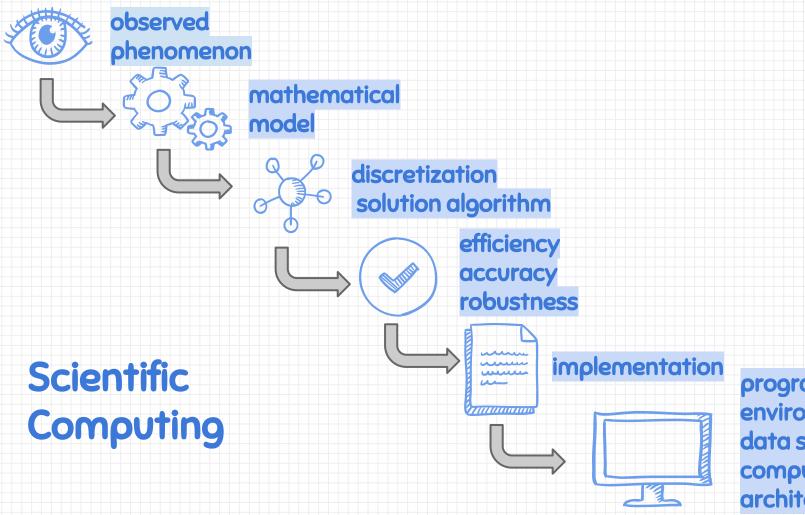
CS 6210 Fall 2016 Bei Wang

### Review Lecture What have we learnt in Scientific Computing?



## Let's recall the scientific computing pipeline





programming environment data structure computing architecture

### We have accomplished our goal and leant a great deal!



### Our Supercomputing Miniseries

Mark Kim (SCI): Fixed-Rate Compressed Floating-Point Arrays

Sidharth Kumar (SoC): Parallel I/O Library

Arnab Das and Vinu Joseph (SoC): Why we are not ready for Exascale Computing?



### **Numerical Algorithms**

Error

\*different types of error (absolute, relative, discretization, convergence, roundoff)

Algorithm properties: accuracy, efficiency, robustness



### Floating point system

Roundoff error accumulation

\*FP system: can you tell me the range of numbers a FP system can provide?



### Solving Nonlinear Equation in 1 variable: f(x) = 0

Bisection Fixed point iteration \*Newton's method \*Secant \*Convergence of various methods Function minimization



### Linear algebra

Vector norm Matrix norm \*Symmetric positive definite Orthogonal matrices \*SVD



### Linear Systems Ax = b: direct methods

Backward and forward substitution \*Gaussian elimination \*LU decomposition Pivoting \*Cholesky decomposition Error estimation Condition number



### Linear least squares: min || b-Ax ||

Uniqueness and normal equation: (A<sup>T</sup>A)x = A<sup>T</sup>b Orthogonal transformation \*QR Householder transformation

Gram-Schmidt orthogonalization



#### Linear Systems Ax = b: Iterative methods

\*Splitting (stationary methods): A = M-N Jacobi method Gauss-Seidel method Convergence of stationary methods Gradient descent \*Conjugate gradient: explain how this works?



### Eigenvalues and singular values: Ax = \lambda x; SVD

Power method for computing dominant eigenvalue and eigen vectors \*SVD Best lower rank approximation \*Geometric intuition behind SVD Least squares via SVD QR for eigenvalues



### Nonlinear systems f(x) = 0 and optimization

Newton's method Unconstrained optimization Taylor's series Gradient descent Linear search Quasi-Newton



### Polynomial interpolation $f(x) = \sum e^{x}$

\*Piecewise linear Piecewise constant Monomial interpolation \*Lagrange interpolation Divided difference (coefficients) f[x\_i...x\_j] \*Error \*Chebyshev interpolation Interpolating derived values f', f"



### Piecewise polynomial interpolation

Broken line Piecewise Hermite interpolation Cubic spline

Parametric curves



### **Best approximation**

Continuous least squares approximation Orthogonal basis function: Legendre polynomial Weighted least squares

