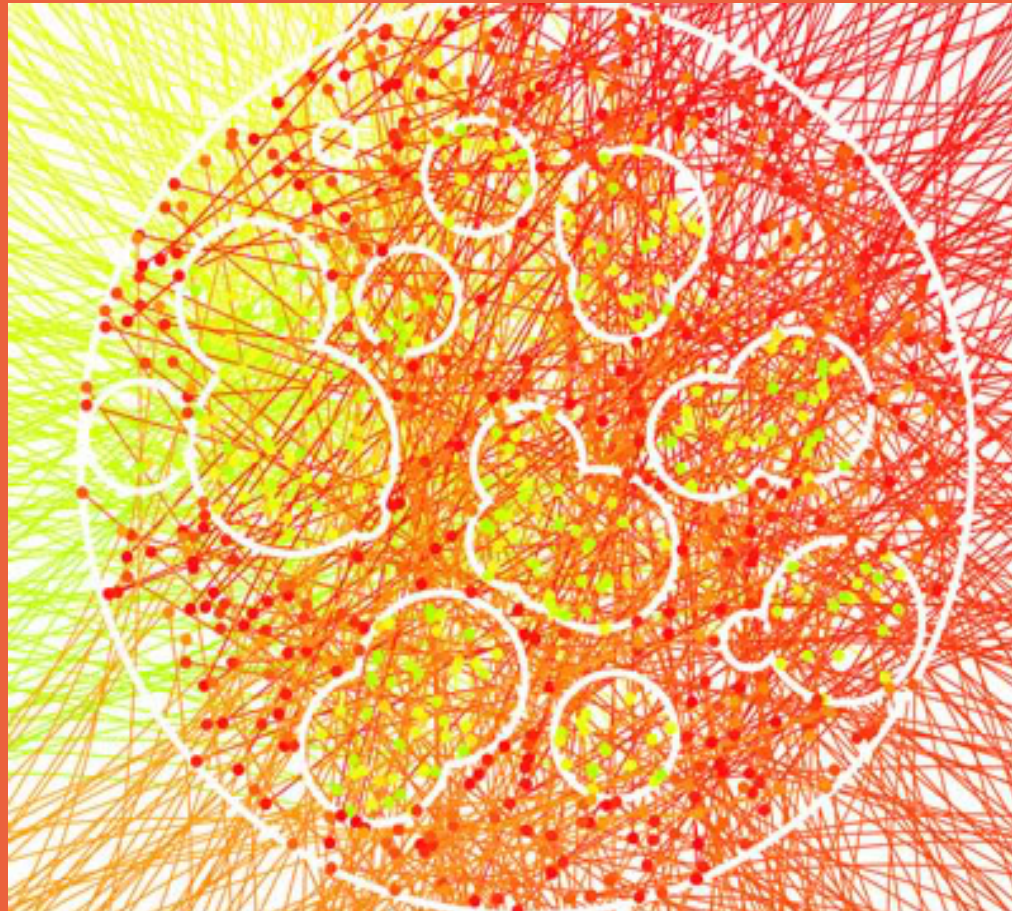


# MONTE CARLO METHODS



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CCD 09/12/2009

# STOCHASTIC ALGORITHMS

PROBLEM = GET OUTPUT FROM INPUT THROUGH AN ALGORITHM

Deterministic algorithm:

$\text{Input}_1 \longrightarrow \text{Output}_1$

Stochastic algorithm:

$\text{Input}_1 + \text{random decision} \begin{cases} \longrightarrow \text{Output}_1 \\ \longrightarrow \text{Output}_2 \\ \longrightarrow \text{Output}_3 \\ \dots \end{cases}$

Example of probabilistic methods:

- **Monte Carlo**: the given results has a probability  $p < 1$  to be the correct solution.
- **Las Vegas**: gives the correct solution or informs that it could not be obtained.

# STOCHASTIC METHODS WITH COMPUTERS? HOW?

Stochastic method = generating random number + performing operation

$$N \rightarrow \infty \Rightarrow t \rightarrow \infty$$

Computers make operations much faster.

Computer are deterministic, no random numbers.

Solution: *pseudo-random numbers*.

## PSEUDO-RANDOM NUMBERS

Finite (but large) lists of numbers generated by an algorithm.

No correlations between the numbers.

Examples:

- *Numerical Recipes*.
- *MKL* (optimized for *iFort*)
- <http://www.psychicscience.org/random.aspx>

*ran2* (Numerical Recipes)

- For any *Fortran* or *C* compiler.
- The authors offer \$1000 to the first person who finds a statistical test that proves that *ran2* fails.

# MONTE CARLO METHODS

## Definition:

Iterative method including random decisions that gives the correct solution of a problem with a certain probability  $< 1$ .



Named after the district of Monte Carlo (Monaco), European gambling capital.



Monte Carlo



Monte Carlo casino

## Origin:

Study of the diffusion of neutrons in a fusion experiment (Los Álamos Laboratory).



## TYPICAL MONTE CARLO METHOD

Input parameters +  $\xi_i \rightarrow x_i$

$$X = \frac{1}{N} \sum_{i=1}^N x_i$$

## CENTRAL LIMIT THEOREM

$\rho(x) =$  Any probability density function with average  $\mu$  and variance  $\sigma^2$ .  
 $x_1, x_2, \dots, x_N =$  collection of  $N$  values sampled through  $\rho$ .

Then, the probability density distribution  $\rho_N(X)$ , which elements are

$$X_N = \frac{1}{N} \sum_{i=1}^N x_i \text{ has a average of } \mu \text{ and a variance of } \frac{\sigma^2}{N}.$$

## LAW OF LARGE NUMBERS

$$N \rightarrow \infty \Rightarrow \rho_N \rightarrow \text{gaussian.}$$



## HOW TO CALCULATE THE ERROR IN A MONTE CARLO METHOD

$$(N \rightarrow \infty)$$

- Fit all calculated  $x_i$  to a gaussian distribution and obtain  $\sigma$ . Let us call the correct solution of the problem  $\mu$ . Then:
- $X \in \left[ \mu - \frac{\sigma}{\sqrt{N}}, \mu + \frac{\sigma}{\sqrt{N}} \right]$  with  $p = 0.682$ .
- $X \in \left[ \mu - 2 \frac{\sigma}{\sqrt{N}}, \mu + 2 \frac{\sigma}{\sqrt{N}} \right]$  with  $p = 0.954$ .
- $X \in \left[ \mu - 3 \frac{\sigma}{\sqrt{N}}, \mu + 3 \frac{\sigma}{\sqrt{N}} \right]$  with  $p = 0.998$ .
- If the accuracy is not enough, increase  $N$  (the error decreases as  $\sim \frac{1}{\sqrt{N}}$ ).

