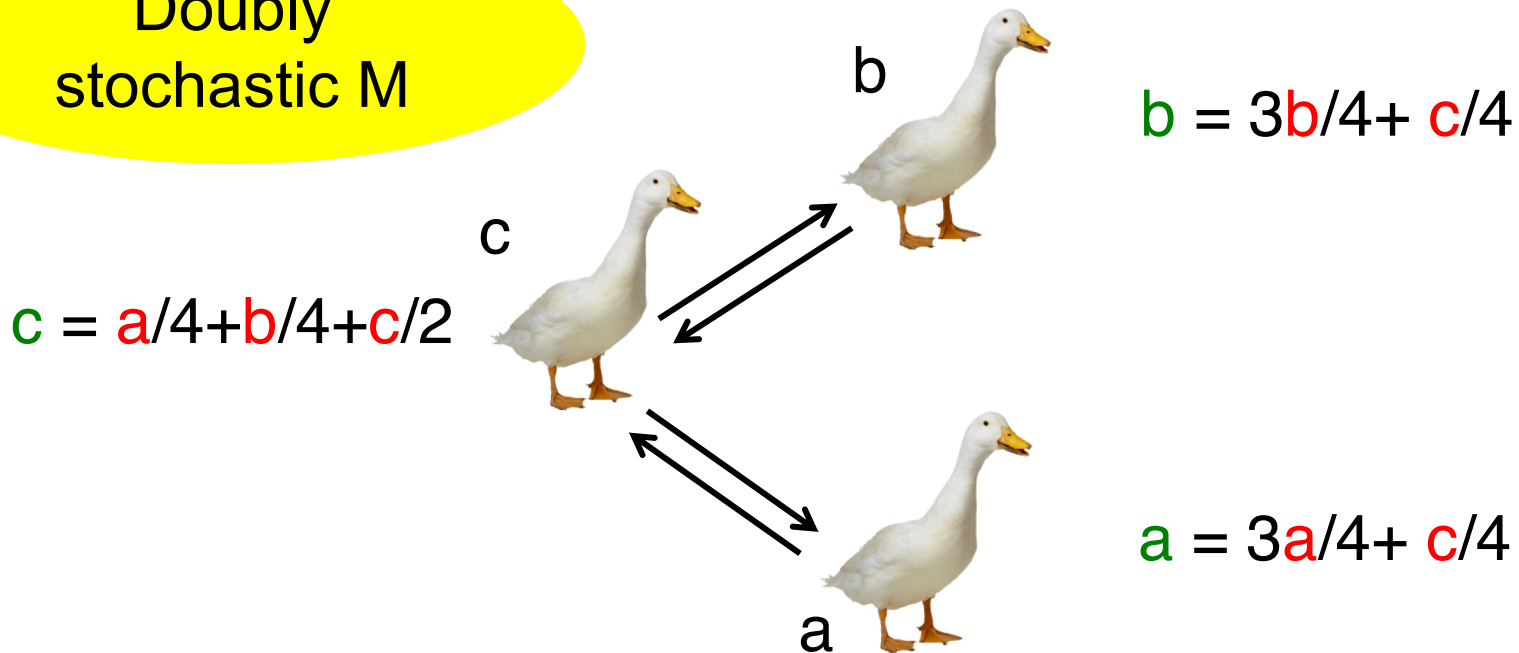
\mathbf{M}

Due to stochastic rows,
each new state
in convex hull
of old states

Due to stochastic columns,
total “mass”
(sum of states)
is preserved

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} := M^k \begin{pmatrix} a \\ b \\ c \end{pmatrix} \rightarrow \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

