Peachy Parallel assignments

https://tcpp.cs.gsu.edu/curriculum/?q=peachy

- Tested
- Adoptable
- Cool and inspirational

Sustainable Research Pathways

Building inclusive pathways to HPC, computational, and data science careers

EXASCALE COMPUTING PROJECT

SC23

Denver, CO | i am hpc.

Argonne NATIONAL LABORATORY

Using MPI For Distributed Hyper-Parameter Optimization and Uncertainty Evaluation

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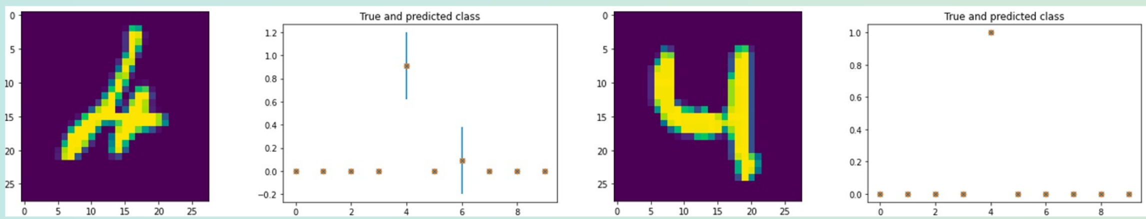
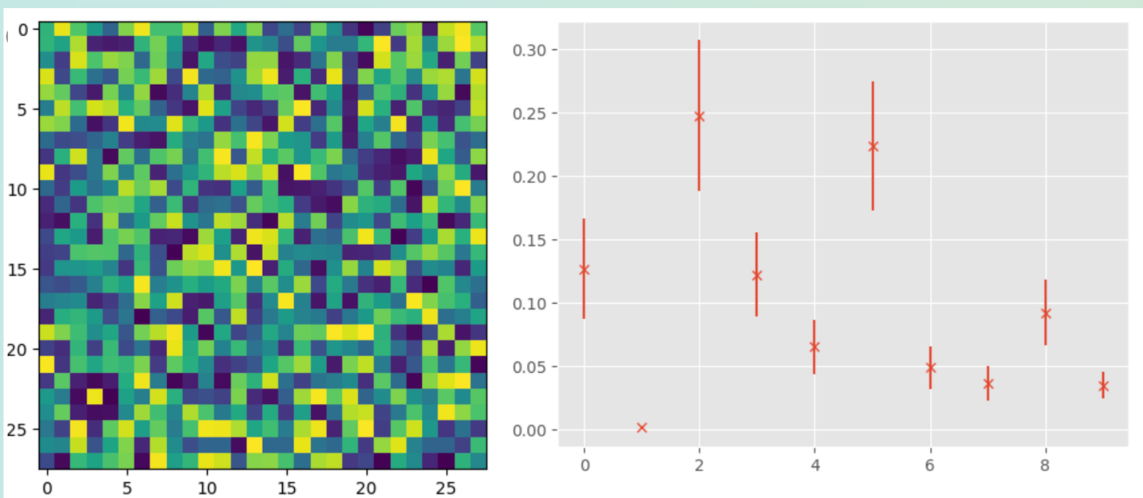
CAL POLY Computer Science Department