RESULTS FROM MONTE CARLO SIMULATIONS HAVE ERRORS!

## MONTÉ CARLO EXAMPLE I: CALCULATING THE TV SHARE

Survey among a small group of people.

$x_i$  = percentage of time that a certain TV channel is watched by a person.

$$X = \frac{1}{N} \sum_{i=1}^N x_i = \text{Monte Carlo estimation of the Share.}$$

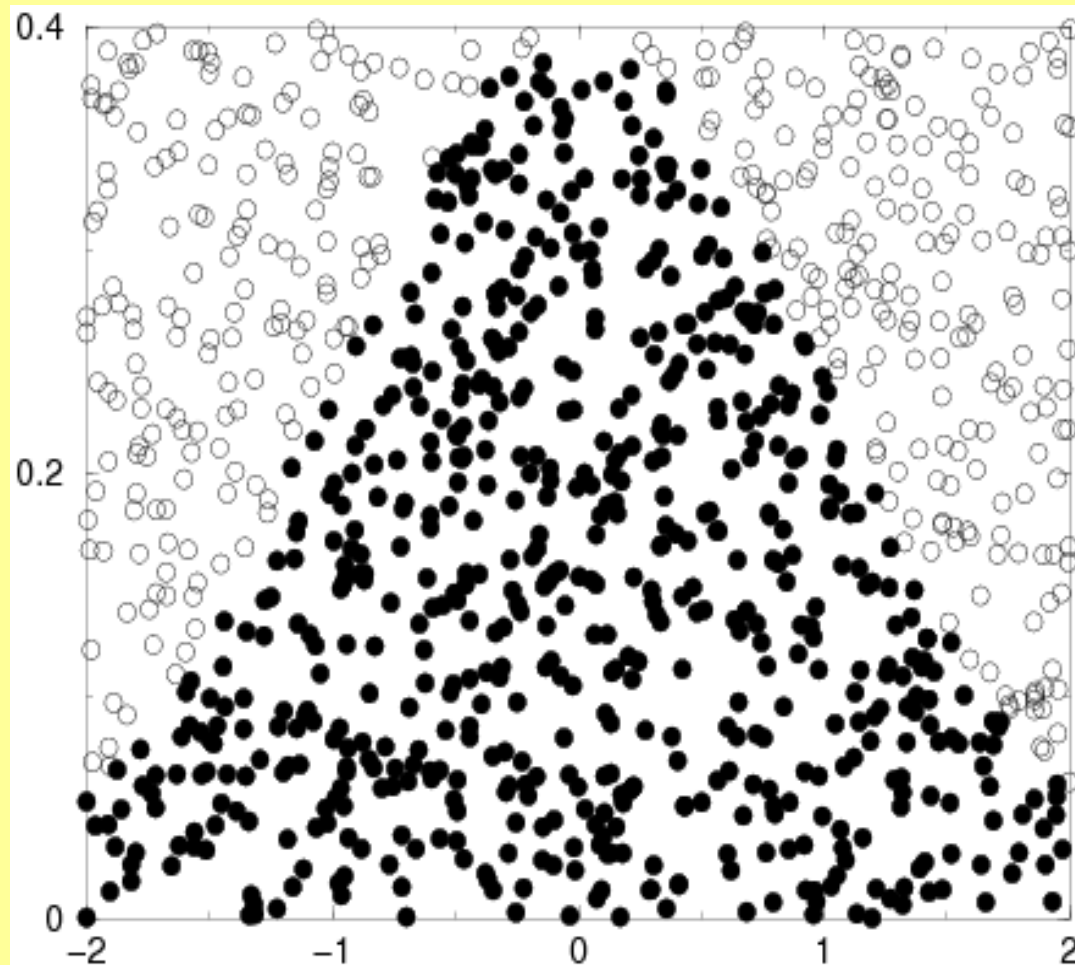
The number of persons to participate in the survey is deduced by calculating  $\sigma$

and assuming a tolerable error  $\frac{\sigma}{\sqrt{N}}$ .

## MONTÉ CARLO EXAMPLE II: PLAYING GUESS WHO



## MONTE CARLO EXAMPLE III: INTEGRATION

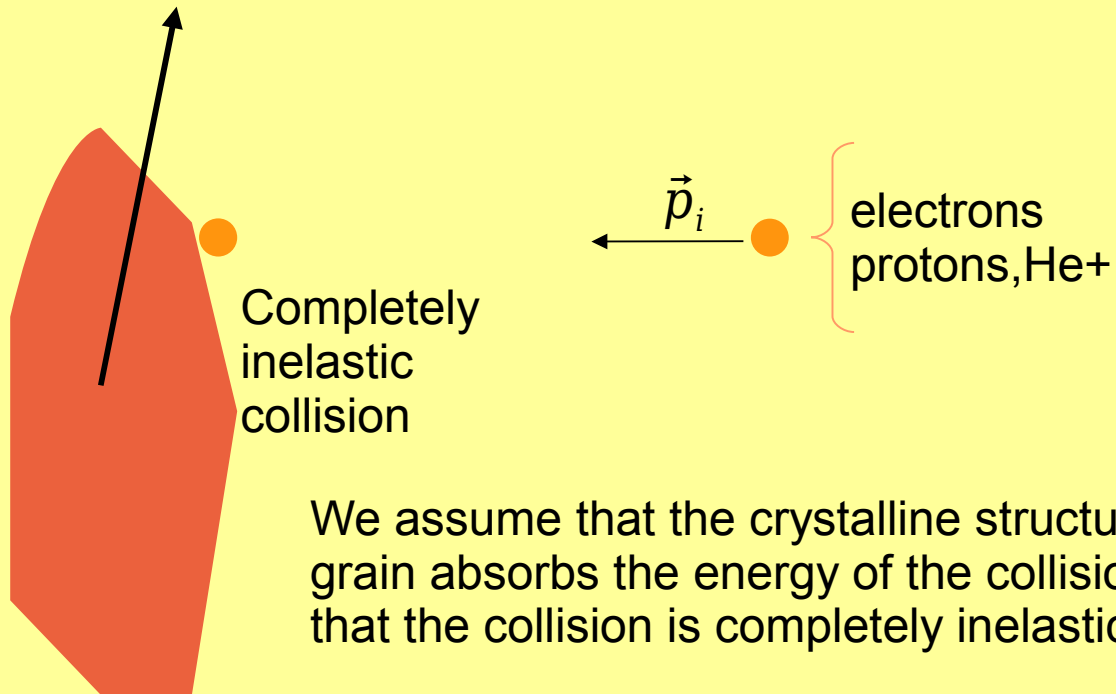


S

A number of points are uniformly randomly distributed over an area  $S$ . Then, the area under the curve is obtained by multiplying  $S$  by the number of points under the curve.



