

N-body issues: softening, tree codes, falcON

Walter Dehnen

Leicester (UK)

contents

- foundations of collisionless N-body methods
- force softening: motivation and limitation
- force approximation: tree code and FMM
- force approximation: falcON

the collisionless N -body code

want to solve:

$$d_t f = \partial_t f + \mathbf{v} \cdot \partial_{\mathbf{x}} f - \partial_{\mathbf{x}} \Phi \cdot \partial_{\mathbf{v}} f = 0$$

$$\partial_{\mathbf{x}}^2 \Phi(\mathbf{x}, t) = 4\pi G \int f(\mathbf{x}, \mathbf{v}) d^3\mathbf{v}$$

$f(\mathbf{x}, \mathbf{v})$ continuous, one-particle DF (lowest in BBGKY hierarchy)

the collisionless N -body code

want to solve:

$$d_t f = \partial_t f + \mathbf{v} \cdot \partial_{\mathbf{x}} f - \partial_{\mathbf{x}} \Phi \cdot \partial_{\mathbf{v}} f = 0$$

$$\partial_{\mathbf{x}}^2 \Phi(\mathbf{x}, t) = 4\pi G \int f(\mathbf{x}, \mathbf{v}) d^3\mathbf{v}$$

$f(\mathbf{x}, \mathbf{v})$ continuous, one-particle DF (lowest in BBGKY hierarchy)

- applicable if $t_{\text{relax}} \gg \text{age} \Rightarrow N \gg 10 \text{ age} / t_{\text{dyn}}$
- no analytic non-trivial non-equilibrium solutions exist
- $f(\mathbf{x}, \mathbf{v})$ is 6D & very inhomogeneous \Rightarrow grid methods difficult
- mixing invalidates continuum limit \Rightarrow grid methods fail
- instead: use the Lagrangian ‘method of characteristics’

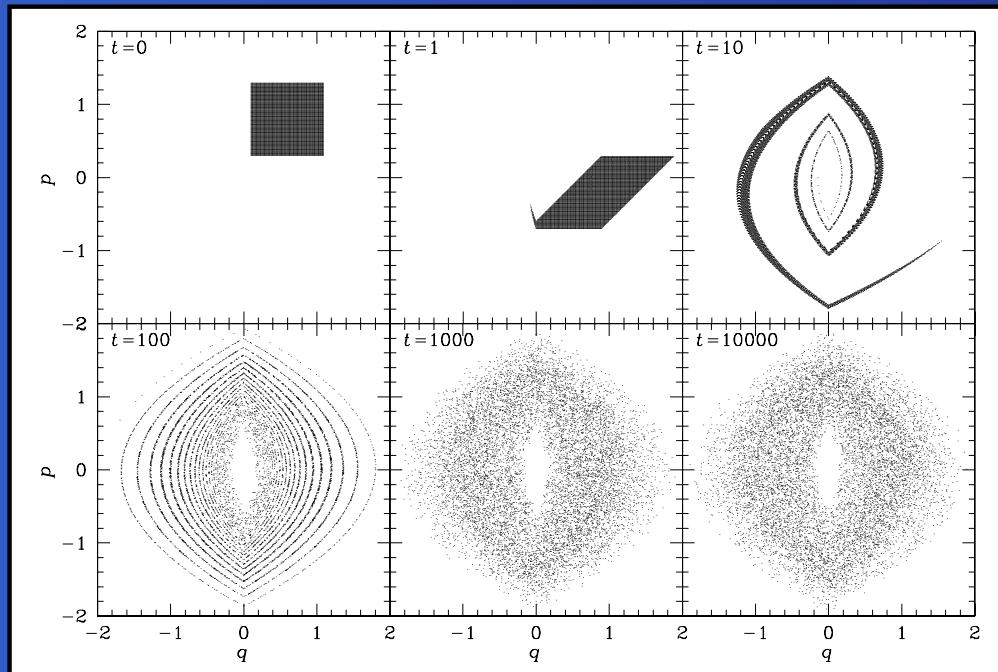
the collisionless N -body code

want to solve:

$$d_t f = \partial_t f + \mathbf{v} \cdot \partial_{\mathbf{x}} f - \partial_{\mathbf{x}} \Phi \cdot \partial_{\mathbf{v}} f = 0$$

$$\partial_{\mathbf{x}}^2 \Phi(\mathbf{x}, t) = 4\pi G \int f(\mathbf{x}, \mathbf{v}) d^3 \mathbf{v}$$