UC San Diego

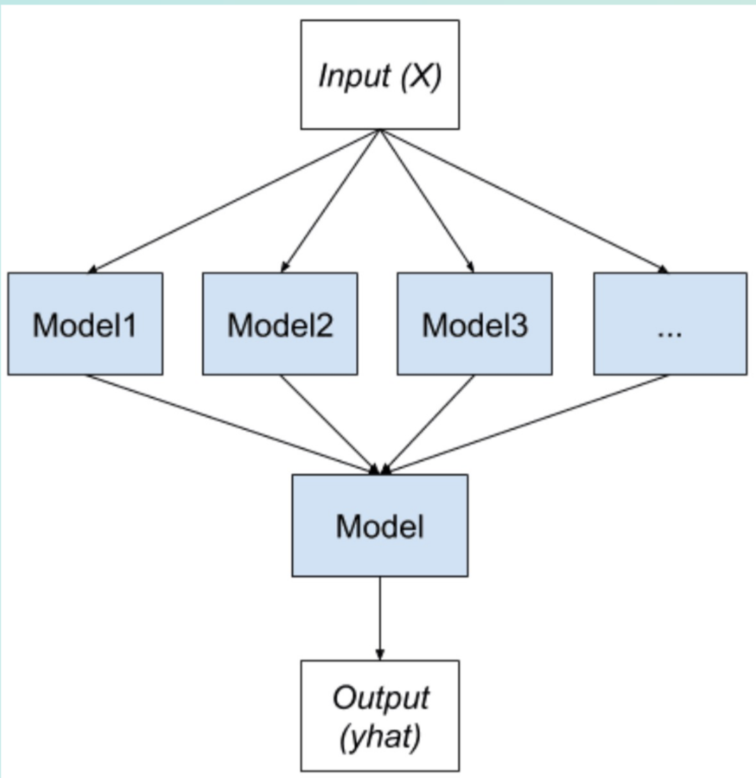
LOYOLA UNIVERSITY CHICAGO

Goal Accelerate Uncertainty Evaluation in AI





How to Accelerate Uncertainty Evaluation




```
# n is # ensembles, size is the # of MPI nodes
count = n // size
# extra catchments if n is not a multiple of size
remainder = n % size
# processes with rank < remainder analyze one extra catchment
if rank < remainder:
    start = rank * (count + 1) # index of first catchment to analyze
    stop = start + count + 1 # index of last catchment to analyze
else:
    start = rank * count + remainder
    stop = start + count
if rank > 0:
    comm.Send(...) # send to leader node
else:
    final_results = .. #final results printed by the leader node
```

Code And Slides

The link for the above assignment can be found
https://drive.google.com/drive/folders/1KrxWlMZpoJzph0Y7VbZj_yYyACK-Jusl?usp=sharing

Thanks to:
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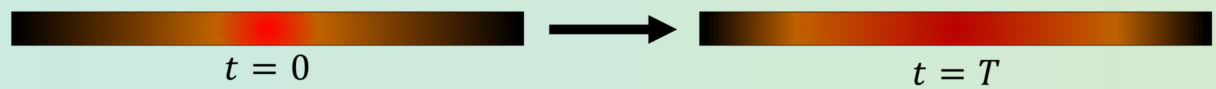
Solving the 1D Heat Equation in Chapel

Jeremiah Corrado

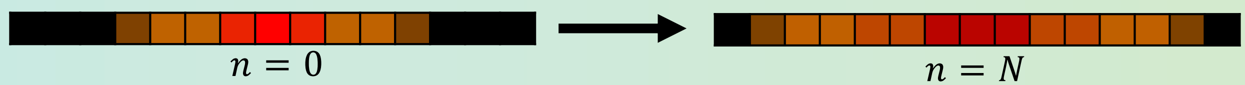
Assignment Summary

Background and Algorithm

1D Heat Equation: $$\frac{\partial u}{\partial t} = \alpha \frac{\partial^2 u}{\partial x^2}$$



Finite-Difference Heat Equation: $$u_i^{n+1} = u_i^n + \alpha \left(u_{i-1}^n - 2u_i^n + u_{i+1}^n\right)$$



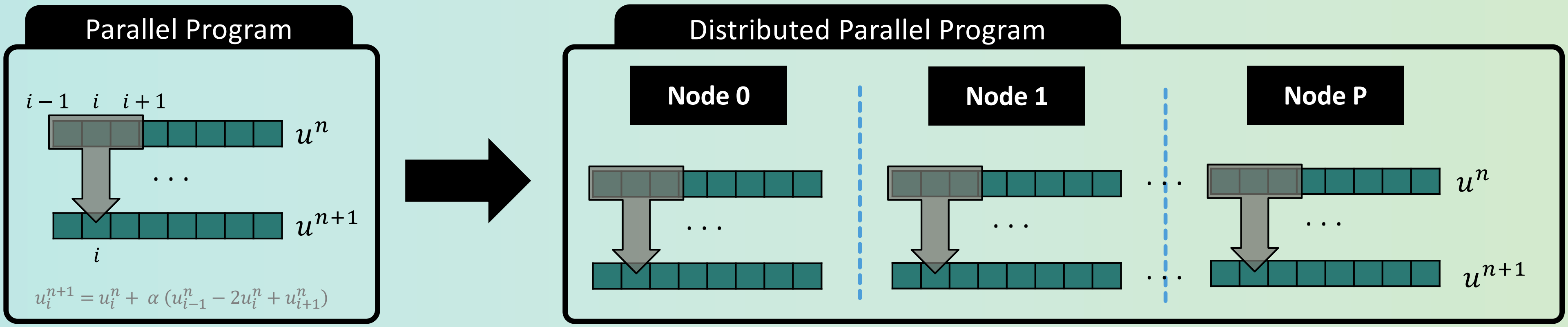
Finite Difference Algorithm:

