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Python tools for simulating beam dynamics

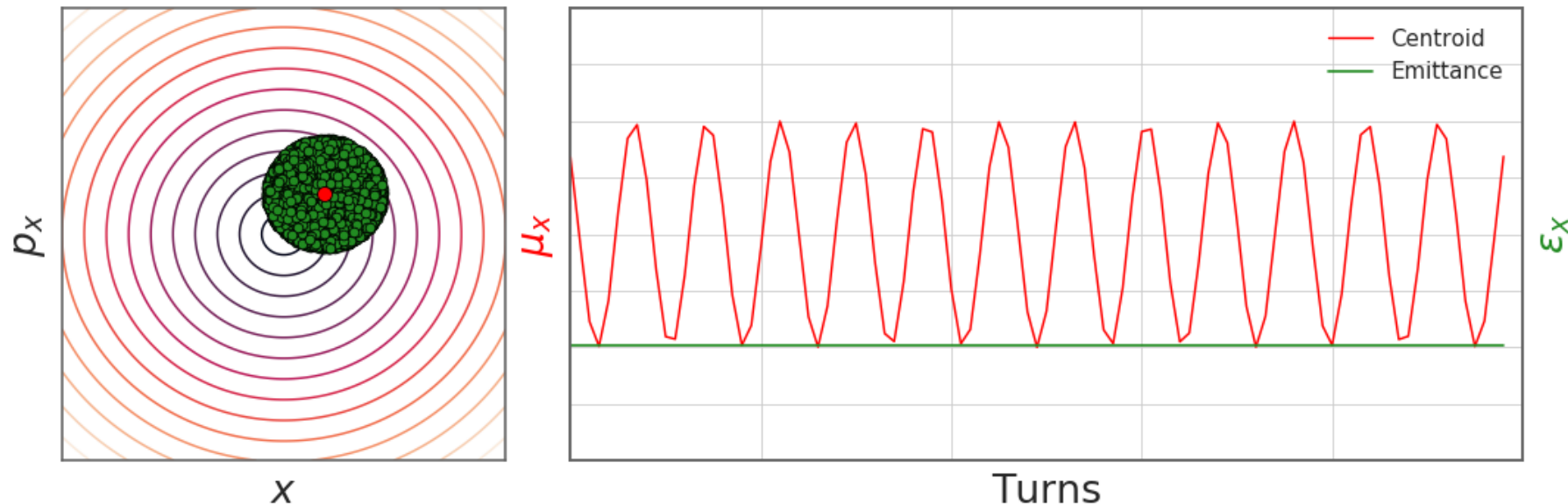
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for the PyHEADTAIL developer team

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Beam dynamics

- Beam dynamics essentially studies the evolution of the phase space variables i.e. the generalized coordinates and canonically conjugate momenta of a beam in an accelerator
- This evolution is primarily determined by external force fields, e.g.
 - Magnets: bending, focusing...

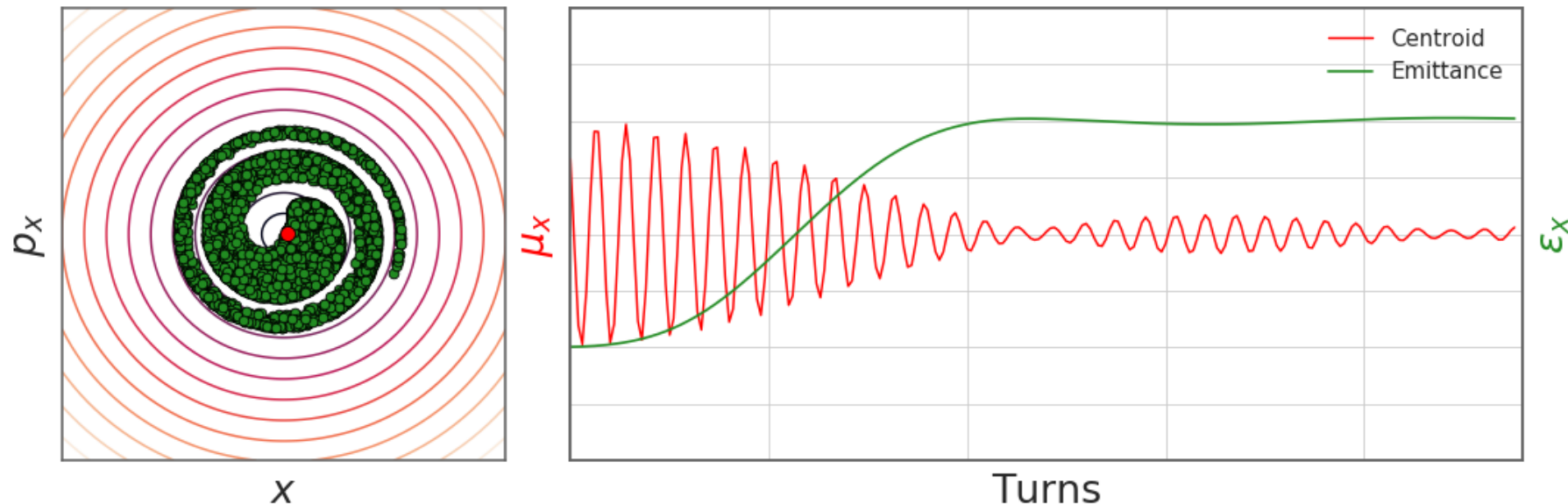
Filamentation and emittance growth due to initial offset (and non-linearities)