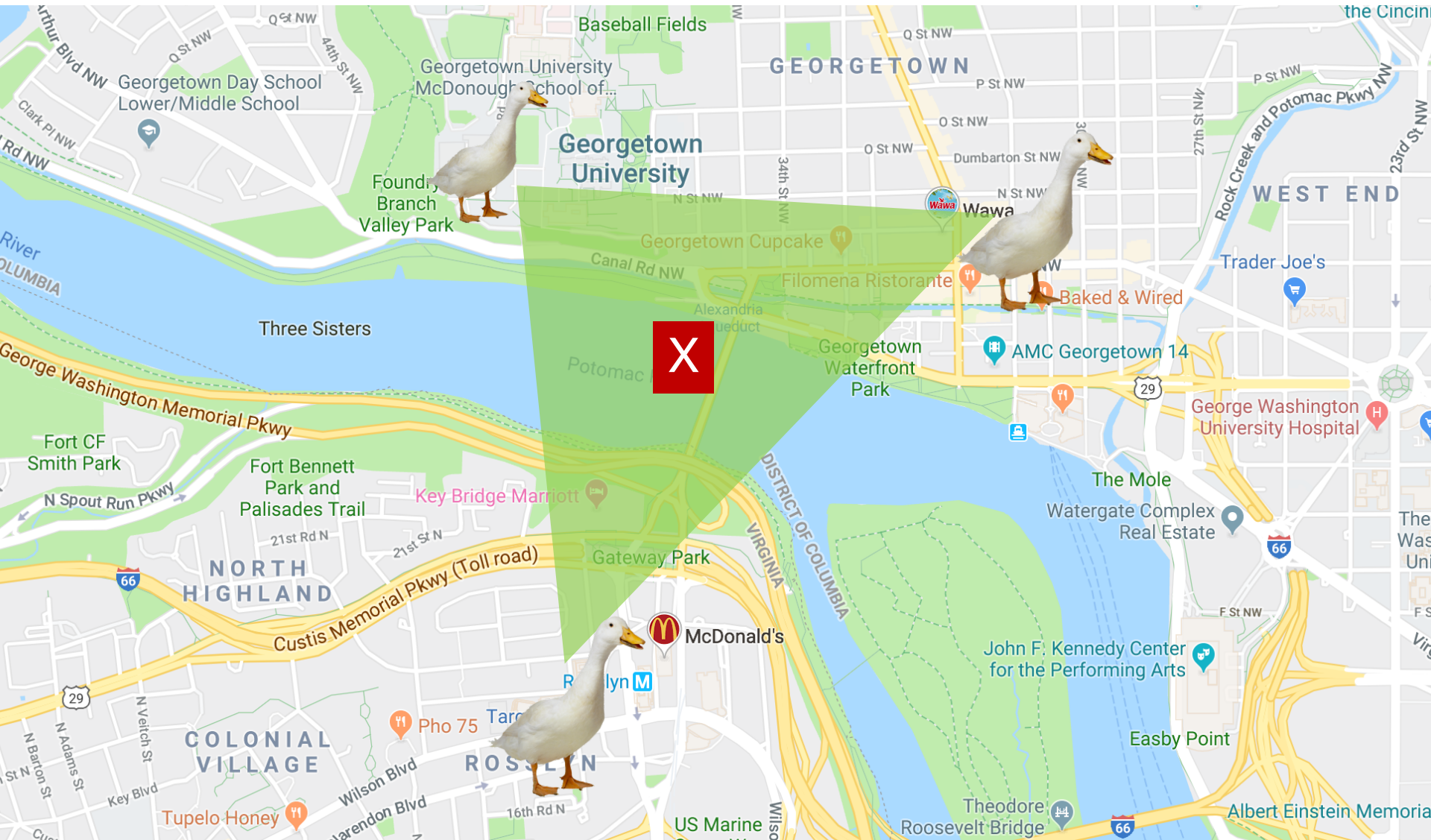
Doubly
stochastic M



Consensus



Average Consensus



Optimization

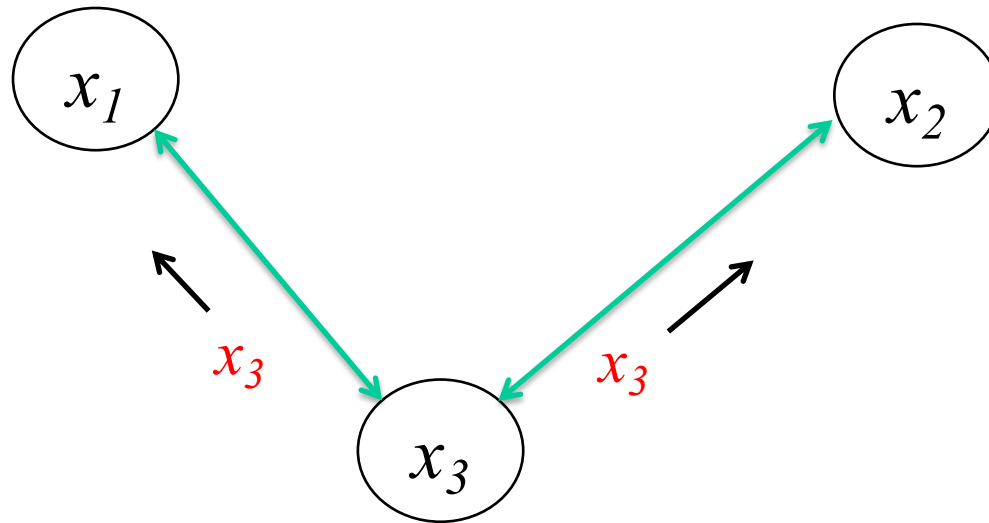
$$\operatorname{argmin} \sum f_i(x)$$



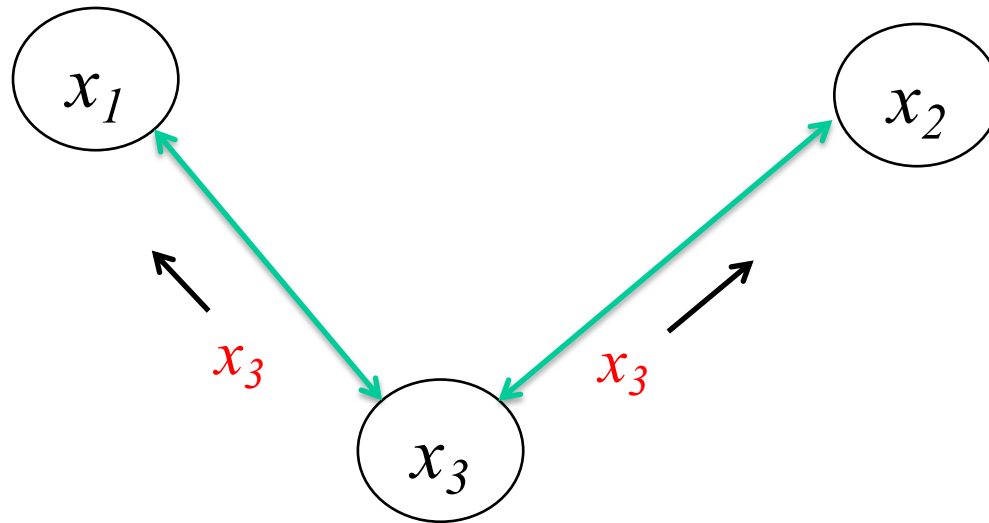