- define Ω to be a set of discrete points along the x-axis
- define $\widehat{\Omega}$ over the same points, excluding the boundaries
- define an array u to over Ω
- set some initial conditions
- create a temporary copy of u, named un
- for N timesteps:
  (1) swap u and un
  (2) compute u in terms of un over $\widehat{\Omega}$

```
const omega = {0..<nx},
      omegaHat = omega.expand(-1);
var u: [omega] real = 1.0;
u[nx/4..3*nx/4] = 2.0;
var un = u;
for 1..N {
  un <=> u;
  forall i in omegaHat do
    u[i] = un[i] + alpha *
             (un[i-1] - 2*un[i] + un[i+1]);
}
```

Assignment Summary

Distributing a parallel program

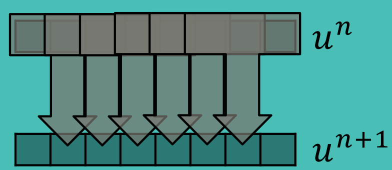


1.
- Start with a simpler data-parallel program
- Provide students with examples of using distributed arrays in Chapel
- Ask students to modify the data-parallel program to use distributed arrays

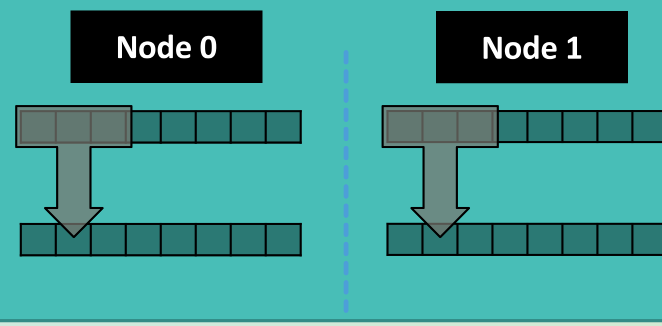
2.
- Start with a lower-level task-parallel program
- Provide students with examples of controlling the locality of task execution in Chapel
- Ask students to modify the task-parallel program to execute tasks across multiple compute nodes

Key HPC Concepts Covered

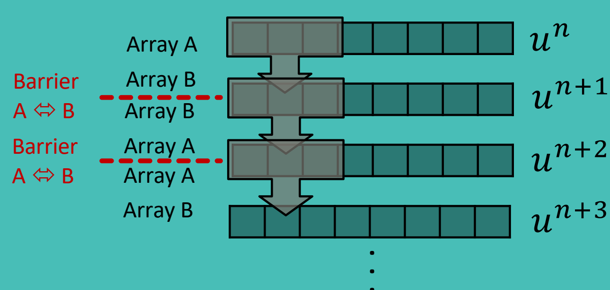
Parallelizing order independent loops



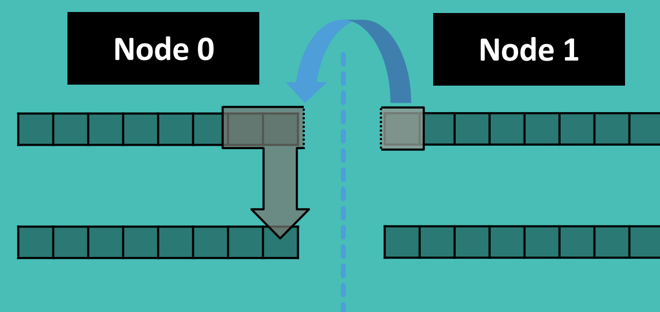
Locality of data and computation



Barriers and synchronization



Inter-node communication



Key HPC Concepts Covered

Parallelizing order independent loops

```
forall i in omegaHat do
    u[i] = un[i] + alpha *
            (un[i-1] - 2*un[i] + un[i+1]);
```

Locality of data and computation

```
const omega = Block.createDomain({0..<nx});
var u : [omega] real;

coforall tid in haloDist do
  on tid.locale do
    taskSimulate(tid);
```