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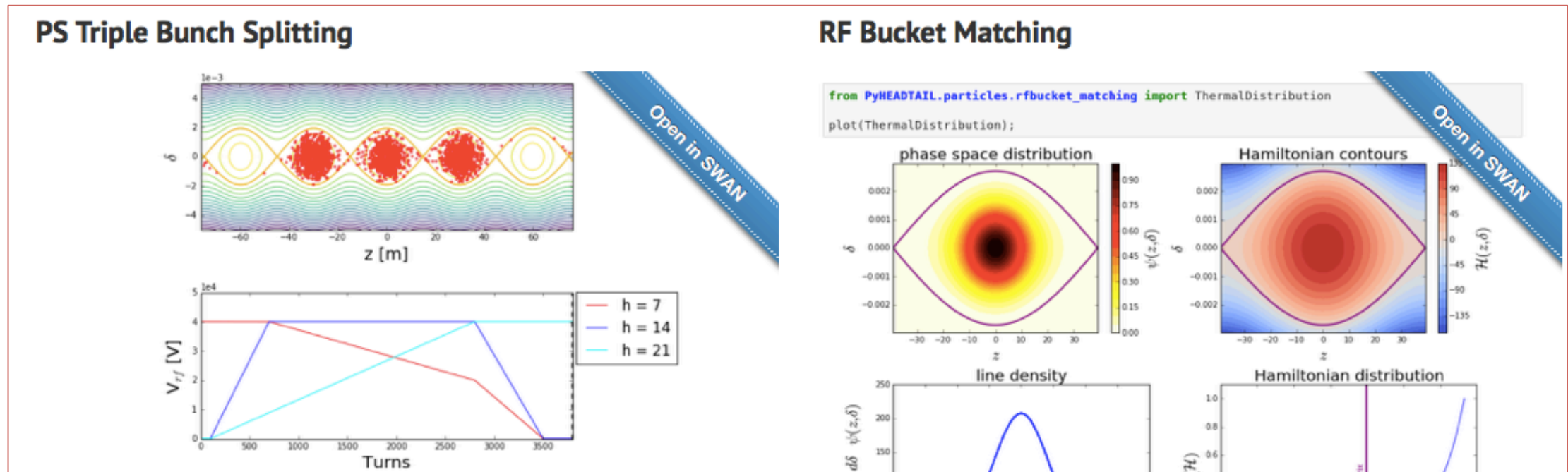
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 - Magnets: bending, focusing...
 - RF fields: confinement in bunches, acceleration...

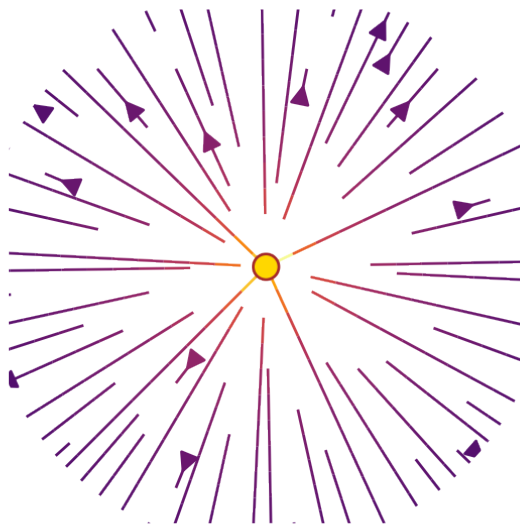
[SWAN Beam dynamics gallery](#)