$f(\mathbf{x}, \mathbf{v})$ continuous, one-particle DF (lowest in BBGKY hierarchy)



Phase-mixing of 10^4 points in 1D Hamiltonian $H = p^2/2 + |q|$ of a point mass in 1D gravity. The fine-grained DF is either 1 or 0, but at late times a smooth distribution appears.

How to solve the CBE?

- sample N trajectories $\{\mu_i, \mathbf{x}_i, \mathbf{v}_i\}$ from $f(\mathbf{x}, \mathbf{v}, t = 0)$
- solve equations of motion $\ddot{\mathbf{x}}_i = -\partial_{\mathbf{x}}\Phi(\mathbf{x}_i, t)$
- CBE: $\mu_i = \text{const}$ along trajectories

How to solve the CBE?

- sample N trajectories $\{\mu_i, \mathbf{x}_i, \mathbf{v}_i\}$ from $f(\mathbf{x}, \mathbf{v}, t = 0)$
- solve equations of motion $\ddot{\mathbf{x}}_i = -\partial_{\mathbf{x}}\Phi(\mathbf{x}_i, t)$
- CBE: $\mu_i = \text{const}$ along trajectories

this implies

- $f(\mathbf{x}, \mathbf{v}, t)$ is unknown (except $f(\mathbf{x}_i, \mathbf{v}_i, t) = f(\mathbf{x}_i, \mathbf{v}_i, t = 0)$), but represented by $\{\mu_i, \mathbf{x}_i(t), \mathbf{v}_i(t)\}$
- automatic *coarse-graining* (\Rightarrow no problems with mixing)
- *moments* of f can be *estimated*
- $N \ll N$ is a *numerical parameter* (unlike collisional N -body)
- \Rightarrow artificial two-body relaxation

How to solve Poisson's equation?

- grid techniques (FFT, multigrid)
 - fast: $O(n_{\text{grid}} \log n_{\text{grid}})$
 - periodic (\Rightarrow cosmology)
 - problem: inhomogeneity (but: adaptive multigrid)
- basic functions (using Y_{lm})
 - fast: $O(N n_{\text{basis}})$
 - problems: central singularity, assumed symmetry

How to solve Poisson's equation?

- Greens-function approach:

$$\Phi(\mathbf{x}, t) = -G \int \frac{f(\mathbf{x}', \mathbf{v}', t)}{|\mathbf{x} - \mathbf{x}'|} d^3\mathbf{x}' d^3\mathbf{v}'$$

- general & adaptive
- problem: $f(\mathbf{x}, \mathbf{v}, t)$ unknown \Rightarrow *estimate*

$$\Phi(\mathbf{x}_i, t) \approx \hat{\Phi}(\mathbf{x}_i, t) = - \sum_{j=1}^N \frac{G\mu_j}{\epsilon} \varphi\left(\frac{|\mathbf{x}_i - \mathbf{x}_j|}{\epsilon}\right)$$

with **softening kernel** $\varphi(r)$ & **softening length** ϵ

- $\varphi(r) \sim r^{-1}$ for $r \gg 1$
- slow: $O(N^2)$, *but* fast approximations

Why softening?

- Without softening ($\epsilon=0$): N -body instead of N -body problem
- close encounters are
 - hard to integrate (ask Sverre Aarseth)
 - artificially so, since $F \propto \mu/d^2 \propto N^{-1}/(N^{-1/3})^2 \propto N^{-1/3}$.

Why softening?