Barriers and synchronization

```
var b = new barrier(nTasks);
...
for 1..nt {
  ...
  b.barrier();
  uLocal1 <=> uLocal2;
  ...
}
```

Inter-node communication

```
if tid != 0 then halos[tid-1][RIGHT] =
                       uLocal2[omegaLocal.low];
if tid != nTasks-1 then halos[tid+1][LEFT] =
                       uLocal2[omegaLocal.high];
```

Summary

- An introductory HPC assignment that uses a practical problem to teach several concepts:
  - parallelism, synchronization, locality, communication
- Leverages Chapel's first-class notions of parallelism, locality and distributed arrays
  - less focus on the software engineering
  - more focus on the HPC concepts themselves
- Students are asked to do the same thing in two different ways (data parallel & task parallel)
  - repetition helps cement fundamental concepts
  - exposes students to multiple perspectives on the same problem

Q &A

Resources:

Github Repo for assignment: https://github.com/jeremiah-corrado/Chapel-Heat1D-PPA

Chapel Homepage: https://chapel-lang.org/

Chapel Blog: https://chapel-lang.org/blog/

Contact:

email: jeremiah.corrado@hpe.com

chapel discourse: https://chapel.discourse.group/

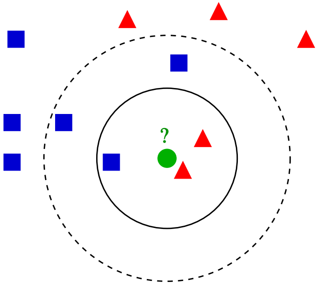
k Nearest Neighbor in MapReduce MPI

MapReduce MPI

- Developped by K. Devine and S. Plimpton at Sandia
- Essentially a distributed hash table processing engine
- Sit atop MPI
- Used for data processing in MPI codes
- Will do out of core if necessary
- If you teach MPI, it's easy to teach MapReduce

k-NN

- N categorized points in d dimensions
- q query points
- For each query points
  - Find the k closest points
  - Vote to guess the category



k Nearest Neighbor in MapReduce MPI

Rough solution

- All processes read queries
- Map the datapoints files in parallel to generate $(query, (dist, class))$ pairs
- Reduce per query to get $(query, (dist1, class1, \dots, distk, classk))$
- Map to get $(query, (pred1, count1, pred2, count2, \dots))$
- Dump to output

Some optimization:

- $O(nq)$ computation
- Reduce causes $O(nq)$ comm
- Local reduce gives comm in $O(qkP)$

Thoughts

- Non trivial application of Map Reduce
- Reinforces locality
- Tons of data available
- Possible optimization to prevent $O(nq)$ calculations
- Can be adapted to MPI for python
- Can be adapted for hybrid MPI-OpenMP
- Can be adapted in Date Structures

Parallelizing a 1-Dim Nagel-Schreckenberg Traffic Model

Ramses van Zon (SciNet HPC, UofT) Marcelo Ponce (Comp. & Math. Sciences, UTSC)