## MONTE CARLO EXAMPLE III: DUST GRAIN ALIGNMENT BY THE SOLAR WIND

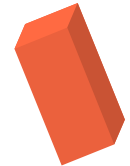


$$\vec{L}_i = m \vec{r}_i \times \vec{p}_i$$

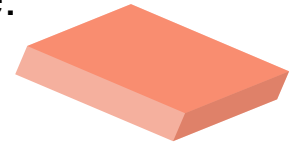
$$\vec{L} = \frac{1}{N} \sum_{i=1}^N \vec{L}_i$$

Grains for testing:

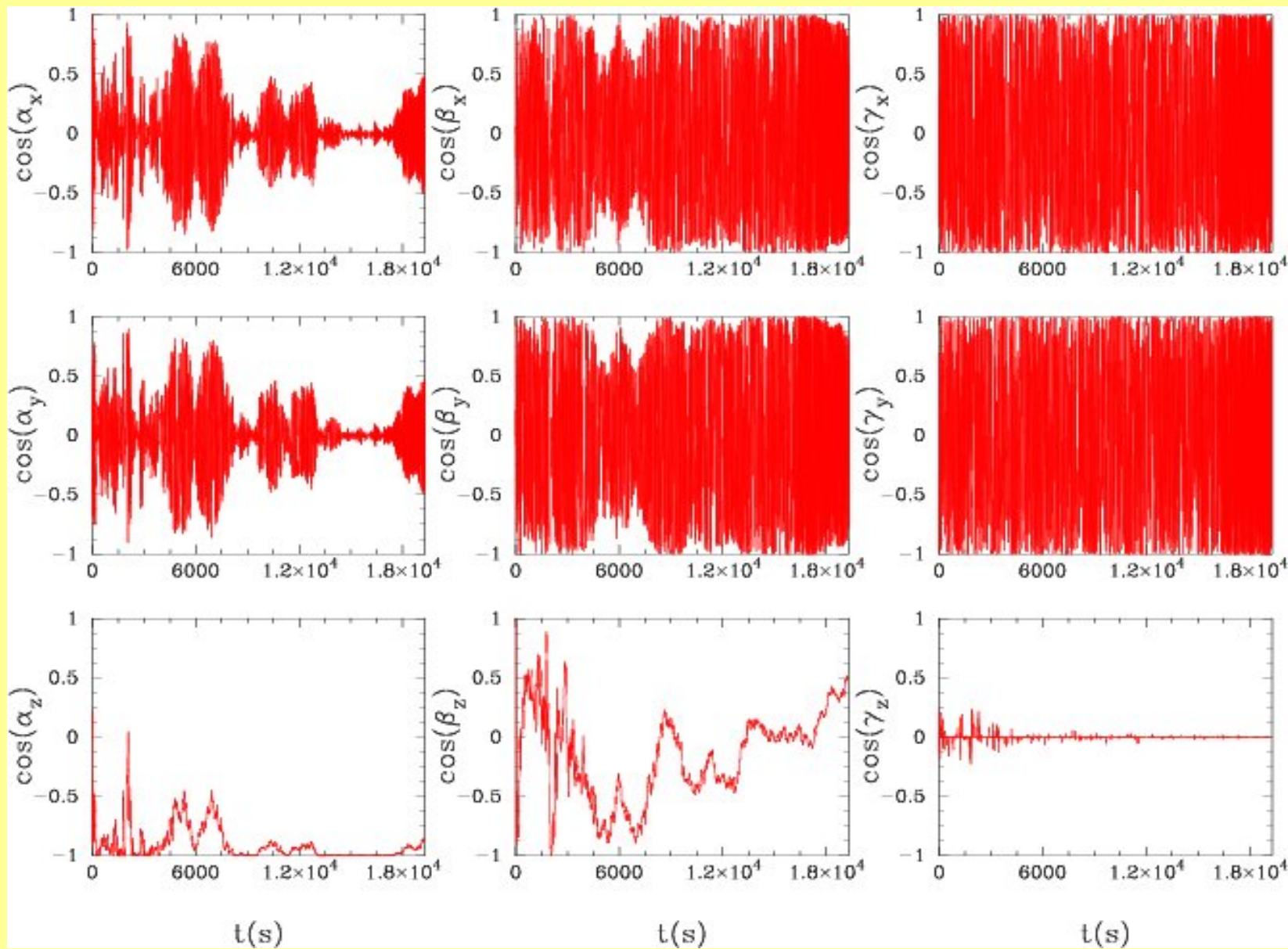
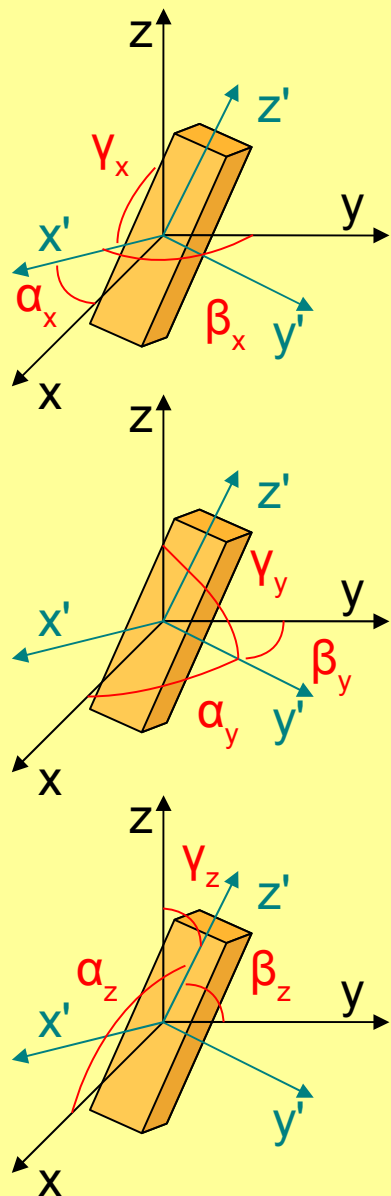
- Rectangular prisms
- Density =  $3 \text{ g cm}^{-3}$
- $0.1 \mu\text{m} \times 0.1 \mu\text{m} \times 0.2 \mu\text{m}$
- (A) Prolate 1:1:2