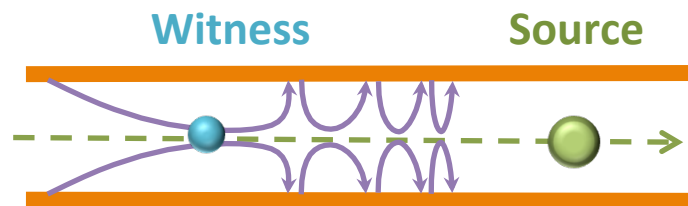
Collective effects

- The evolution can be affected by collective effects – fields that are caused by the beam itself and depend on its phase space distribution, e.g.
 - Space charge: Coulomb repulsion between particles within beam
 - Wake fields: beam-induced image charges and currents in the surrounding structure
 - Electron cloud: beam-induced exponential electron accumulation

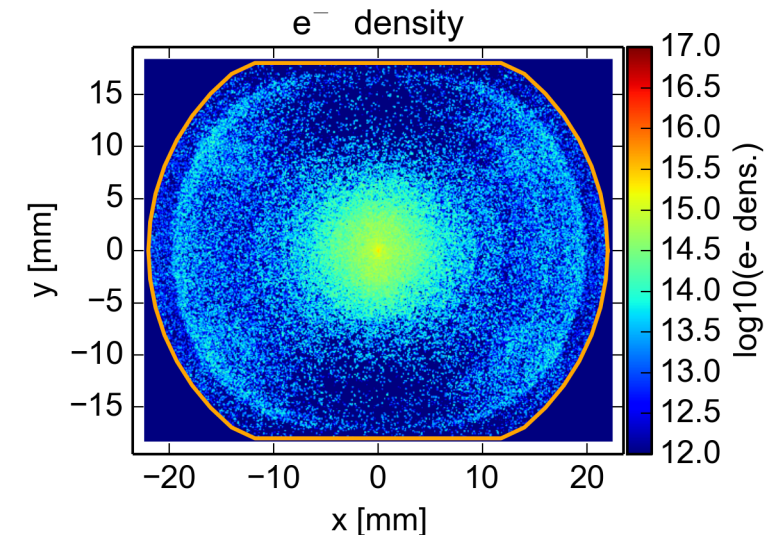
Space charge



Wake fields

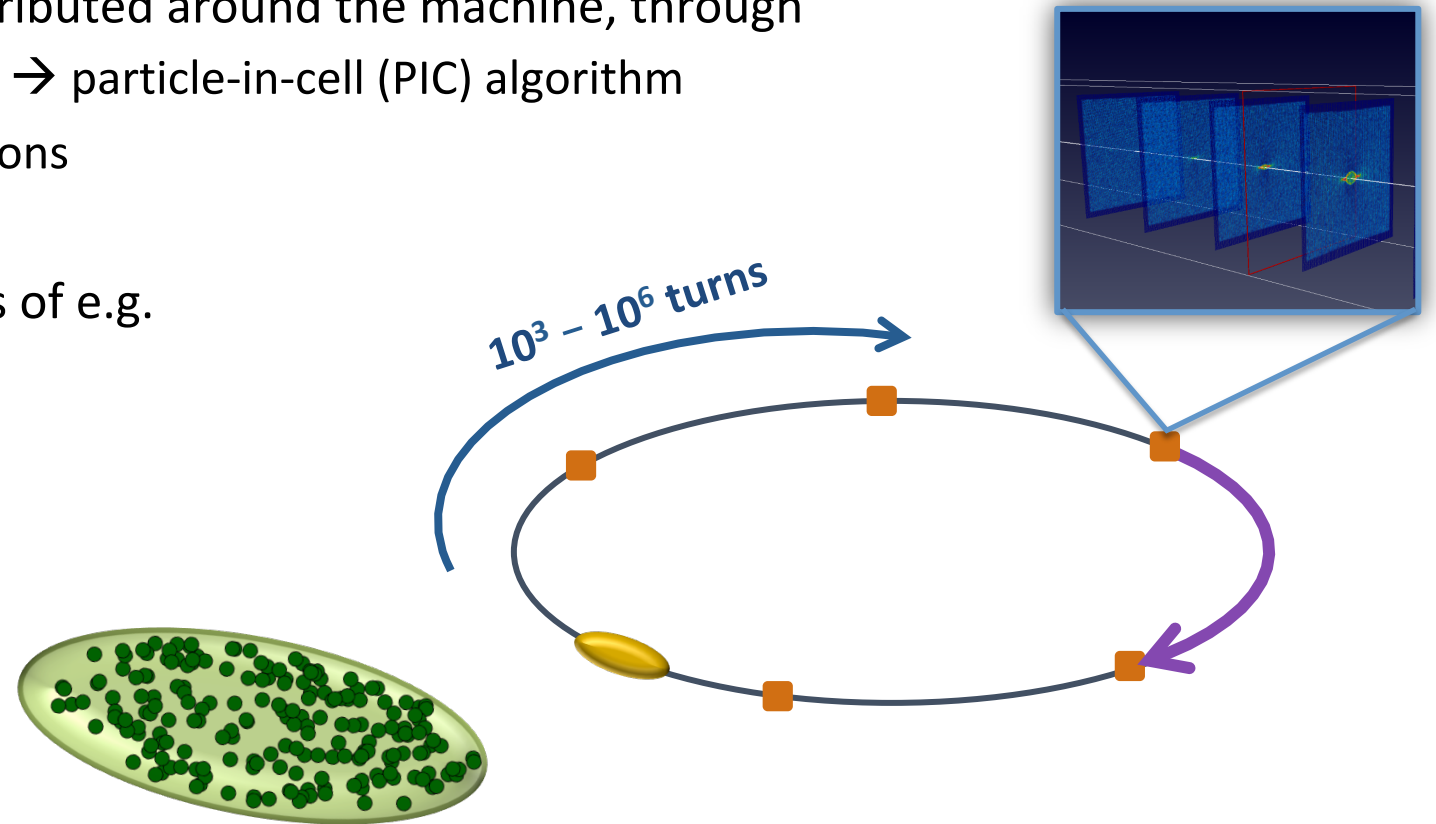


Electron cloud