EduHPC-23, SC23, Denver

November 13, 2023

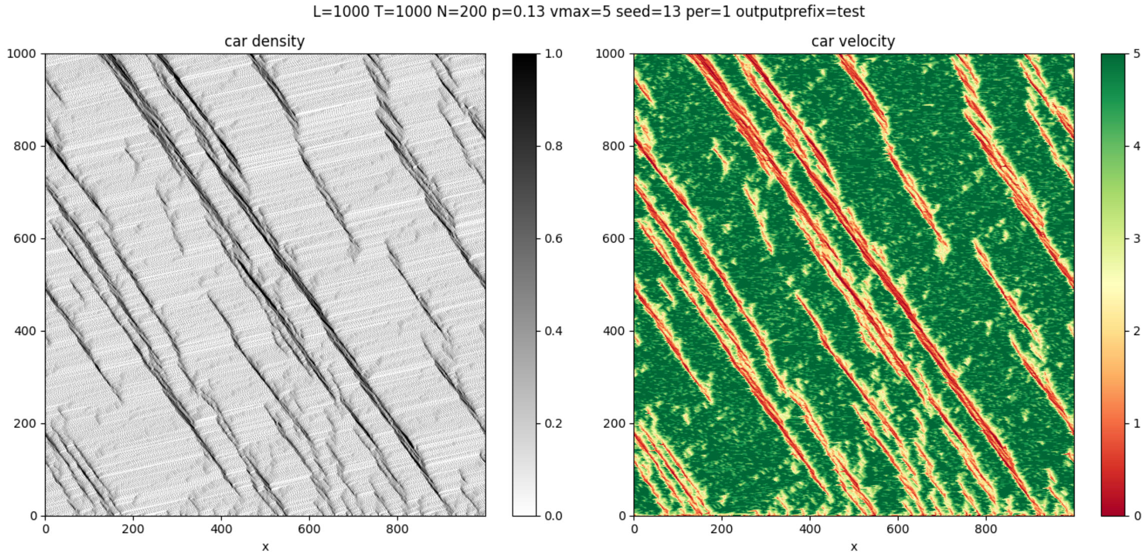
Peachy Assignment

- The Nagel-Schreckenberg traffic model is a simulation using **pseudo-random numbers**.
- A serial starter code in **C++** is provided.
- Task:
  - Parallelize with **OpenMP**.
  - Do so in a **reproducible** way: output has to be independent of number of threads.
  - Aim for **good strong and weak scaling**.

Model

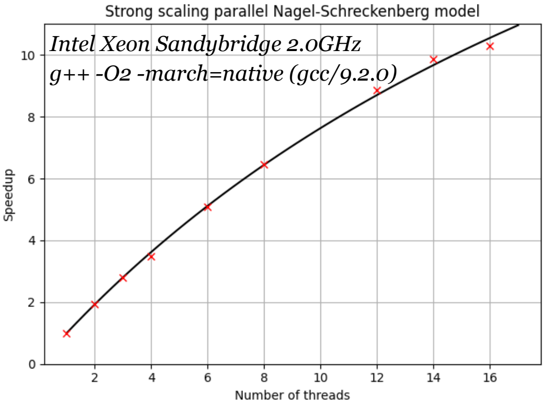
- Cars have discrete positions and velocities on a circular road.
- At discrete time steps, for each car:
  - *Speed-up:* If velocity $v < v_{max}$, increase v by one.
  - *Avoid collision:* If v would lead to a collision with car in front, reduce v.
  - *Randomly break:* With given probability p, reduce v by one.
  - *Drive:* Move car forward by v steps.

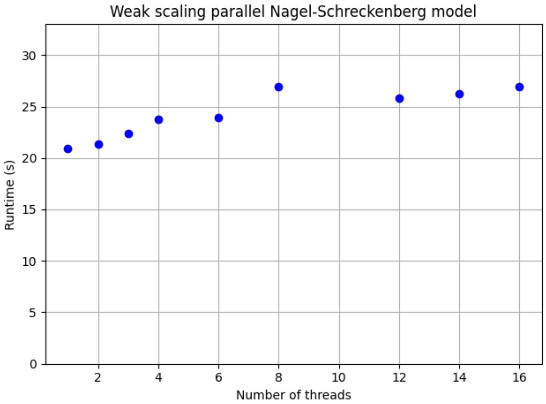
Nagel-Schreckenberg traffic model results



Crux of the solution

PRNG are generated serially but some PRNG allow $\log(n)$ skip-ahead.





- **Archive paper**: https://arxiv.org/abs/2309.14311
- **Starter code and assignment description**: https://github.com/Practical-Scientific-and-HPC-Computing/Traffic_EduHPC-23