\*Chebyshev polynomial: geometric intuition



### Numerical differentiation

\*Taylor series 2 point, 3 point, 5 point formula Richardson extrapolation Using Lagrange polynomial interpolation Roundoff errors



#### Numerical integration

Quadrature rule: \sum a\_j f(x\_j)

\*Basic rules (trapezoidal, Simpson, midpoint)

Error

\*Composite rules (similar to piecewise polynomial interpolation) Gaussian quadrature



## You should be proud of what we've accomplished together!



### More on the final



### Notes on final exam

Open book, open notes, close internet

Please bring your calculator (recommended); TA will have a calculator that you can borrow, if needed.

20 T/F questions (2 points each)
5-10 questions that require derivation
10 T/F question for extra credits
1 extra derivation question for extra credits



### Possible topics of interests (see \* from topic review)

Errors **IEEE** standard Fixed point methods GE Least squares SOR CG SD **OR** Condition number

Polynomial interpolation SVD Linear systems of equations Taylor series Unconstrained optimization LU Chelosky decomposition

Normal equations

...



### **Example questions**

1. In unconstrained optimization, a necessary condition for having a global min at point x is for x being a critical point (T/F)?

2. Give polynomial interpolation to some data using different interpolation schemes.



### Answer to the questions

In unconstrained optimization, a necessary condition for having a global min at point x is for x being a critical point (T/F)?

False: Page 260. A necessary condition for having a local minimum at x is that x be a critical point and that the symmetric Hessian matrix being positive semidefinite.

#### **Example questions**

3. Consider the linear system given below with a, b > 0:

$$\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} a & b \\ b & a \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

a) If  $a \approx b$ , what is the numerical difficulty in solving the linear system? b) Suggest a numerically stable formula for computing z = x + y, given a and b.



