Keeping the Chandra Satellite Cool with Python

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SciPy2010 conference
July 1, 2010

Chandra satellite (at launch)

- Chandra X-ray Observatory launched by NASA in July 1999
- X-rays reveal energetic processes from black holes, supernova explosions, massive galaxy clusters, pulsars, and more
- Factor of 8 better angular resolution than any other X-ray observatory
- Operating superbly since launch with many ground-breaking discoveries

Chandra satellite (now)

- Ionizing particle radiation environment was worse than expected and was degrading the silverized teflon insulation
- Early in the mission spacecraft temperatures began rising faster than expected
- No repair possible

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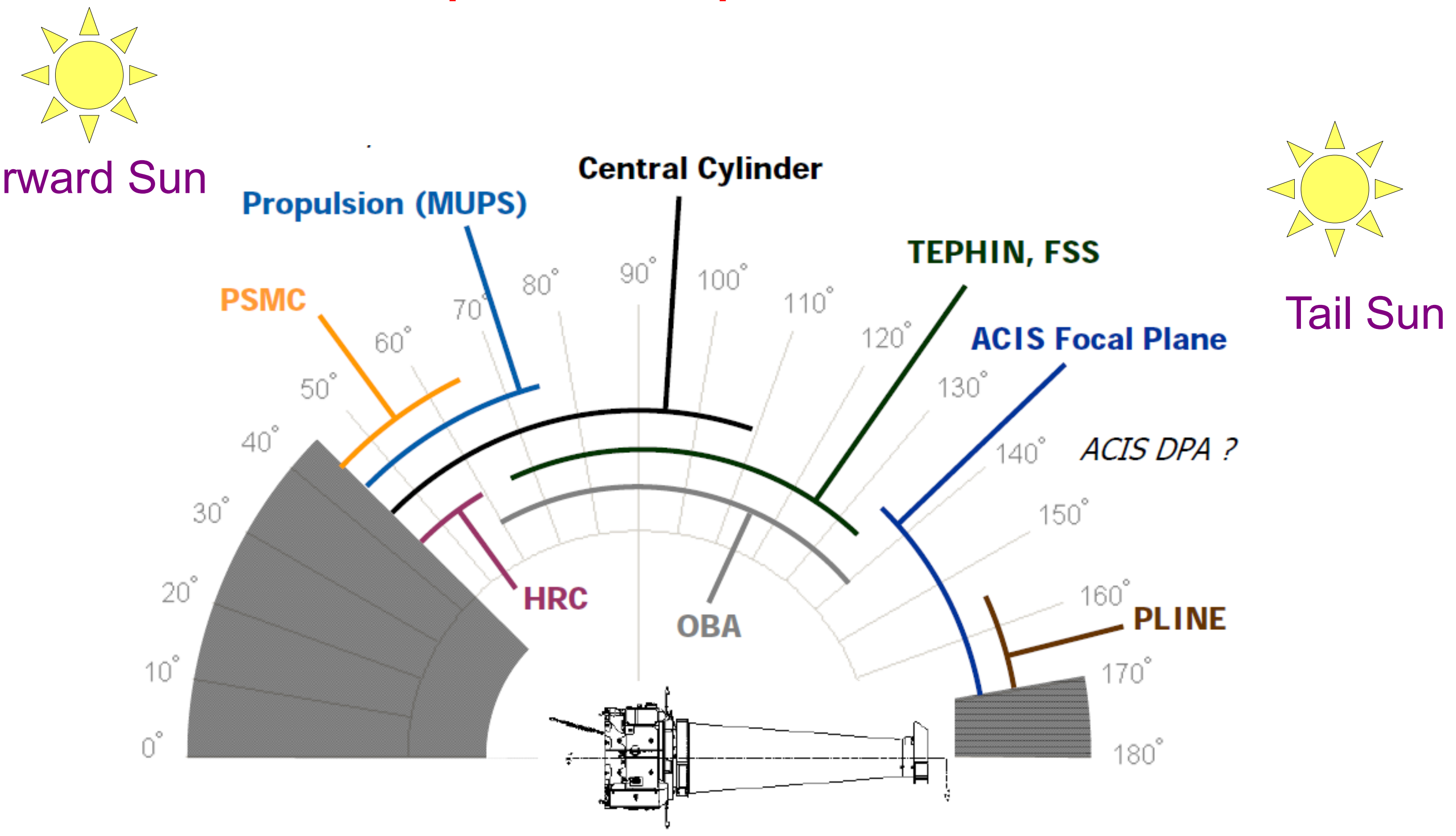
Impact to operations