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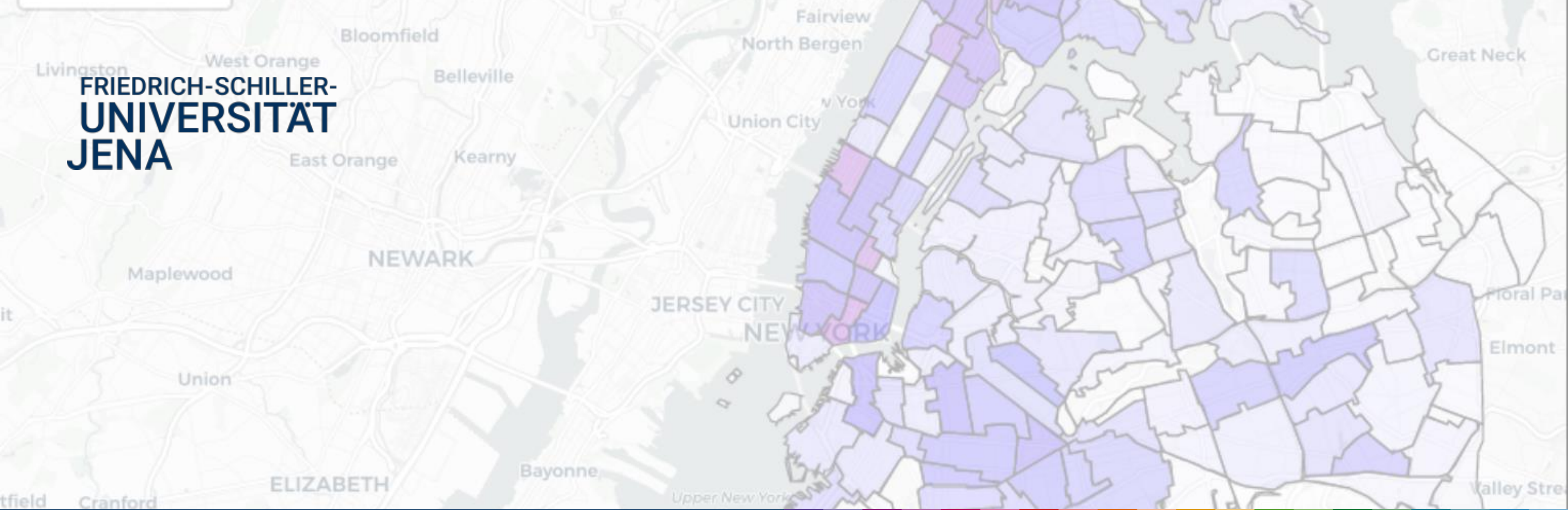


FRIEDRICH-SCHILLER-
UNIVERSITÄT
JENA

Marieke Plesske
H. Martin Bücker, Johannes Schoder, Wolf Weber

Favorite Data Science Pipeline

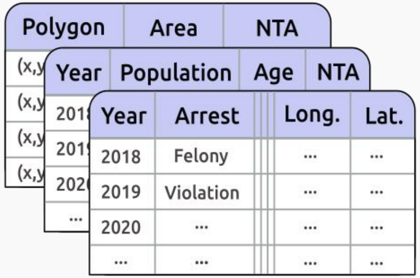
11/13/2023

Program Your Favorite Data Science Pipeline

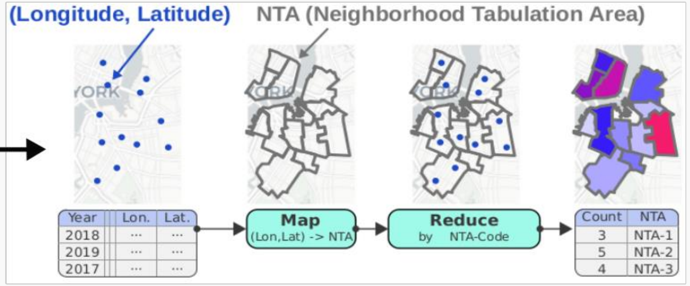
- ~ 3 data analyses on ~ 2 datasets
- in teams (~ 3 students)
- 3 weeks
- presentation of results
- submission of report and executable code