Distributed Optimization

$$f(x) = \sum f_i(x)$$

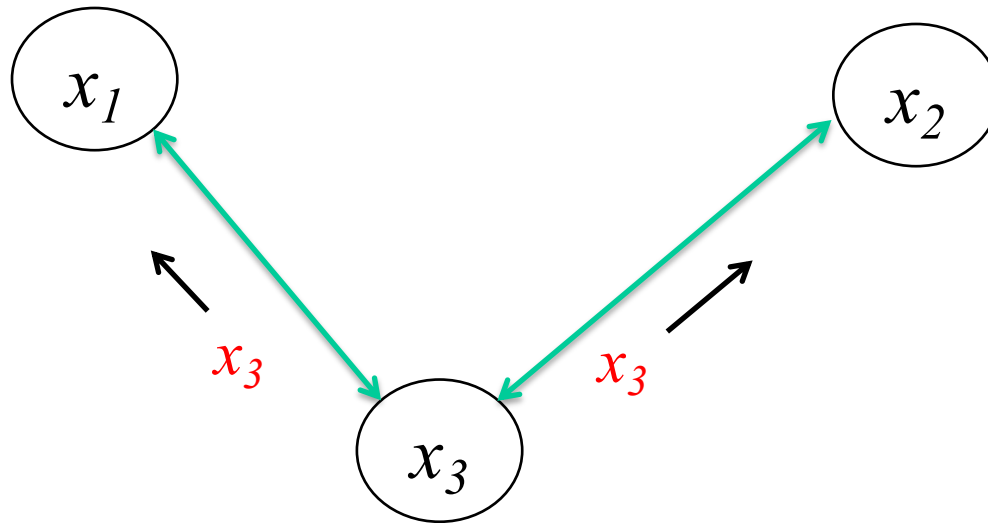
- Each agent maintains an estimate
- Local estimates shared with neighbors & updated
- Estimates converge to optimum



Example based on [Nedic and Ozdaglar, 2009]