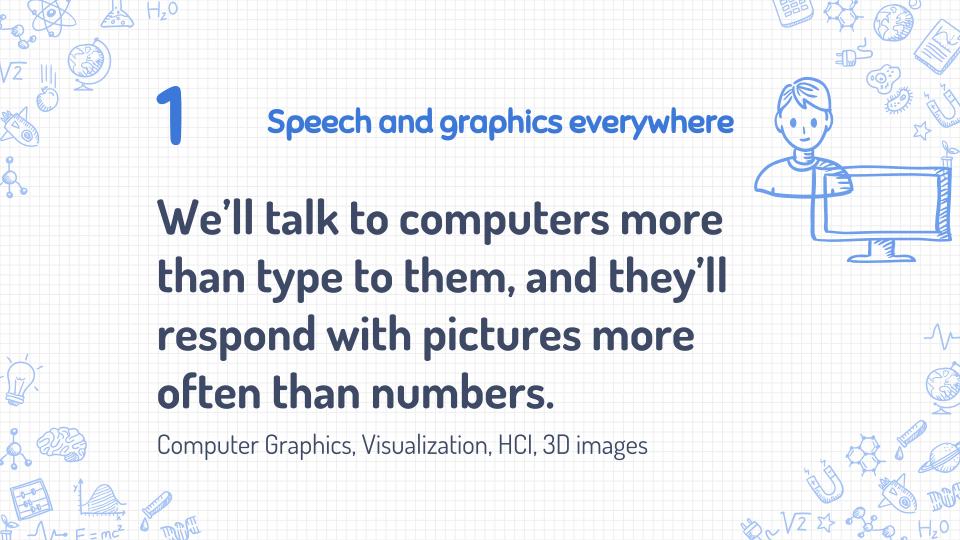
#### **Example questions**

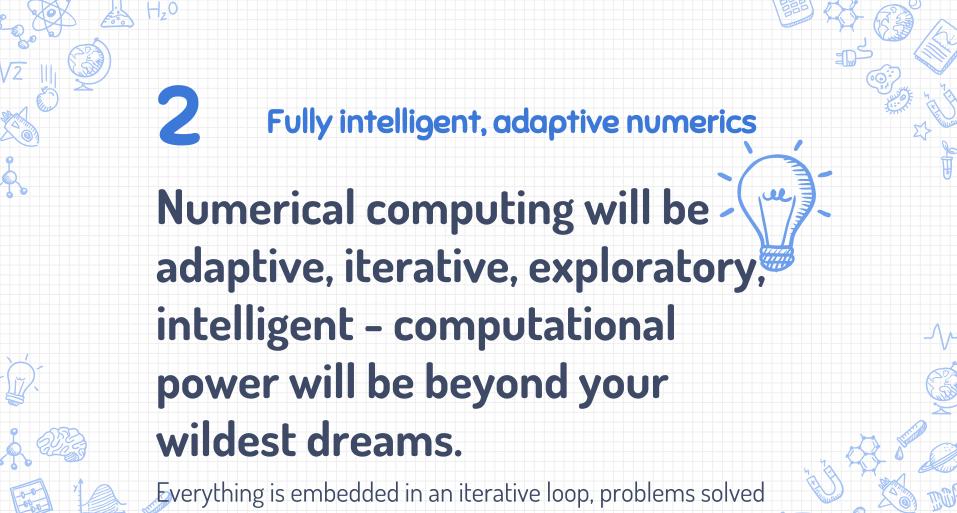
- 5. Consider the following:
  - (a) (8 points) Suppose you are using the trapezoidal rule to approximate an integral over an interval [a, b]. If you wish to obtain a more accurate approximation of the integral, which will gain more accuracy: (1) dividing the interval in half and using the trapezoidal rule on each subinterval, or (2) using Simpson's rule on the original interval? Note that either approach will use the same three function values, at the endpoints and the midpoint of the original interval. Support your answer with an error analysis. Test your conclusion experimentally with a simple integral example of your choice.

### Revisit: The Future of Scientific Computing 50 years from now

[Trefethen 2000]







atop an encyclopedia of numerical methods



# Determinism in numerical computing will be gone.

It is not reasonable to ask for exactness in numerical computation...we may not ask for repeatability either.





### Floating point arithmetic: best general purpose approximation

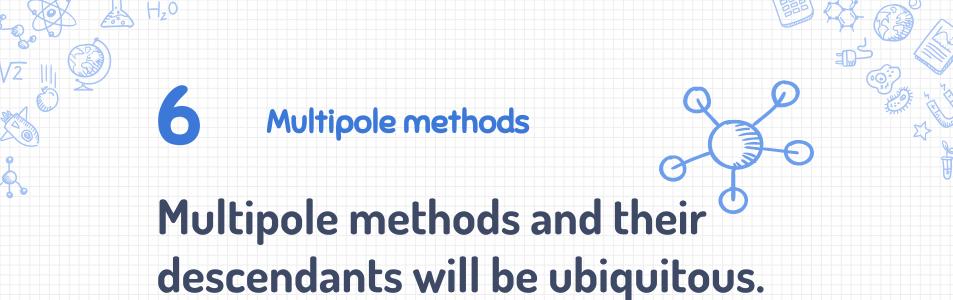
# The importance of floating point arithmetic will be undiminished.

128 bit plus word lengths, most numerical problems can not be solved symbolically still, still need approximations.