Data Science Pipeline – NYC Crime

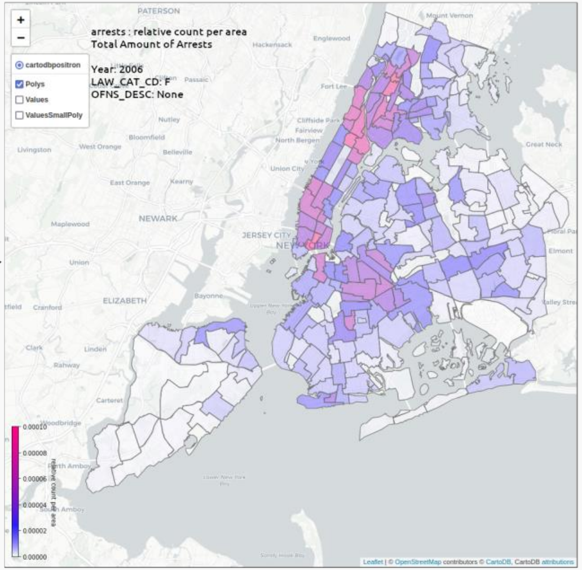
Data Aggregation



Cleaning, Filtering & Analysis



Visualization & Presentation

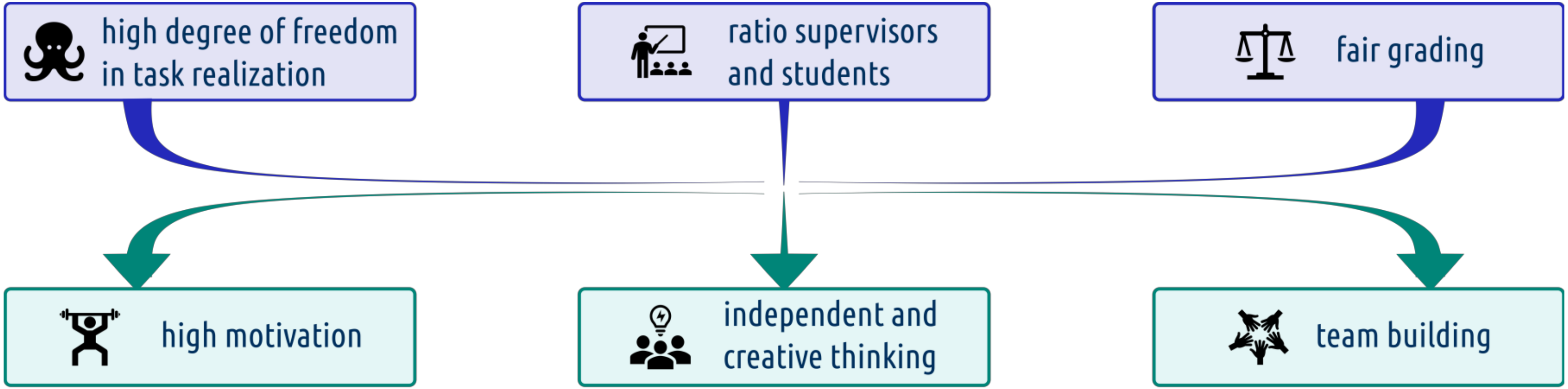


https://git.uni-jena.de/big_data_assignments/projects

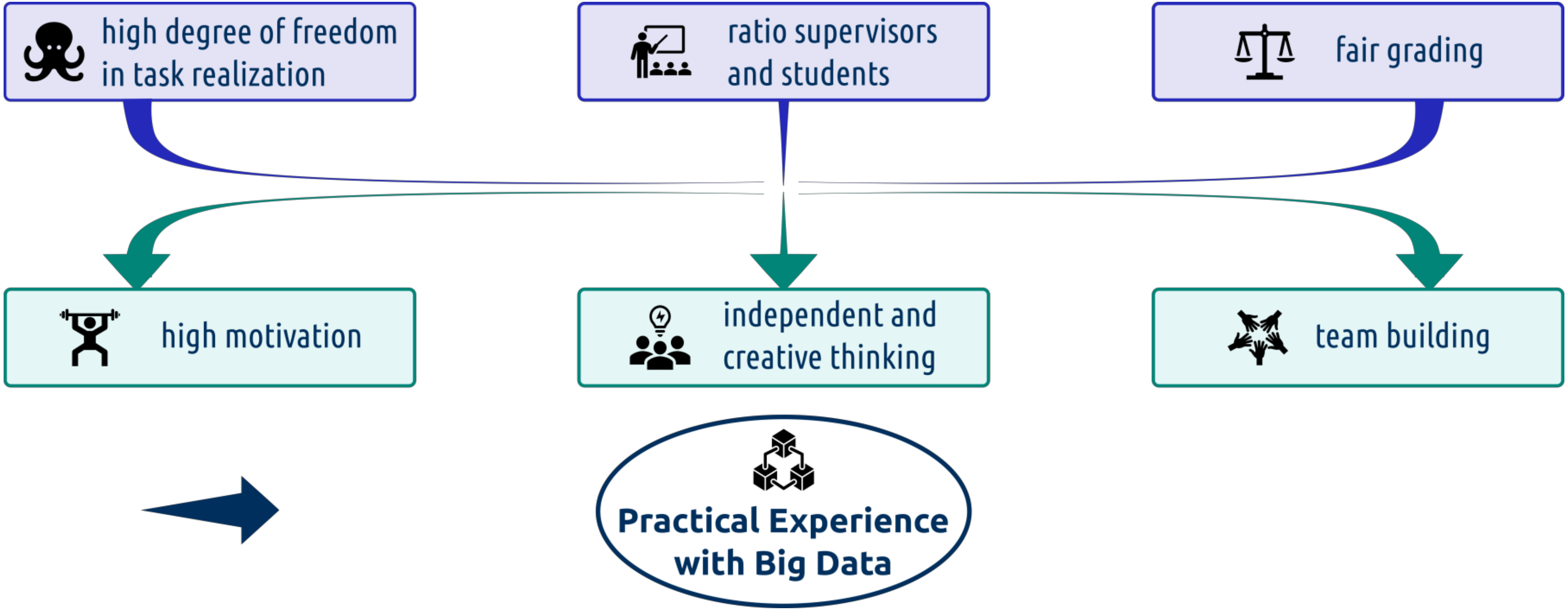
Assignment Evaluation

- high degree of freedom in task realization
- ratio supervisors and students
- fair grading

Assignment Evaluation



Assignment Evaluation



Find our NYC Crime example at …

https://git.uni-jena.de/big_data_assignments/projects

Thank you for your attention!

Marieke Plesske

K-Means:
An assignment for OpenMP, MPI and CUDA/OpenCL

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EduHPC'2023
Nov 13th, 2023

Grupo Trasgo
Universidad de Valladolid

Universidad de Valladolid

Context

- Different parallel programming models
  - Different approaches for parallelizing the same problem
  - Understand the differences is key
  - Needed in modern heterogeneous systems
- Target: Parallel Computing course
  - Computer Engineering degree, 3rd year, Major elective
  - Three practical programming blocks: OpenMP, MPI, CUDA
- Teaching methodology:
  - Based on projects
  - Competitive + Collaborative gamification
- Series of peachy assignments used for the contest activity:
  EduHPC'18, '19, '20, '21, '22

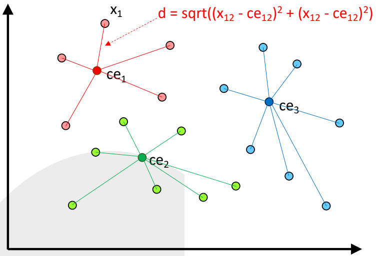
Assignment objectives

- Use the same example program in the three blocks
- Show portability of different key parallelization approaches and techniques
- Observation: Large gap between examples of programming primitives/structures and complex contest codes
- This year: A simpler assignment, focus on basic concepts and their portability
- Students start with:
  - Handout
  - Sequential code with the part to parallelize clearly marked
  - Some examples of input arguments (more can be easily generated)

K-means clustering

- Powerful and popular data mining algorithm:
  Segmentation, pattern analysis, image compression, etc.