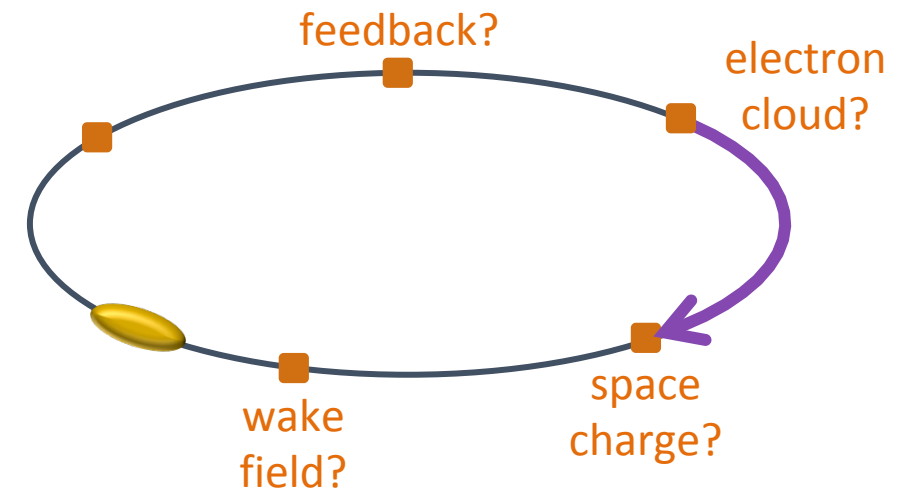
The simulation model

- The beam is modelled as macro-particles, typically $N \approx 10^6$
 - The effect of external force fields can be applied with analytical expressions
- Collective effects are modelled as kicks distributed around the machine, through
 - solving for the electric field of the particles \rightarrow particle-in-cell (PIC) algorithm
 - or a convolution over macro-particle positions
- Similar models and dynamics to simulations of e.g. large scale structure, plasma physics...



Why Python?