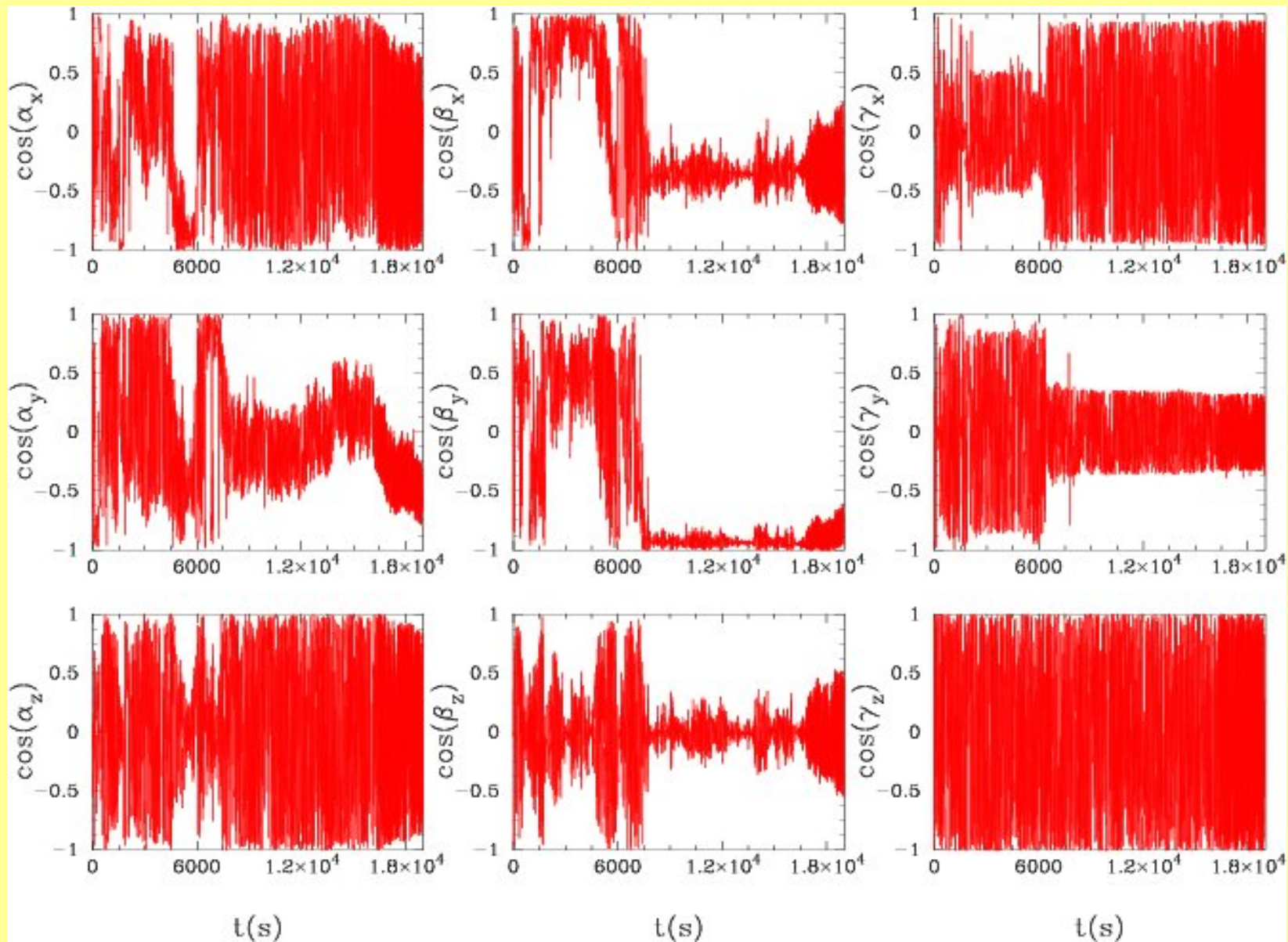
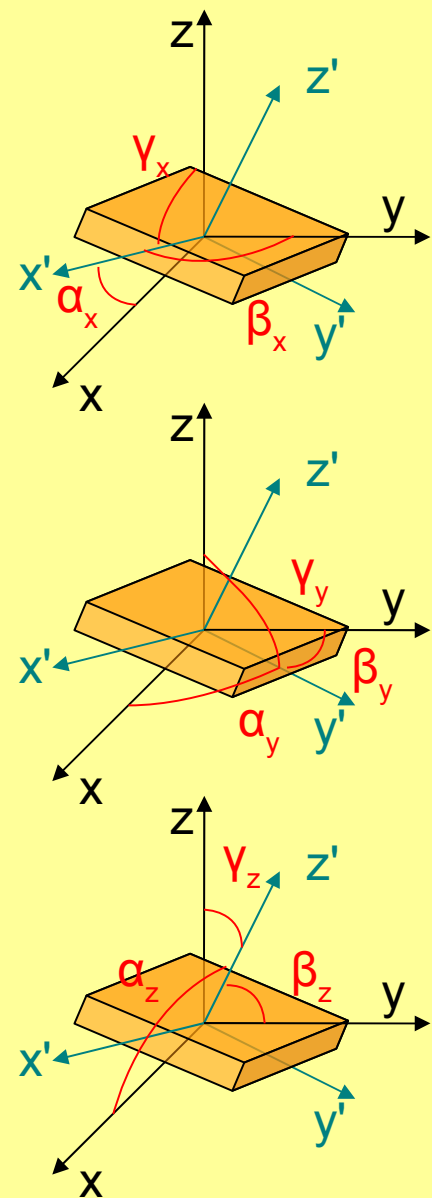
- (B) Oblate 2:2:1
- Same volume as the prolate.