- Each year observers submit proposals, selected on scientific merit
- Need to get to each target (nightmare traveling salesman problem)
- Until recently used very simple thermal models and constraints to maintain spacecraft components within thermal limits
- *Major driver in operations and mission scheduling*

Thermal modeling

- Eventually the simple models became inadequate
- In 2007 a joint working group including scientists and engineers was formed to address thermal issues and develop higher fidelity thermal models.

Python was chosen to support this effort:

- Ease of development and strong interactive analysis environment
- NumPy (consolidated numerical support)
- IPython
- Matplotlib
- SciPy
- Other 3rd party packages (PyTables, Sherpa, etc)

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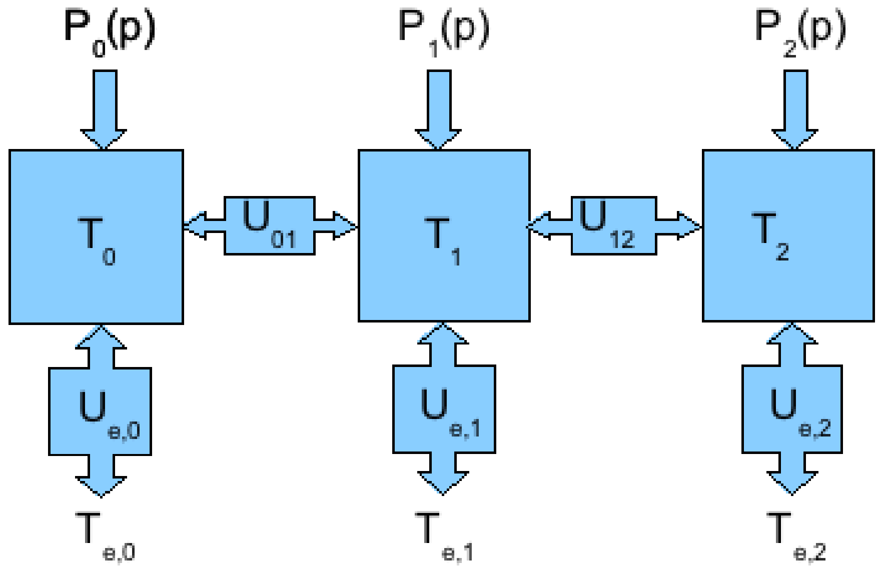
Telemetry access