- Are compiled languages not ideal for simulations that rely on repeating a few core algorithms?
 - Indeed, we have (had) such codes, and the good ones are (were) robust, powerful and fast
 - However, we would like our tools to also be versatile, extendible and easily maintainable
- A large part of the users need to modify/extend the code to study specific physics cases
 - Development should be as simple and fast as possible
 - We also want to avoid several independently developing forks of the same code (**old oak vs. bonsai**)
- Different users want to use different combinations of ingredients
 - We need a modular structure
 - Object-oriented programming



- Because we can make it:



Simple

- Easy to fix
- Easy to read
- Easy to maintain



Modular

- Easy to extend
- Easy to combine
- Easy to maintain



Dynamic

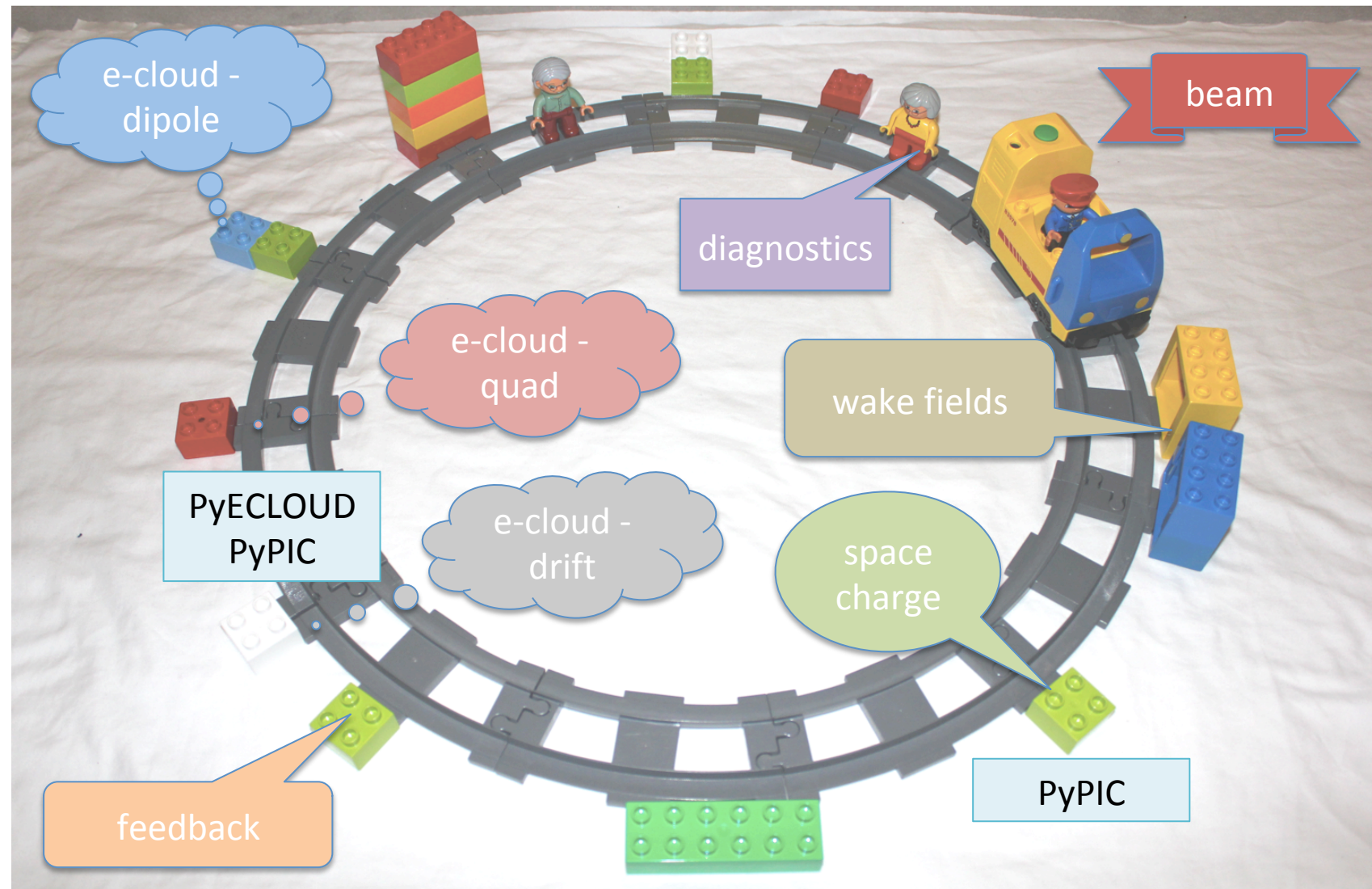
- Fast
- Flexible
- Interactive

A library of beam dynamics tools:

- particles
- machines
- trackers
- space charge, wake fields
- monitors...