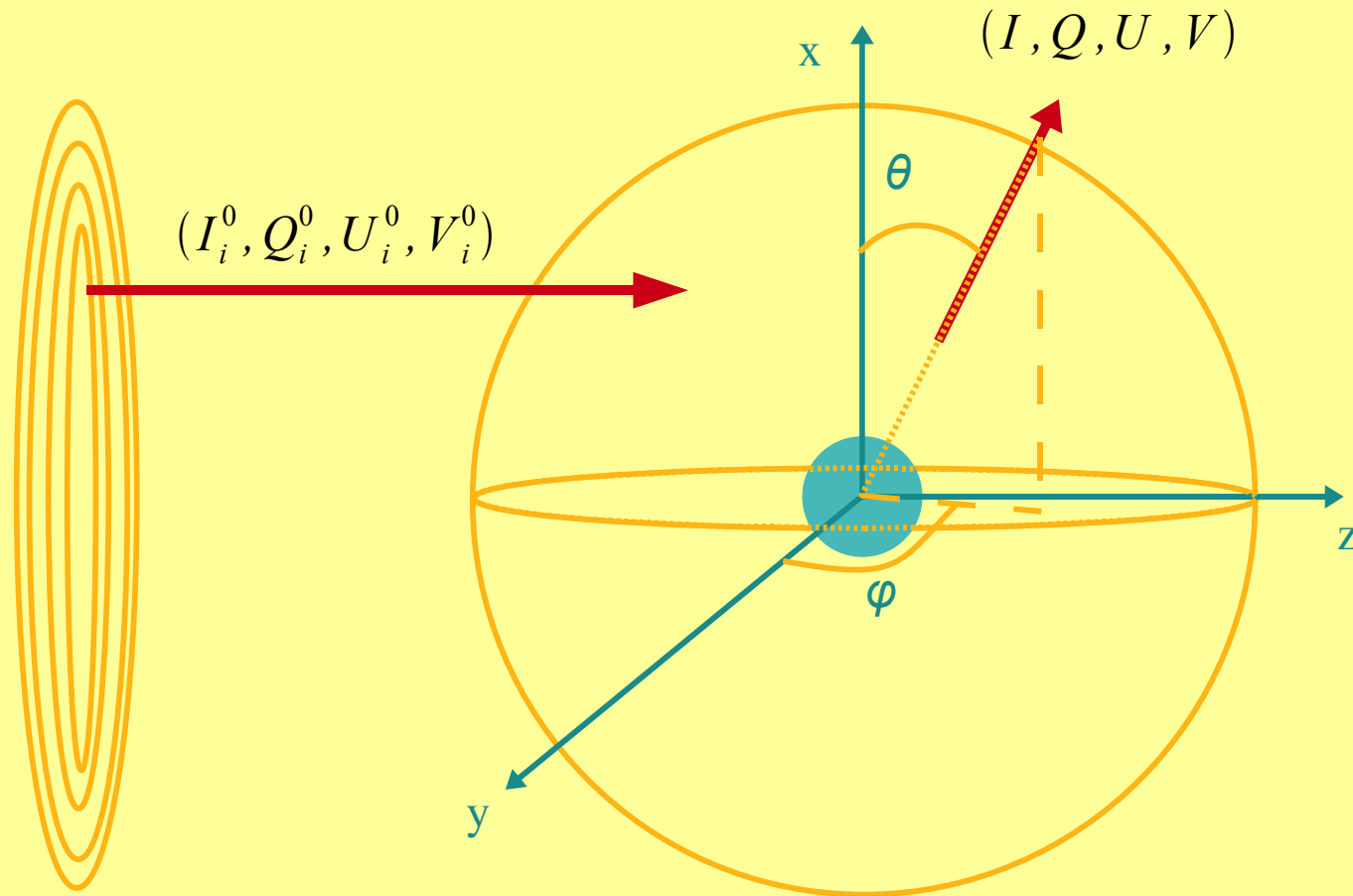
# ALIGNMENT OF PROLATE GRAINS



# ALIGNMENT OF OBLATE GRAINS

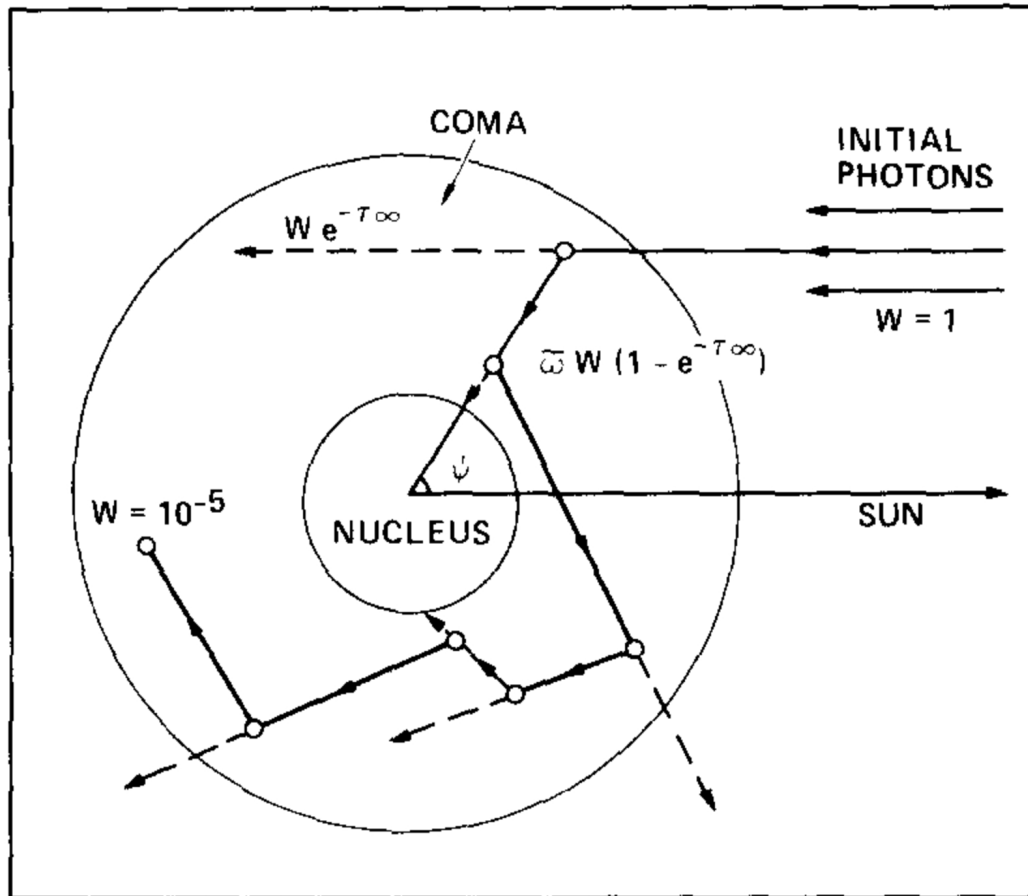


# MONTE CARLO EXAMPLE IV: RADIATIVE TRANSFER IN A COMET



$$(I, Q, U, V) = \frac{1}{N} \sum_{i=1}^N (I_i^0, Q_i^0, U_i^0, V_i^0)$$

# DESCRIPTION OF THE RADIATIVE TRANSFER MODEL



## Particles:

- Any size distribution.
- Any refractive index (even optically activity).
- Any geometry.
- Any orientation (aligned or not).

Any optical thickness of the coma (single or multiple scattering).

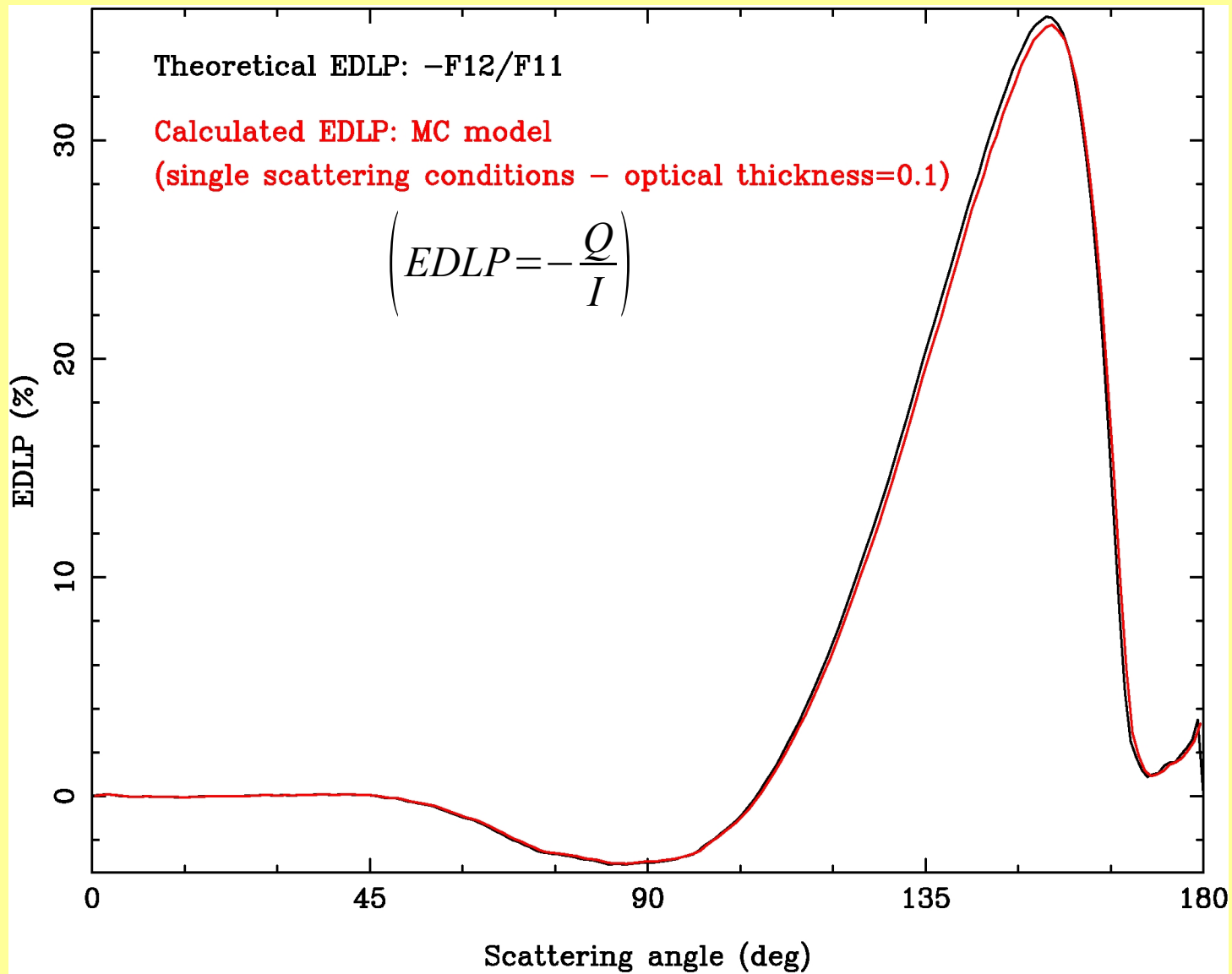
Inhomogeneous coma.

Packet of photons ( $W$ ) {

- Improves statistics.
- Reduces computation time.

$W=1$  at the beginning  
Ends when  $W < W_{min}$

## EXACTITUDE OF THE MODEL



For  $10^8$  packets of photons (~4 hours/core).



# LAS VEGAS ALGORITHM

## Definition:

Iterative method including random decisions that may either give the correct solution of a problem or inform that the solution has been not obtained.



RESULTS COMING FORM LAS VEGAS ALGORITHM DO NOT HAVE ERRORS

## LAS VEGAS EXAMPLE I: ROCK, PAPER, SCISSORS, LIZARD, SPOCK



## LAS VEGAS EXAMPLE II: LOTTERY

LOTERÍAS Y APUESTAS DEL ESTADO JUEVES + SÁBADO 117

Este boleto sirve únicamente para la lectura de apuestas por un terminal en línea con un ordenador central.