## Linear systems of equations will be solved in time O(N^{2+e})

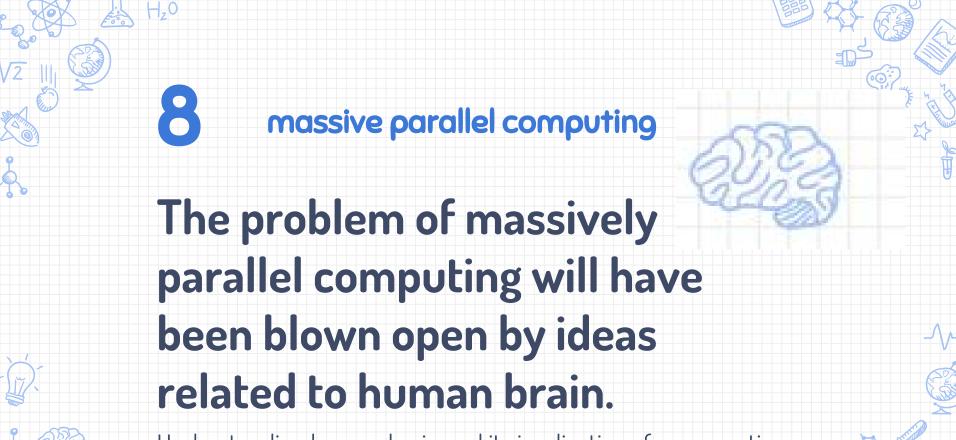
Complexity of matrix multiplication = complexity of "almost all" matrix problems: inverse, determinants, solve linear systems... How fast can we multiply two n by n matrices? Standard O(N<sup>3</sup>). Strassen's algorithm O(N<sup>2</sup>.81). Coppersmith and Winograd's algorithm O(N<sup>2</sup>.38)...Is O(N<sup>2</sup>) achievable?



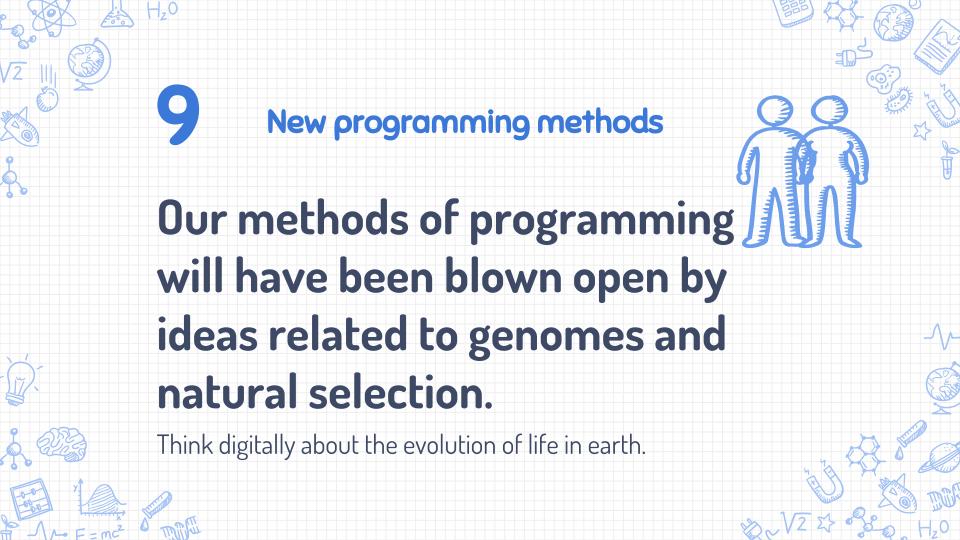
Speed up the calculation of long-ranged forces in the n-body problem. Large-scale numerical computations rely more on approximate algorithms...more robust and faster than exact ones.



No separation between numerical and symbolic calculations, work across different discretizations and grids, removing humans from the loop.



Understanding human brain and its implications for computing.



# What's your prediction of the future of scientific computing?





- 2. Nano computing
- 3. Personal computing
- 4. Crowdsourcing
- 5. Human-computer interaction
- 6. Big data
- 7. Visualization needs
- 8. Web computing
- 9. Blurry boundary between SC and machine learning
- 10. Security
  - 11. Your laptop and your other multimedia devices; internet of things



### Take home message

- 1. **Think Big**: how SC could transform your research?
- 2. Keep your eyes open: identify the newest advancement in SC.
- 3. Master the fundamentals: practice makes perfect.
- 4. Have some fun while learning!

### TA Friday (12/8) review hour: 1:30 p.m - 2:30 pm















So it goes.





Special thanks to all the people who made and released these awesome resources for free:

- ✗ Presentation template by <u>SlidesCarnival</u>
- ✗ Photographs by <u>Unsplash</u>