In fact we have a collection of compatible libraries:

- PyECLOUD: e-cloud dynamics
- PyPIC: PIC routines
- Py(CERN)Machines...



Running PyHEADTAIL

- Instead of running the simulations using the classic:

input file(s) + main executable

we can simply use a Python script

→ The full power of Python is available in the input file

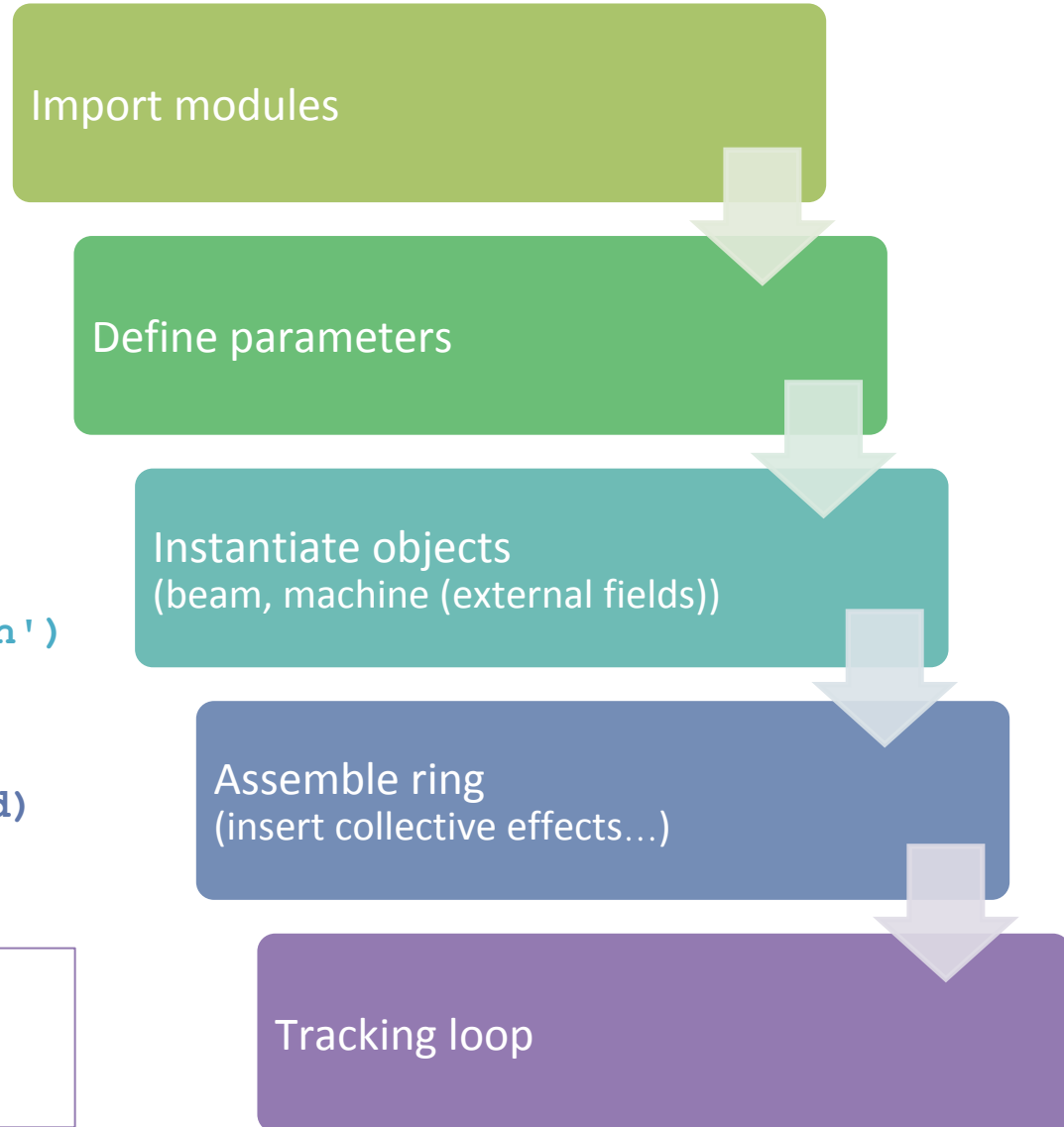
→ Simple, highly customizable, interactive

```
machine = SPS(n_segments = n_seg,
             machine_configuration = 'Q26-injection')
```

```
# install eclouds
machine.install_after_each_transverse_segment(ecloud)
```