**La Primitiva**

1	10	20	30	40	2	10	20	30	40	3	10	20	30	40	4	10	20	30	40	5	10	20	30	40	6	10	20	30	40	7	10	20	30	40	8	10	20	30	40
11	21	31	41	1	11	21	31	41	1	11	21	31	41	1	11	21	31	41	1	11	21	31	41	1	11	21	31	41	1	11	21	31	41	1	11	21	31	41	1
22	32	42	2	12	22	32	42	2	12	22	32	42	2	12	22	32	42	2	12	22	32	42	2	12	22	32	42	2	12	22	32	42	2	12	22	32	42	2	12
33	43	3	13	23	33	43	3	13	23	33	43	3	13	23	33	43	3	13	23	33	43	3	13	23	33	43	3	13	23	33	43	3	13	23	33	43	3	13	23
44	14	24	34	44	44	14	24	34	44	44	14	24	34	44	44	14	24	34	44	44	14	24	34	44	44	14	24	34	44	44	14	24	34	44	44	14	24	34	44
55	15	25	35	45	55	15	25	35	45	55	15	25	35	45	55	15	25	35	45	55	15	25	35	45	55	15	25	35	45	55	15	25	35	45	55	15	25	35	45
66	16	26	36	46	66	16	26	36	46	66	16	26	36	46	66	16	26	36	46	66	16	26	36	46	66	16	26	36	46	66	16	26	36	46	66	16	26	36	46
77	17	27	37	47	77	17	27	37	47	77	17	27	37	47	77	17	27	37	47	77	17	27	37	47	77	17	27	37	47	77	17	27	37	47	77	17	27	37	47
88	18	28	38	48	88	18	28	38	48	88	18	28	38	48	88	18	28	38	48	88	18	28	38	48	88	18	28	38	48	88	18	28	38	48	88	18	28	38	48
99	19	29	39	49	99	19	29	39	49	99	19	29	39	49	99	19	29	39	49	99	19	29	39	49	99	19	29	39	49	99	19	29	39	49	99	19	29	39	49

Si juega múltiple, marque aquí el número de apuestas

Si desea jugar más veces las mismas apuestas no doble, arrugue ni rompa este boleto

## LAS VEGAS EXAMPLE III: SINGLE FECUNDATION



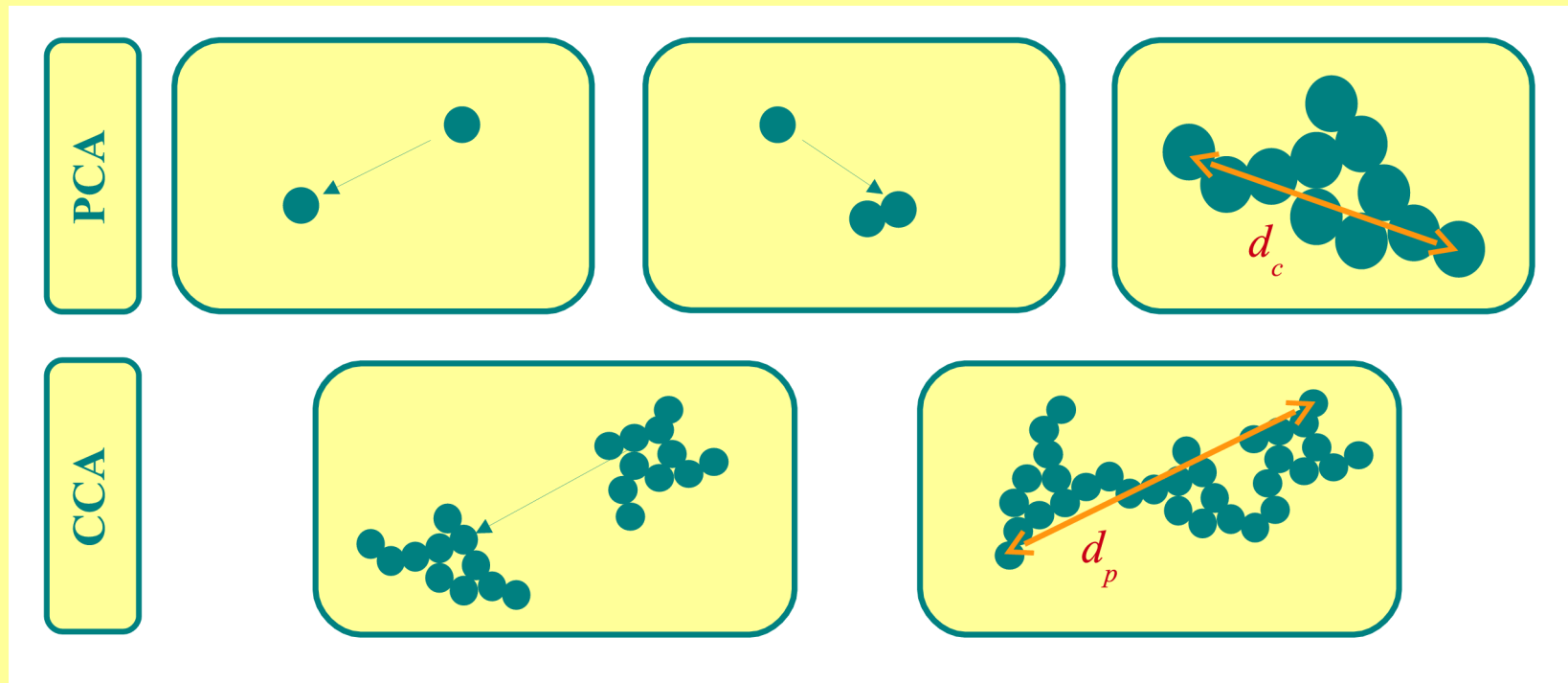
## LAS VEGAS EXAMPLE IV: SOLVING EQUATIONS

By randomly exploring around the zone of parameters where we know that the solution is.