- Without softening ($\epsilon=0$): N -body instead of N -body problem
- close encounters are
 - hard to integrate (ask Sverre Aarseth)
 - artificially so, since $F \propto \mu/d^2 \propto N^{-1}/(N^{-1/3})^2 \propto N^{-1/3}$.
- thus, softening
 - significantly simplifies the time integration
 - avoids artifacts due to *close* encounters (such as formation of binaries)
 - but *does not avoid artificial two-body relaxation*, because that is driven by encounters on *all* scales
 \Rightarrow softening can only reduce it by a factor ~ 2

Softening as Optimal Force Estimation

The *estimated* force

$$\hat{\mathbf{F}}(\mathbf{x}) = - \sum_{j=1}^N \frac{G\mu_j}{\epsilon^2} \varphi' \left(\frac{|\mathbf{x} - \mathbf{x}_j|}{\epsilon} \right) \frac{\mathbf{x} - \mathbf{x}_j}{|\mathbf{x} - \mathbf{x}_j|}$$

is a random variable (like the \mathbf{x}_i) with mean-square error

$$\text{MSE}(\hat{\mathbf{F}}) \equiv \langle (\hat{\mathbf{F}}(\mathbf{x}) - \mathbf{F}(\mathbf{x}))^2 \rangle = \text{bias}(\hat{\mathbf{F}}(\mathbf{x}))^2 + \text{var}(\hat{\mathbf{F}}(\mathbf{x}))$$

with

$$\text{bias}(\hat{\mathbf{F}}(\mathbf{x})) = \langle \hat{\mathbf{F}}(\mathbf{x}) \rangle - \mathbf{F}(\mathbf{x})$$

$$\text{var}(\hat{\mathbf{F}}(\mathbf{x})) = \langle (\hat{\mathbf{F}}(\mathbf{x}) - \langle \mathbf{F}(\mathbf{x}) \rangle)^2 \rangle = \langle \hat{\mathbf{F}}^2(\mathbf{x}) \rangle - \langle \hat{\mathbf{F}}(\mathbf{x}) \rangle^2$$

Softening as Optimal Force Estimation

The *estimated* force

$$\hat{\mathbf{F}}(\mathbf{x}) = - \sum_{j=1}^N \frac{G\mu_j}{\epsilon^2} \varphi' \left(\frac{|\mathbf{x} - \mathbf{x}_j|}{\epsilon} \right) \frac{\mathbf{x} - \mathbf{x}_j}{|\mathbf{x} - \mathbf{x}_j|}$$

is a random variable (like the \mathbf{x}_i) with mean-square error

$$\text{MSE}(\hat{\mathbf{F}}) \equiv \langle (\hat{\mathbf{F}}(\mathbf{x}) - \mathbf{F}(\mathbf{x}))^2 \rangle = \text{bias}(\hat{\mathbf{F}}(\mathbf{x}))^2 + \text{var}(\hat{\mathbf{F}}(\mathbf{x}))$$

with

$$\text{bias}(\hat{\mathbf{F}}(\mathbf{x})) = -a_0 \epsilon^2 G \partial_x \rho(\mathbf{x}) - a_2 \epsilon^4 G \partial_x (\partial_x^2 \rho(\mathbf{x})) + O(\epsilon^6)$$