→ The “simulation”:

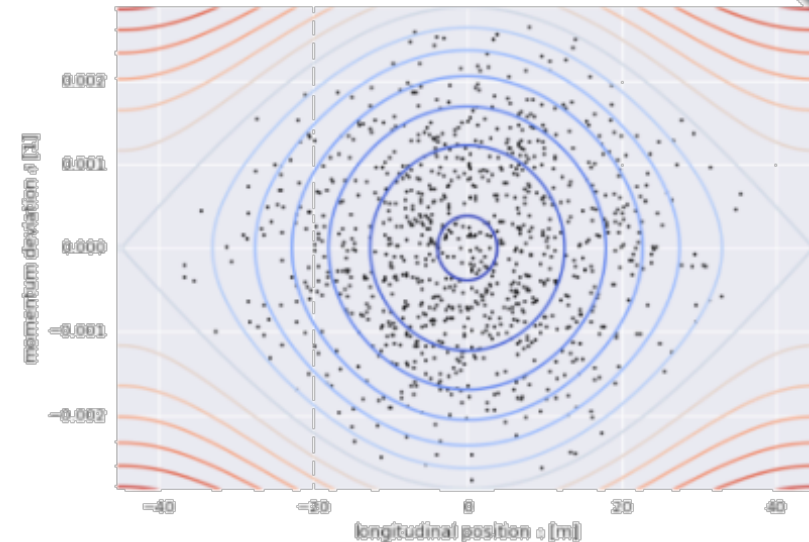
```
for i in range(nturns):
    for m in one_turn_map:
        m.track(beam)
```



- PyHEADTAIL documentation is in the form of Jupyter notebooks: PyHEADTAIL-playground
 - Instructive notebooks that outline the different use cases of the code
 - Have been used at several accelerator physics schools etc.
 - Work also as a testing suite
- The PyHEADTAIL-playground could be put on SWAN after PyHEADTAIL was added to pip
 - Makes the notebooks even more accessible, since no local installation or specific environment needed
- Accompanied by the **beam dynamics gallery**: illustrative notebooks with visual representations
 - Accessible from SWAN front page

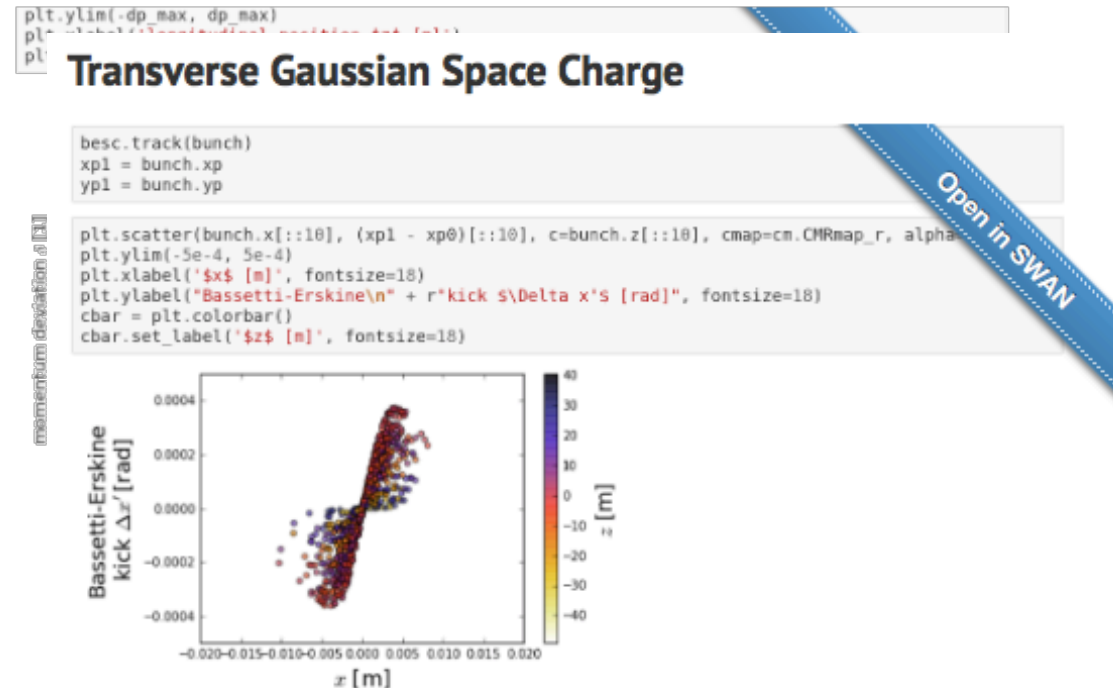
Quick Start Tutorial

```
plt.ylim(-dp_max, dp_max)  
plt.xlabel('longitudinal position $z$ [m]')  
plt.ylabel('momentum deviation $\delta$ [1]');
```