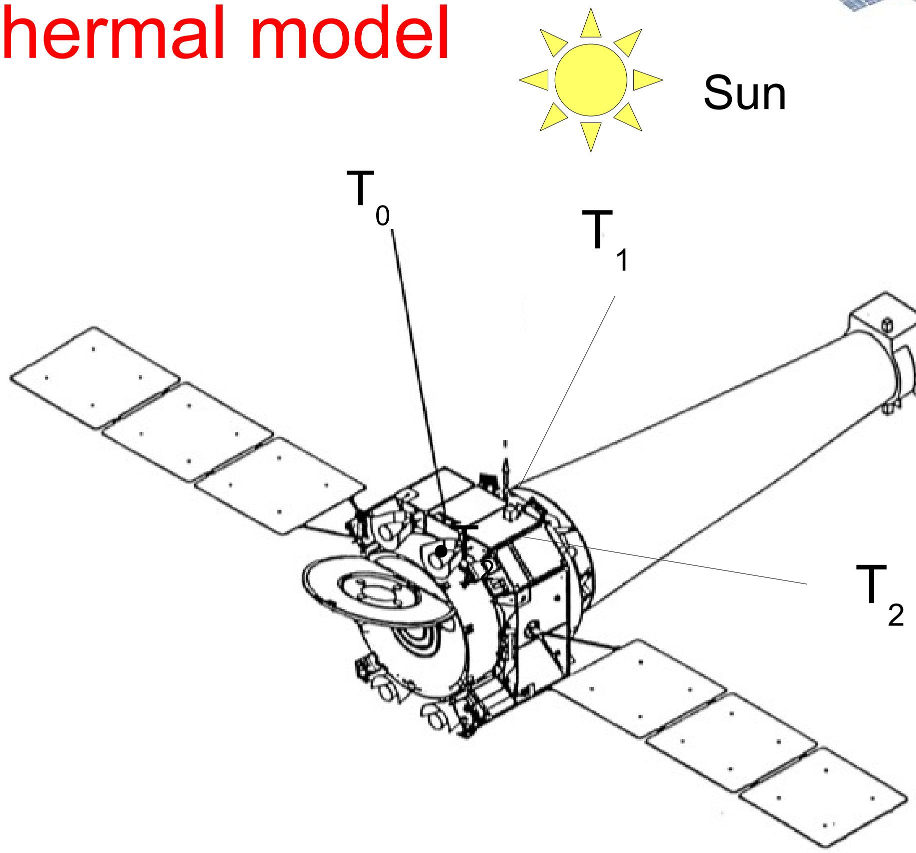
Problem: Developing models requires fast access to years of thermal data

- Chandra records science and engineering data onboard at 32 kbit/s
- Engineering data consists of over 6000 distinct data items (“MSIDs”)
- Data volume meager but telemetry access tools spec'd to 1990's hardware
  - These tools can take hours to retrieve a year of data (10^7 elements/hour...)
  - One tool always decommutates from raw telemetry
  - Other method puts hundreds of related MSIDs in a file spanning just a few hours => getting one MSID is very inefficient

- PyTables and HDF5 to the rescue:
  - Tables with 10^{10} elements are no problem, fast random access and easy appends
  - Solution: *use one huge table per MSID covering the entire duration of the mission*
  - Compression especially efficient since many MSIDs change slowly
  - Entire telemetry archive is less than 300 Gb
  - PyTables is simple to use with good documentation and examples
  - Data retrieval speed ~10^7 elements/sec from NetApp disk (fast enough)

A data-driven thermal model





- Each box (T_0, T_1, T_2) represents a spacecraft node with a thermistor
- Node *i* has an external heat input $P_i(p)$ and conductances $U_{i,j}$ to other nodes
- Throw in an ad-hoc external heat bath with temperature $T_{e,i}$
- $P_i(p)$: spacecraft pitch angle to Sun and possibly internal electronics heat

A data-driven thermal model

- This model has an exact analytic solution with a nice matrix formulation:

$$
\begin{aligned}
\dot{\mathbf{T}} &= \tilde{\mathbf{A}}\mathbf{T} + \mathbf{b} \\
\mathbf{T}(t) &= \int_0^t e^{\tilde{\mathbf{A}}(t-u)}\mathbf{b}\,du + e^{\tilde{\mathbf{A}}t}\mathbf{T}(0) \\
&= [\mathbf{v}_1\ \mathbf{v}_2]\begin{bmatrix} \frac{e^{\lambda_1 t}-1}{\lambda_1} & 0 \\ 0 & \frac{e^{\lambda_2 t}-1}{\lambda_2} \end{bmatrix}[\mathbf{v}_1\ \mathbf{v}_2]^{-1}\mathbf{b} \\
&\quad + [\mathbf{v}_1\ \mathbf{v}_2]\begin{bmatrix} e^{\lambda_1 t} & 0 \\ 0 & e^{\lambda_2 t} \end{bmatrix}[\mathbf{v}_1\ \mathbf{v}_2]^{-1}\mathbf{T}(0)
\end{aligned}
$$