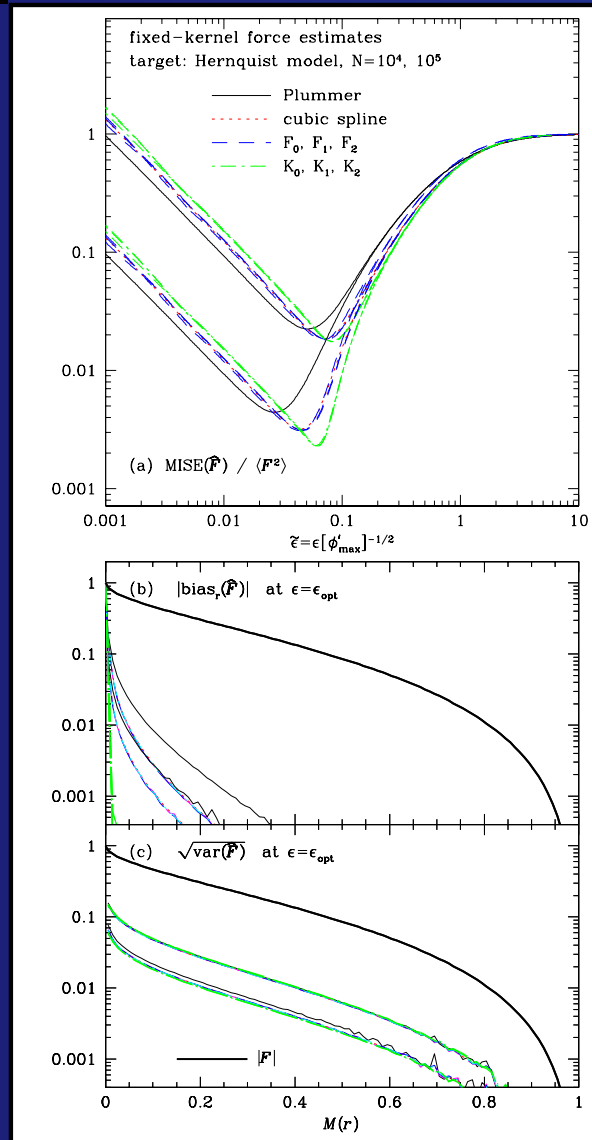
$$N \text{var}(\hat{\mathbf{F}}(\mathbf{x})) = b_F \epsilon^{-1} G^2 M \rho(\mathbf{x}) + O(\epsilon^0)$$

and

$$a_k = \frac{4\pi}{(k+1)!} \int_0^\infty dr r^{k+2} (r^{-1} - \varphi(r))$$

$$b_F = 4\pi \int_0^\infty dr r^2 \varphi'^2(r)$$

Softening as Optimal Force Estimation



$$\text{MSE}(\hat{\mathbf{F}}) \approx a_0^2 \epsilon^4 G^2 (\partial_x \rho)^2 + b_F N^{-1} \epsilon^{-1} G^2 M \rho$$

is minimal at

$$\epsilon_{\text{opt}} \propto N^{-1/5}$$

with

$$\text{MSE}_{\text{opt}}(\hat{\mathbf{F}}) \propto N^{-4/5}$$

Is ϵ_{opt} the best choice for the dynamics?

Top: mean integrated squared error (MISE) of the force for $N = 10^4$ and $N = 10^5$ and a Hernquist sphere plotted vs. ϵ for various softening kernels. *Bottom:* run of bias and variance at minimal $\text{MISE}(\hat{\mathbf{F}})$.

Force Approximation

- force *estimation error* is unavoidable
- we can tolerate an approximation as long as
approximation error \ll *estimation error*

Force Approximation

- force *estimation error* is unavoidable
- we can tolerate an approximation as long as *approximation error* \ll *estimation error*
- approximating direct summation: tree code
 - use hierarchical tree (usually: oct-tree) \Rightarrow fully adaptive
 - faster than direct summation: $O(N \log N)$
 - $\mathbf{F}_{i \rightarrow j} + \mathbf{F}_{j \rightarrow i} \neq 0 \Rightarrow$ total momentum not conserved

Force Approximation

- force *estimation error* is unavoidable
- we can tolerate an approximation as long as *approximation error* \ll *estimation error*
- approximating direct summation: tree code
 - use hierarchical tree (usually: oct-tree) \Rightarrow fully adaptive
 - faster than direct summation: $O(N \log N)$
 - $\mathbf{F}_{i \rightarrow j} + \mathbf{F}_{j \rightarrow i} \neq 0 \Rightarrow$ total momentum not conserved
- approximating direct summation: fast multiple method
 - use hierarchy of cartesian grids \Rightarrow not fully adaptive
 - uses spherical multipoles & complex Y_{lm}
 - numerics complicated & cumbersome
 - high orders \Rightarrow high accuracy
 - formally $O(N)$ *but* slower than tree code