- Beam dynamics gallery and PyHEADTAIL-playground
 - Easy introduction for newcomers, students, etc
 - Can be useful also for non-experts, e.g. machine operators for visualisation
 - Motivation among users to add additional examples
- In addition to developing and using instructive material, more generally PyHEADTAIL on SWAN can be useful for quick simulations and for testing and exploring purposes
 - Full “production” simulations typically done on batch service or HPC clusters
- The prospect of using SWAN as an interface and manager for batch jobs could be interesting for our users (but mainly if access to significant resources)

Quick Start Tutorial



Performance

- To try to maximize the performance, we use:
 - NumPy `ndarrays` for basic data structures
 - SciPy where appropriate
 - FFTW with **pyFFTW**
 - Output in HDF5 with **h5py**...
- Some of the core algorithms are implemented in C(++) or Fortran, binding to Python through
 - Cython, **f2py**
- With the caveat that our codes are not necessarily maximally optimized, to be fair, they are not as fast as they could be e.g. in C
 - However, an increase in runtime of some tens of per cent feels like a small price to pay for the other benefits

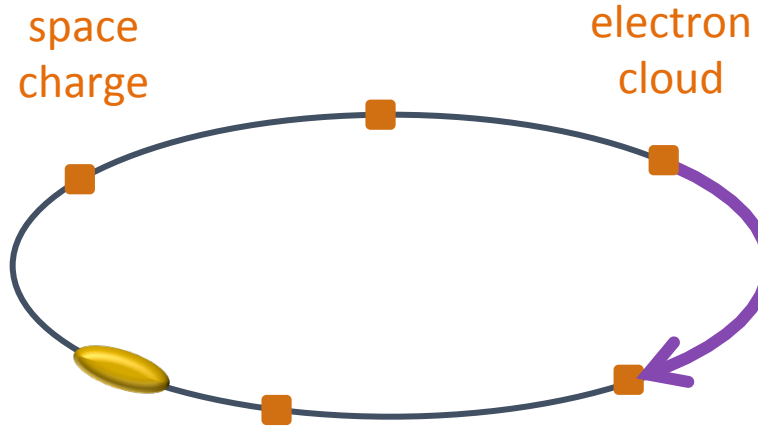


Parallelisation

- Many of our use cases are quite demanding in terms of computation time, despite optimization
- Abstract parallelisation layers implemented to keep main code unchanged
- Different physics models require different parallelisation methods:

PyCUDA

Space charge instantaneously couples all particles within the bunch
→ the same calculation to be done for large number of particles – suited for GPU-parallelization



mpi4py

The electron cloud interaction must be done sequentially over several slices of a single bunch → parallelisation only over different kicks, which are treated slice-by-slice

simulations still take weeks/months

- Context manager for GPU-parallelisation handles all dispatches of function calls according to context (GPU/CPU)
- Parallel ring simulator (PyPARIS) distributes the different electron cloud kicks in the machine over several processors and passes beam slices around the ring

Conclusion & final remarks

- Python allows us to keep our tools concise, neat and organised, yet versatile and dynamic, without compromising much on performance
 - Even if Python isn't the ideal language for the rest of eternity, it provides a good starting point for the next step
- Jupyter Notebooks are great for documentation, education, and exploring
 - PyHEADTAIL on SWAN makes them even more easily accessible and available
 - SWAN as an interface for batch jobs could be very interesting for us
- Python 2 to 3
 - Currently our tools are in Python 2.7
 - Many parts of the codes are compatible with Python 3, but migration needs to be done collectively
 - Foreseen for LS2 when the machines will need less follow-up
- <https://github.com/PyCOMPLETE>

A brief history of codes