For a 2-node model

- The **A** matrix depends on the conductances and **b** vector on external power
- Accuracy is independent of step size

A fast thermal model

First implementation was a literal transcription for each time step – SLOW

Optimization steps:

- Include time dimension in arrays to compute with a single NumPy expression (factor of 10-20 improvement)
- Refactor equations to avoid any repetitions within loops
- Cache various intermediate results
- Overall factor ~40 improvement over initial literal implementation

These straightforward steps made “plain Python” code pretty fast:

Can compute a year of temperatures in ~1 sec

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Fitting model parameters

These thermal models contain 15 to 80 free parameters (conductances, solar heating vs. pitch, long-term and annual variations)

CIAO Sherpa modeling and fitting package to the rescue:

- Powerful model language
  - Complex models as a Python expression
  - Parameter linking, freezing
- Good optimization methods for many-parameter fits
- Good documentation and support
- Well-suited to interactive analysis

Good reasons to worry about fitting 80 parameter models, but IT WORKS.

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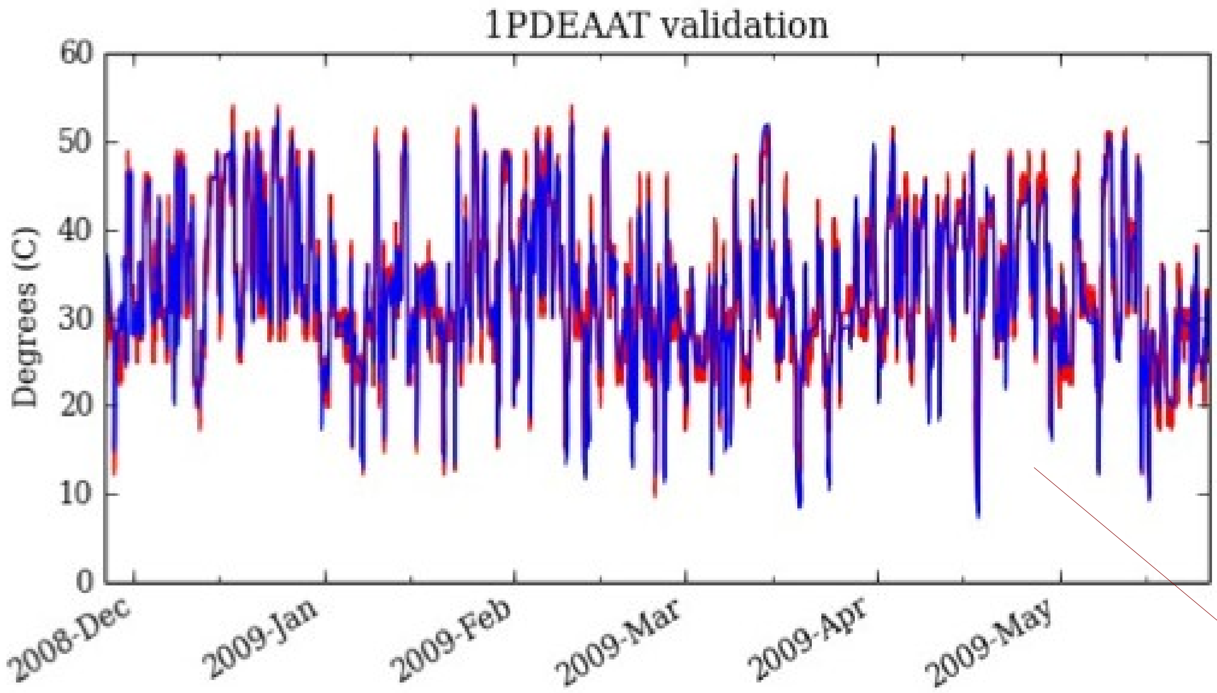
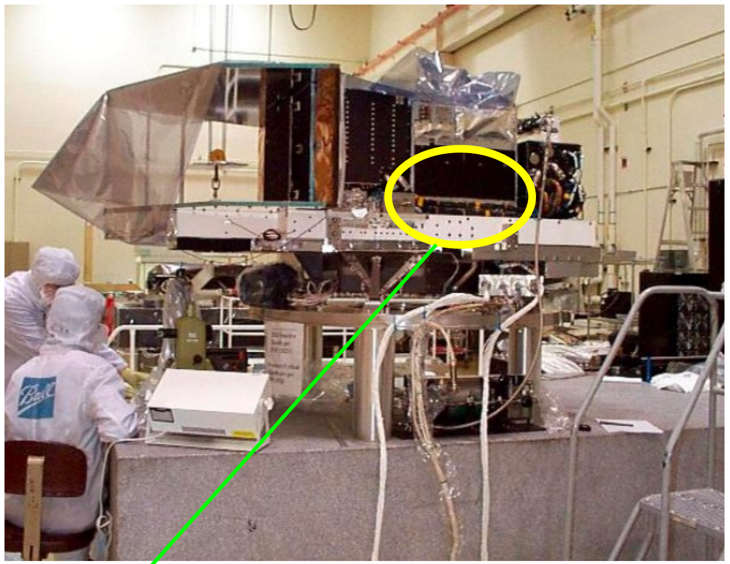
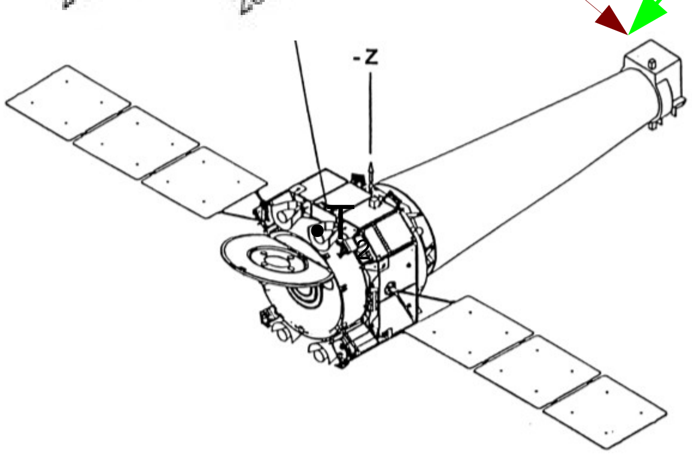
Calibrated model

Fitting process finds parameters so the model calculation matches thermal data over the previous ~5 years (red is data, blue is model):