- Split a cloud of n-Dimensional points in clusters with minimum distance to a centroid
  - Init: Read points, randomly fix centroid positions
  - Main clustering loop
    - Re-assign points to the nearest centroid
    - Compute new centroid locations:
      Arithmetic mean of assigned points

  (until few re-assignments or max. iterations)



Approach and concepts covered

- Previous educational approaches for OpenMP, MPI, and/or CUDA:
  - Skip to parallelize the computing of new centroid locations (load-balance problems)
  - Use dynamic buffers for cluster points
- Our approach:
  - Parallelize all stages; static data structures (simple to manage, easier to debug)
  - Parallelization strategy provided: Help students to apply theory systematically
    - Loop parallelization
    - Solve *write* and *update* race conditions: Critical regions, atomics, reductions
    - Basic collective operations and communications, distributed reduction
    - Thread-blocks, coalesced memory access
    - Reduction porting and evaluation
    - Advanced students: Locality optimizations, load balancing problems, ...

Using the assignment

- Course and students:
  - Students background: O.S. and concurrency, C programming
  - 48 students enrolled, working in small teams (2 people)
  - One week time for the solution on each model
- Tools:
  - Modern C compiler with OpenMP, any MPI library, CUDA or OpenCL toolkit
  - Code output can be automatically checked for correctness: Tablon
  - Better a shared platform for students to compare and discuss results
  - In our case: AMD server 64 cores + Intel servers 12 cores, 32 cores + 4 NVIDIA CUDA 3.5 GPUs

Results

- Lower complexity than previous peachy assignments: Lower number of test submissions to the cluster
- Personal interview for each block + survey at the end of the course
- All students agreed that the project improves the concepts understanding
- For the first time: 60% students prefer MPI over OpenMP !!
- Solving race conditions is always nasty, Collective communications + static data structures are easy