tree code: details

- preparation phase
 - build a hierarchical tree \Rightarrow cost: $O(N \log N)$
 - pre-compute multipole moments etc
- force computation: 'tree walk'
 - for each body: compute forces due to root cell
 - to compute force from a cell:
 - if body is *well-separated* from cell:
compute force from multipole moments
 - otherwise: forces from daughter cells (recursive)
 - cost: $O(\log N)$ per body $\Rightarrow O(N \log N)$
- this algorithm clearly is *sub-optimal*:
forces of neighbours similar yet independently computed

fast multipole method: details

- preparation phase
 - build a hierarchy of cartesian grids
 - pre-compute multipole moments etc (*upward pass*)
- force computation
 - on each grid level: ‘intermediate-field’ interactions: compute & accumulate multipoles of gravity field
 - *downward pass*
 - pass field-multipoles down the hierarchy
 - compute forces on finest grid
- interaction criterion purely geometric \Rightarrow errors unbalanced
- theoretically $O(N)$, but not demonstrated in practice
- not competitive with tree code in low-accuracy regime

falcON: details

falcON = force algorithm with complexity $O(N)$
hybrid of tree & FMM, takes the better of each.

- preparation phase (same as for tree code)
 - build a hierarchical tree \Rightarrow cost: $O(N \log N)$
 - pre-compute multipole moments etc

falcON: details

falcON = force algorithm with complexity $O(N)$
hybrid of tree & FMM, takes the better of each.

- preparation phase (same as for tree code)
- *interaction phase*:
 - compute root-root interaction
 - to compute node-node interaction:
 - if node-node interaction well-separated:
accumulate field tensors
 - otherwise: split & continue with child interactions
(recursive)
 - cost: (better than) $O(N)$, dominates

falcON: details

falcON = force algorithm with complexity $O(N)$
hybrid of tree & FMM, takes the better of each.

- preparation phase (same as for tree code)
- *interaction phase*:
 - compute root-root interaction
 - cost: (better than) $O(N)$, dominates
- *evaluation phase*:
 - pass field tensors down the tree
 - compute forces at body positions
 - cost: $O(N)$
- ~ 10 times faster than tree or FMM (at low accuracy)
- simple error balancing (could be done with tree too)

falcON: numerics

wanted: $\Phi(\mathbf{x}_i) = - \sum_{j \neq i} \mu_j g(\mathbf{x}_i - \mathbf{y}_j)$. Taylor expand g about $\mathbf{R} = \mathbf{x}_0 - \mathbf{y}_0$:

$$g(\mathbf{x} - \mathbf{y}) = \sum_{n=0}^p \frac{1}{n!} (\mathbf{x} - \mathbf{y} - \mathbf{R})^{(n)} \odot \partial_{\mathbf{x}}^{(n)} g(\mathbf{R}) + \mathcal{R}_p(g).$$

Insert & sum over source cell B (Warren & Salmon 1995, CPC, 87, 266):

$$\Phi_{B \rightarrow A}(\mathbf{x}) = - \sum_{m=0}^p \frac{1}{m!} (\mathbf{x} - \mathbf{x}_0)^{(m)} \odot \mathbf{C}^{m,p} + \mathcal{R}_p(\Phi_{B \rightarrow A})$$

$$\mathbf{C}^{m,p} = \sum_{n=0}^{p-m} \frac{(-1)^n}{n!} \partial_{\mathbf{x}}^{(n+m)} g(\mathbf{R}) \odot \mathbf{M}_{\mathbf{B}}^n,$$

$$\mathbf{M}_{\mathbf{B}}^n = \sum_{\mathbf{y}_i \in \mathbf{B}} \mu_i (\mathbf{y}_i - \mathbf{y}_0)^{(n)}.$$

falcON: numerics

wanted: $\Phi(\mathbf{x}_i) = - \sum_{j \neq i} \mu_j g(\mathbf{x}_i - \mathbf{y}_j)$. Taylor expand g about $\mathbf{R} = \mathbf{x}_0 - \mathbf{y}_0$:

$$g(\mathbf{x} - \mathbf{y}) = \sum_{n=0}^p \frac{1}{n!} (\mathbf{x} - \mathbf{y} - \mathbf{R})^{(n)} \odot \partial_{\mathbf{x}}^{(n)} g(\mathbf{R}) + \mathcal{R}_p(g).$$