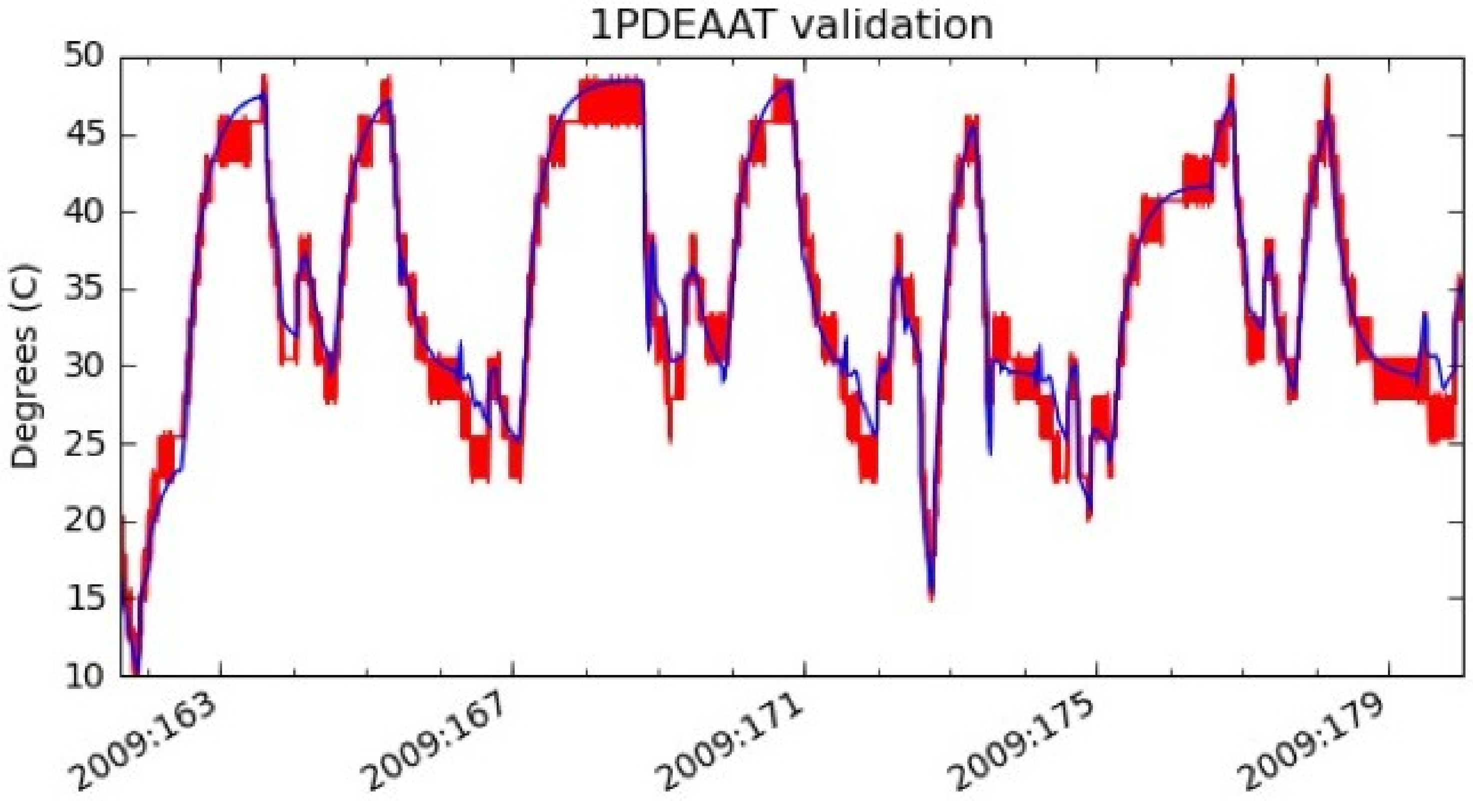




Calibrated model prediction

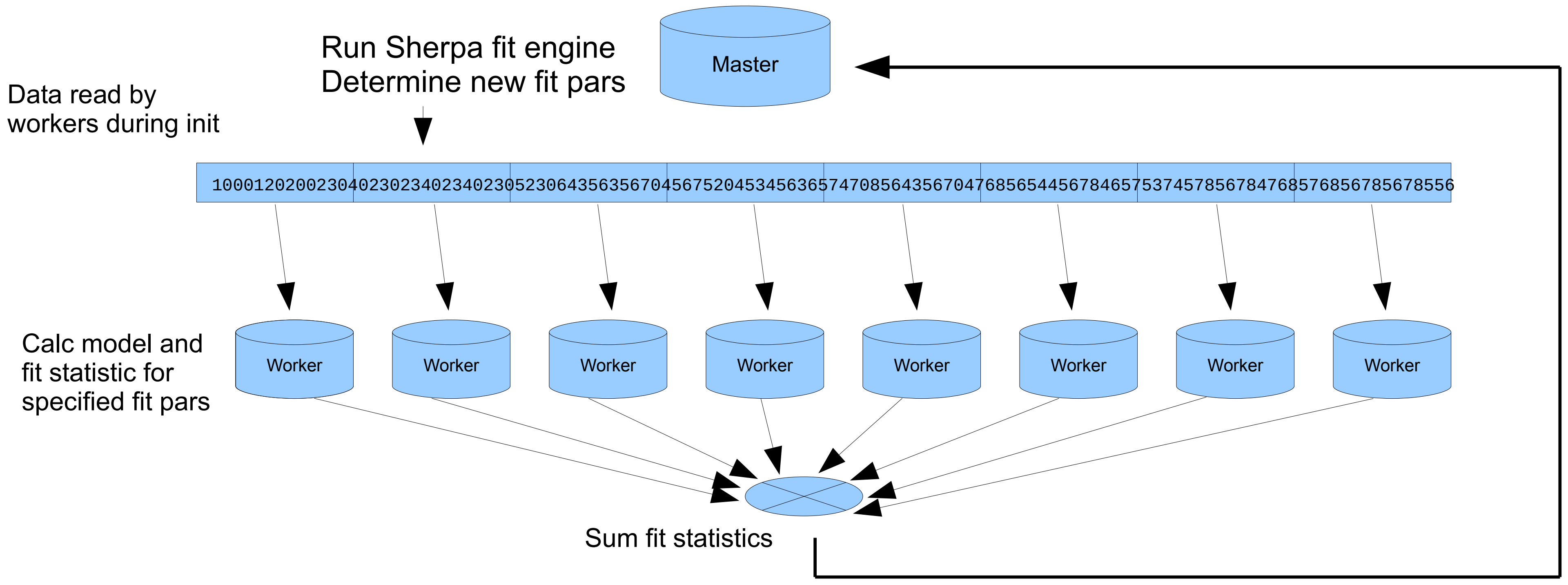
Calibrated model is then used to predict temperatures for *planned* observations

Power supply temperature
Possible damage at 62C



Parallelization

- Computation is easily parallelized by splitting into independent time segments
- Simple code extension with mpi4py with MPICH2
- Master-worker architecture:
  - Master controls the fit process and initialization
  - Workers read in thermal data, calculate model and χ^2 fit statistic over time segment



Parallelization with MPI

In the master program replace data initialization, model and fit statistic calculation functions with new functions:

```
comm = MPI.COMM_SELF.Spawn(sys.executable,
                           args=['fit_worker.py'],
                           maxprocs=n_workers)

def init_workers(metadata)
    """Init workers using values in metadata dict"""
    msg = {'cmd': 'init', 'metadata': metadata}
    comm.bcast(msg, root=MPI.ROOT)

def calc_model(pars):
    """Calculate the model for given pars"""
    comm.bcast(msg={'cmd': 'calc_model', 'pars': pars},
               root=MPI.ROOT)

def calc_stat()
    """Calculate chi^2 diff between model and data"""
    msg = {'cmd': 'calc_statistic'}
    comm.bcast(msg, root=MPI.ROOT)
    fit_stat = numpy.array(0.0, 'd')
    comm.Reduce(None, [fit_stat, MPI.DOUBLE],
                op=MPI.SUM, root=MPI.ROOT)
    return fit_stat
```

Parallelization with MPI

The main logic of the master fit program is nearly unchanged except for the addition of code to dynamically spawn workers:

```
init_workers({"start": date_start, "stop": date_stop})

# Sherpa commands to register and configure a function
# as a user model
load_user_model(calc_model, 'mpimod')
add_user_pars('mpimod', parnames)
set_model(mpimod)

# Configure the fit statistic
load_user_stat('mpistat', calc_stat)
set_stat(mpistat)

# Do the fit
fit()
```