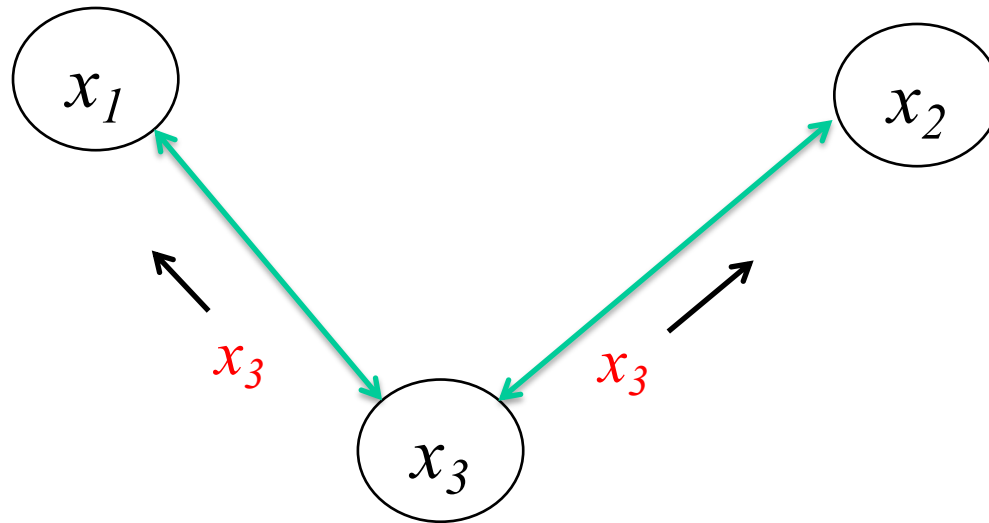


$$x_1 \leftarrow \frac{2}{3}x_1 + \frac{1}{3}x_3 - \alpha \nabla f_1(x_1)$$



$$x_1 \leftarrow \frac{2}{3}x_1 + \frac{1}{3}x_3 - \alpha \nabla f_1(x_1)$$

$$x_3 \leftarrow \frac{1}{3}x_1 + \frac{1}{3}x_2 + \frac{1}{3}x_3 - \alpha \nabla f_3(x_3)$$



$$x_1[t+1] \leftarrow \frac{2}{3}x_1[t] + \frac{1}{3}x_3[t] - \alpha \nabla f_1(x_1[t])$$

$$x_3[t+1] \leftarrow \frac{1}{3}x_1[t] + \frac{1}{3}x_2[t] + \frac{1}{3}x_3[t] - \alpha \nabla f_3(x_3[t])$$