Insert & sum over source cell B (Warren & Salmon 1995, CPC, 87, 266):

$$\Phi_{B \rightarrow A}(\mathbf{x}) = - \sum_{m=0}^p \frac{1}{m!} (\mathbf{x} - \mathbf{x}_0)^{(m)} \odot \mathbf{C}^{m,p} + \mathcal{R}_p(\Phi_{B \rightarrow A}) \quad \text{evaluation}$$

$$\mathbf{C}^{m,p} = \sum_{n=0}^{p-m} \frac{(-1)^n}{n!} \partial_{\mathbf{x}}^{(n+m)} g(\mathbf{R}) \odot \mathbf{M}_{\mathbf{B}}^n, \quad \text{interaction}$$

$$\mathbf{M}_{\mathbf{B}}^n = \sum_{\mathbf{y}_i \in B} \mu_i (\mathbf{y}_i - \mathbf{y}_0)^{(n)}. \quad \text{preparation}$$

\sum_m : evaluation of gravity, represented by the *field tensors* $\mathbf{C}^{m,p}$, at position \mathbf{x}

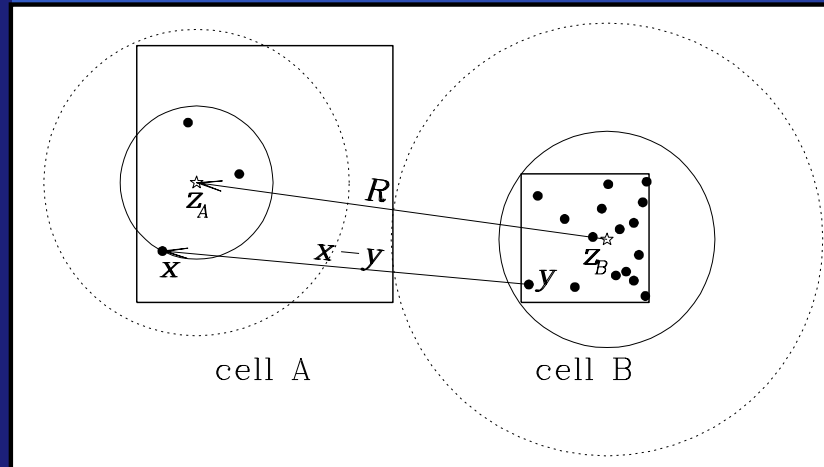
\sum_n : interaction between source cell B, represented by the *multipoles* $\mathbf{M}_{\mathbf{B}}^n$, and the sink cell A.

Difference to tree code:

expansion in \mathbf{x} (tree code: $\mathbf{x} \equiv \mathbf{x}_0$)

mutuality of *interactions*

falcON: error balancing



cells are *well-separated* if

$|\mathbf{R}| > r_{A,\text{crit}} + r_{B,\text{crit}}$ with $r_{\text{crit}} = r_{\text{max}}/\theta$,

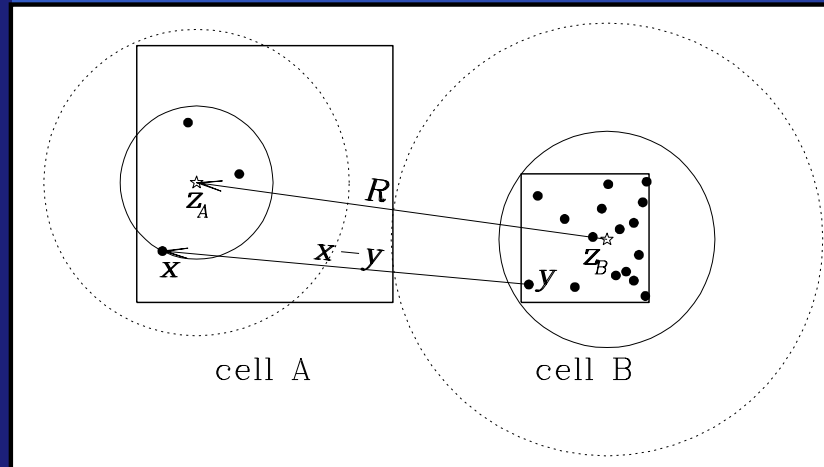
$\Rightarrow |\mathbf{x} - \mathbf{y} - \mathbf{R}| < \theta |\mathbf{R}| \quad \forall \mathbf{x} \in A, \mathbf{y} \in B$