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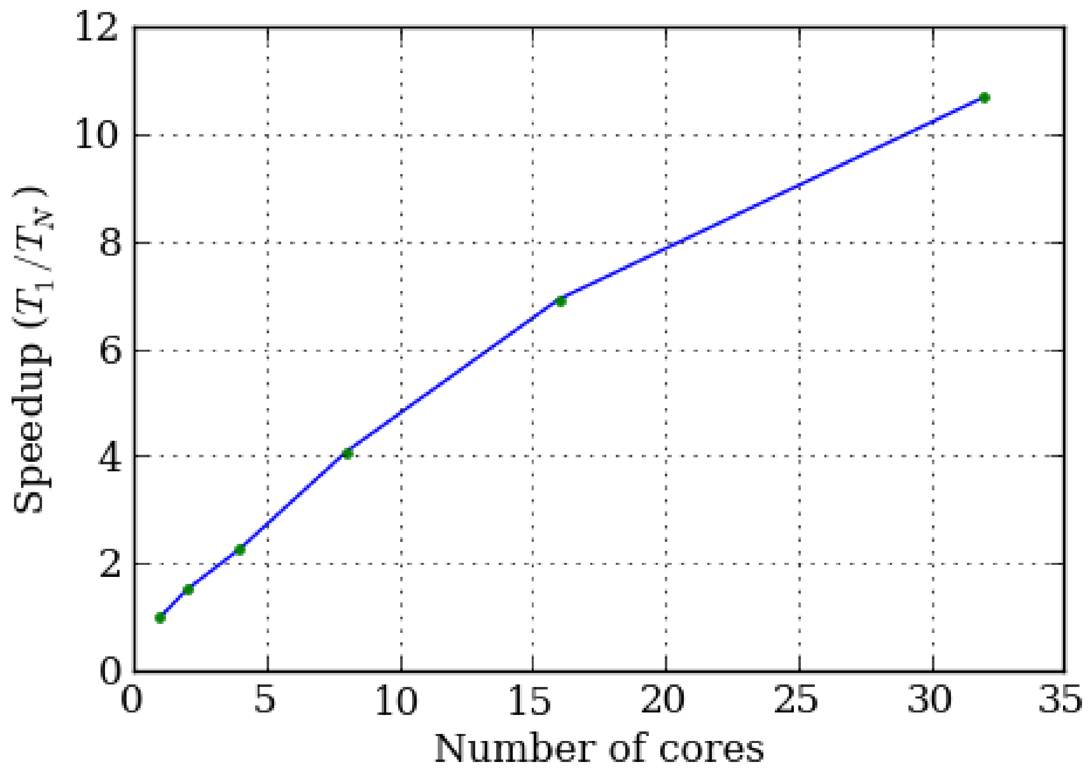
Parallelization with MPI

The fit worker code just waits around to get instructions:

```
comm = MPI.Comm.Get_parent()
size = comm.Get_size()
rank = comm.Get_rank()

while True:
    msg = comm.bcast(None, root=0)

    if msg['cmd'] == 'stop':
        break

    elif msg['cmd'] == 'init':
        x, y = get_data(msg['metadata'], rank, size)

    elif msg['cmd'] == 'calc_model':
        model = calc_model(msg['pars'], x, y)

    elif msg['cmd'] == 'calc_statistic':
        fit_stat = numpy.sum((y - model)**2)
        comm.Reduce([fit_stat, MPI.DOUBLE], None,
                    op=MPI.SUM, root=0)
comm.Disconnect()
```

Parallelization speedup

- The speedup obtained is useful
- Parallel fraction = 0.94
- Ultimate speedup = 16



Putting it all together

Two certified (NASA Level-4 review board) thermal models are being used in Chandra operations:

- Power Supply and Motor Controller for the Advanced Chandra Imaging Spectrometer (ACIS PSMC)
- “Minus-Z” model of 5 nodes on the Sun-pointed (-Z) side of the spacecraft

Formal command load review process verifies no thermal limit violations in the schedule of planned observations for the next week.

Developing higher-fidelity thermal models for Chandra was a difficult thing that was made possible by the Python ecosystem.

The reason we bother