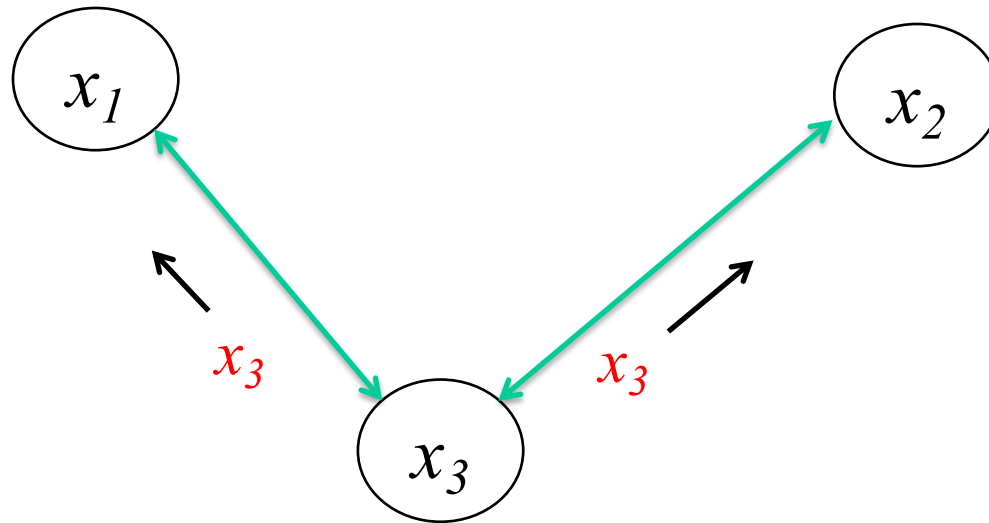
Distributed Optimization

As time $\rightarrow \infty$

- **Consensus:** All agents converge to same estimate

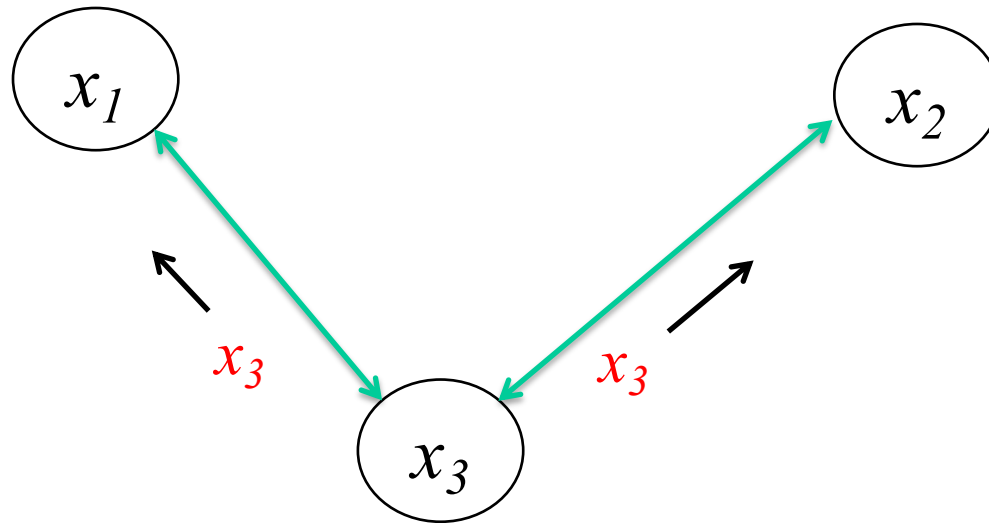
- **Optimality**

$$\operatorname{argmin} \sum f_i(x)$$



$$x_1 \leftarrow \frac{2}{3}x_1 + \frac{1}{3}x_3 - \alpha \nabla f_1(x_1)$$

$$x_3 \leftarrow \frac{1}{3}x_1 + \frac{1}{3}x_2 + \frac{1}{3}x_3 - \alpha \nabla f_3(x_3)$$



$$x_1[t + 1] \leftarrow \frac{2}{3}x_1[t] + \frac{1}{3}x_3[t] - \alpha \nabla f_1(x_1[t])$$

$$x_3[t + 1] \leftarrow \frac{1}{3}x_1[t] + \frac{1}{3}x_2[t] + \frac{1}{3}x_3[t] - \alpha \nabla f_3(x_3[t])$$

$$\begin{bmatrix} x_3[t] \\ x_3[t] \\ x_3[t] \end{bmatrix}$$



$$\begin{bmatrix} f_1(x_1[t]) \\ f_2(x_2[t]) \\ f_3(x_3[t]) \end{bmatrix}$$



$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x_1[t + 1] \leftarrow \frac{2}{3}x_1[t] + \frac{1}{3}x_3[t] - \alpha_t \nabla f_1(x_1[t])$$

$$x_3[t + 1] \leftarrow \frac{1}{3}x_1[t] + \frac{1}{3}x_2[t] + \frac{1}{3}x_3[t] - \alpha_t \nabla f_3(x_3[t])$$



$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

Doubly
stochastic
M

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[2] \leftarrow M x[1] - \alpha_1 \nabla f(x[1])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[2] \leftarrow M x[1] - \alpha_1 \nabla f(x[1])$$

$$= M^2 x[0] - \alpha_0 M \nabla f(x[0]) - \alpha_1 \nabla f(x[1])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[2] \leftarrow M x[1] - \alpha_1 \nabla f(x[1])$$

$$= M^2 x[0] - \alpha_0 M \nabla f(x[0]) - \alpha_1 \nabla f(x[1])$$

$$x[3] \leftarrow M x[2] - \alpha_2 \nabla f(x[2])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[2] \leftarrow M x[1] - \alpha_1 \nabla f(x[1])$$

$$= M^2 x[0] - \alpha_0 M \nabla f(x[0]) - \alpha_1 \nabla f(x[1])$$

$$x[3] \leftarrow M x[2] - \alpha_2 \nabla f(x[2])$$

$$= M^3 x[0]$$

$$- \alpha_0 M^2 \nabla f(x[0]) - \alpha_1 M \nabla f(x[1]) - \alpha_2 \nabla f(x[2])$$

$$x[t + 1] \leftarrow M x[t] - \alpha_t \nabla f(x[t])$$

$$x[1] \leftarrow M x[0] - \alpha_0 \nabla f(x[0])$$

$$x[2] \leftarrow M x[1] - \alpha_1 \nabla f(x[1])$$

$$= M^2 x[0] - \alpha_0 M \nabla f(x[0]) - \alpha_1 \nabla f(x[1])$$

$$x[3] \leftarrow M x[2] - \alpha_2 \nabla f(x[2])$$

$$= M^3 x[0]$$

$$- \alpha_0 M^2 \nabla f(x[0]) - \alpha_1 M \nabla f(x[1]) - \alpha_2 \nabla f(x[2])$$

Claims

- Estimates at different nodes converge → Consensus
- The estimates converges to $\text{argmin} \sum f_i(x)$