## LAS VEGAS EXAMPLE V: OBTAINING A PASSWORD



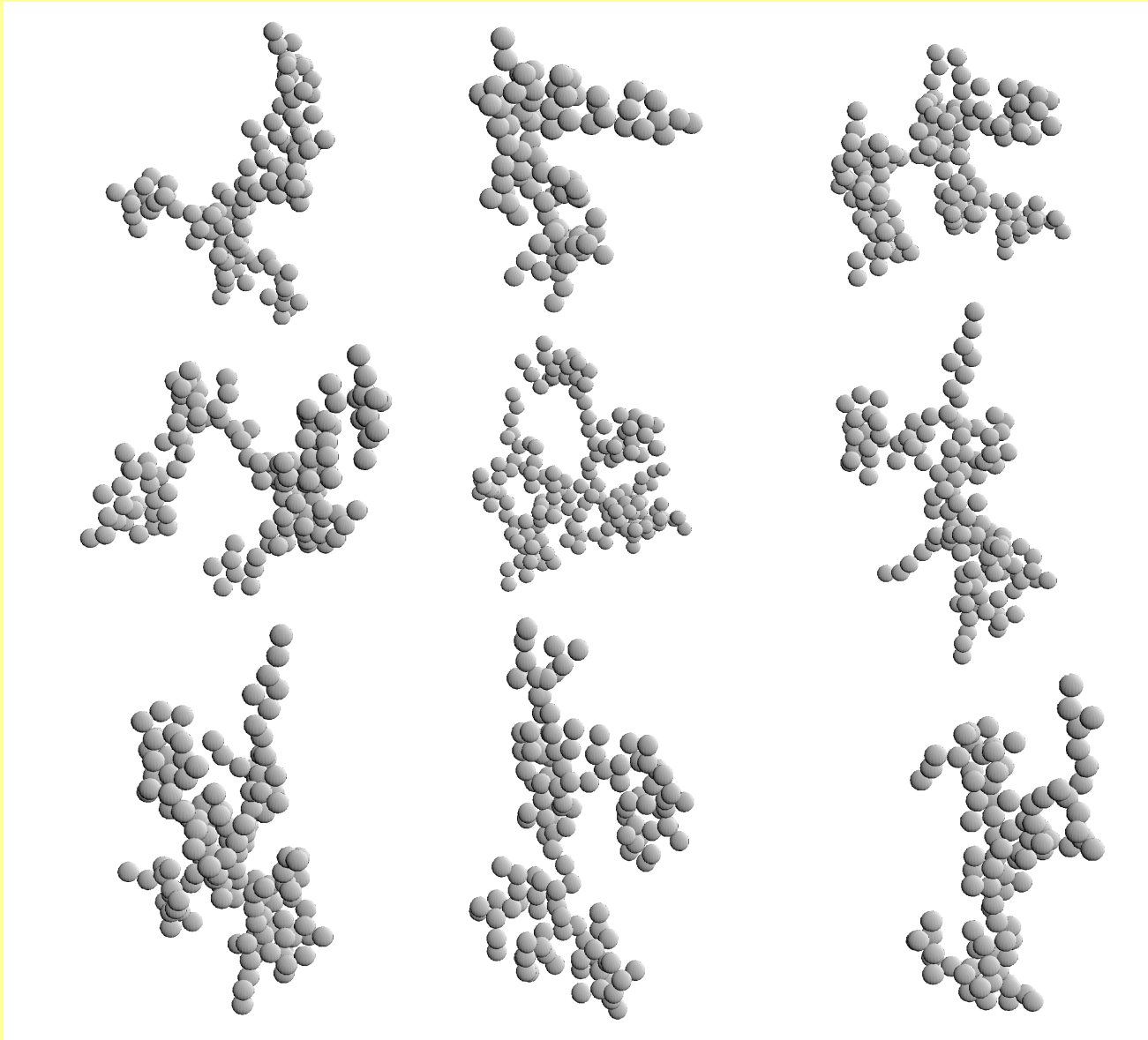
## LAS VEGAS EXAMPLE VI: BUILDING RANDOM AGGREGATES OF SPHERES



Arbitrary maximum size imposed to clusters ( $d_c$ ) and the whole particle ( $d_p$ ).

Maximum size  $\longleftrightarrow$  maximum distance between two monomers (realistic criterium).

## AGGREGATES OF SPHERES



A solution to the problem is always achieved in this case.

## MONTE CARLO COMPARED TO LAS VEGAS

- Monte Carlo methods always give a solution, along with a certain probability for this solution to be correct. Las Vegas either gives a correct solution to the problem or informs that no solution could be achieved.
- In problems solved by Monte Carlo methods, there is a unique solution, and the method converges to it while increasing the number  $N$  of iterations. Several correct solutions may exist for problems solved with Las Vegas algorithms.

## SOME COMMENTS

Monte Carlo and Las Vegas codes require a large amount of memory and computational time to accomplish their tasks. However, Monte Carlo methods are able to exactly reproduce the microscopical elements of a complex system and reproduce their macroscopical properties. Personal computers have become fast enough for seriously considering this option when modelling a complex system.

# PARALLELIZE YOUR CODE

1 sequential program runs in 1 only core.

As Monte Carlo and Las Vegas codes basically consist of a large *do* loop with a number  $N$  of independent iterations, two solutions to accelerate the calculations by one of these codes in a multicore computer could be:

- Run the Monte Carlo code for  $N/m$  iterations, where  $m$  is the number of cores, and make a summation of the results.
- Parallelize the code.

Classical method: MPI. New easier alternative: **OpenMP** (Fortran and C).

How it works:

```
PROGRAM OMP_SUM2
INTEGER NMAX
PARAMETER(NMAX=20000)
INTEGER I
REAL A(NMAX),C(NMAX)
DO I = 1,NMAX
  A(I) = I * 1.0
  C(I)=1.
ENDDO
C$OMP PARALLEL shared(A,B,C,NMAX) private(I,J)
C$OMP DO
  DO I = 1,NMAX
    DO J=1,I
      C(I)= C(I)+A(J)
    END DO
  ENDDO
C$OMP END DO
C$OMP END PARALLEL
WRITE(*,*)C(NMAX)
END
```

gfortran omp\_sum2.f -o omp\_sum2



Sequential omp\_sum2

gfortran -fopenmp omp\_sum2.f -o omp\_sum2



Parallel omp\_sum2



## CONCLUSIONS

- Monte Carlo & Las Vegas are two stochastic methods for the solution of problems.
- Monte Carlo gives a solution along with a certain probability of the solution to be correct.
- Las Vegas either gives the correct solution or informs that no solution could be obtained.
- Monte Carlo methods deal with problems with one single solution, and it reduces its error while the number of iterations increases.
- Monte Carlo codes are usefull to simulate the microscopical elements of a complex system, and derive the macroscopical properties of the system.
- Monte Carlo and Las Vegas codes require a large ammount of computational resoruces: time and memory.
- Monte Carlo and Las Vegas codes may run faster in a multicore computer by adding the OpenMP directives to the programs and using the corresponding flags when compiling.