\Rightarrow Taylor series converges

error of individual interaction:

$$|\partial_{\mathbf{x}} \mathcal{R}_p(\Phi_{B \rightarrow A})| \leq \frac{(p+1)\theta^p}{(1-\theta)^2} \frac{M_B}{R^2} \propto \frac{\theta^{p+2}}{(1-\theta)^2} M_B^{1/3}$$

falcON: error balancing



cells are *well-separated* if

$|\mathbf{R}| > r_{A,\text{crit}} + r_{B,\text{crit}}$ with $r_{\text{crit}} = r_{\text{max}}/\theta$,

$\Rightarrow |\mathbf{x} - \mathbf{y} - \mathbf{R}| < \theta |\mathbf{R}| \quad \forall \mathbf{x} \in A, \mathbf{y} \in B$

\Rightarrow Taylor series converges

error of individual interaction:

$$|\partial_{\mathbf{x}} \mathcal{R}_p(\Phi_{B \rightarrow A})| \leq \frac{(p+1)\theta^p}{(1-\theta)^2} \frac{M_B}{R^2} \propto \frac{\theta^{p+2}}{(1-\theta)^2} M_B^{1/3}$$

with $\theta = \text{const}$: *relative* error constant, *absolute* error $\propto M_B^{1/3}$

\Rightarrow *total error* dominated by few interactions with large cells

better: *balance* absolute errors by $\theta = \theta(M)$ with

$$\frac{\theta^{p+2}}{(1-\theta)^2} = \frac{\theta_{\min}^{p+2}}{(1-\theta_{\min})^2} \left(\frac{M}{M_{\text{tot}}} \right)^{1/3}$$

falcON: complexity analysis

• eight-folding $N \Rightarrow N_I \rightarrow 8N_I + N_+$ and thus

$$\frac{dN_I}{dN} \simeq \frac{N_I}{N} \frac{\Delta \ln N_I}{\Delta \ln N} \approx \frac{N_I}{N} + \frac{N_+}{N 8 \ln 8},$$

with solution

$$N_I = c_0 N + \frac{N}{8 \ln 8} \int \frac{N_+}{N^2} dN$$

falcON: complexity analysis

- eight-folding $N \Rightarrow N_I \rightarrow 8N_I + N_+$ and thus

$$\frac{dN_I}{dN} \simeq \frac{N_I}{N} \frac{\Delta \ln N_I}{\Delta \ln N} \approx \frac{N_I}{N} + \frac{N_+}{N 8 \ln 8},$$

with solution

$$N_I = c_0 N + \frac{N}{8 \ln 8} \int \frac{N_+}{N^2} dN$$

- tree code: $N_+ \propto N \Rightarrow N_I \propto N \log N$
- falcON: $N_+(N)$ grow less than $O(N) \Rightarrow N_I \propto N$
- with error-balancing: at error $\simeq \text{const}$: $N_I \propto N^{0.91}$
- typical for $N = 10^6$ CPU time: 0.5 + 4.5 sec (Opteron)

to-do & yet-to-understand list

- softening: dynamical effects, resolution & noise
- force approximation:
 - effects of approximation errors, shadow forces (grid)
 - non-conservative force approximation: a problem?
- time integration: what is right & wrong?
- comparative N -body studies (Katrin Heitmann)
- initial conditions