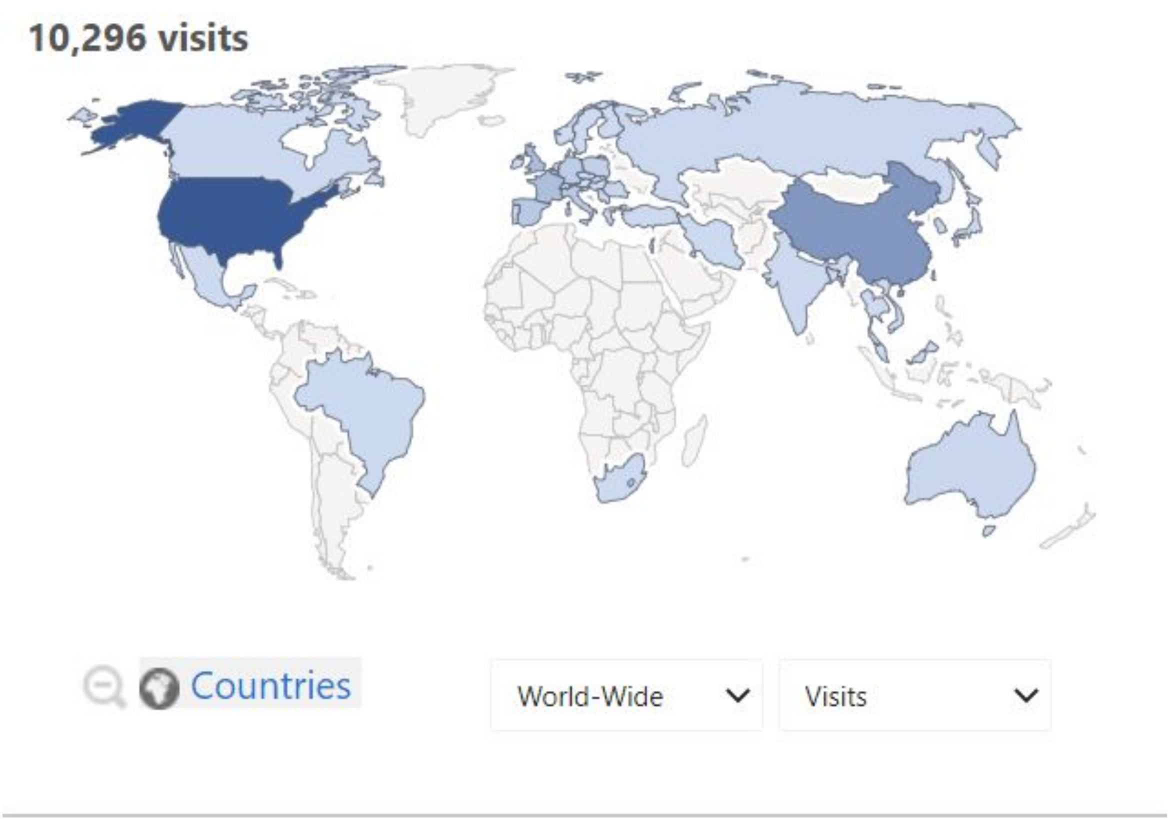
The GTOC series, a brief history of an unexpected journey.

Dario Izzo
European Space Agency, Advanced Concepts Team

Portal visits during gtoc11



COUNTRY	VISITS
United States	4,043
China	2,010
United Kingdom	874
France	770
Spain	513
Italy	438
Germany	365
Unknown	300
Poland	293
South Korea	92
Romania	91
Japan	89
Australia	76

Portal unique visits during Sept-Dec 2021 (i.e. before during and after gtoc11) with long permanence (>1min)

2004 … all very unclear … (to me)

The procedure is tested by analyzing direct and multiple-gravity-assist missions to Mars; results show that the procedure is effective in finding many local optima and missions with different trip times in the case of direct trajectories, and does not require particular knowledge by the user;

On the more complex problem it is one order of magnitude more reliable than the tested stochastic methods and outperforms the deterministic ones.

is a smart global trajectory optimization method that requires only the target body/state and intervals for the initial conditions (e.g., launch date, hyperbolic excess velocity, etc.) as input to find a near-globally optimal trajectory for the specified problem.

significantly outperform others on a majority of the benchmark functions, especially in solving an optimization problem that has high dimensionality. Additionally, the superior identification capability of the proposed algorithm is evident from the results obtained through the simulation study compare to other ...ms. All the results prove the superiority of the

trajectory design problems. The novel algorithm displays a remarkable robustness, i.e., the ability to repeatedly converge to solutions with a value of the cost function close to the best known solution to date. Furthermore, it shows the desirable characteristic of increasing its performance with the number of function evaluations, reaching in some cases success rates which are up to around 25 times higher than the standard DE. These considerations

Trajectory Optimization felt like a closed door!

- Difficult to reproduce results
- Lack of common benchmarks
- Absence of a common validated code base
- Extreme repetitions by different groups
- Most code in Fortran and Matlab shared via mails / websites.

a) make them compete on a well defined trajectory problem

b) have the winner define a next problem (brilliant … from Franco Ongaro)

c) open it to the widest possible audience, including non space experts

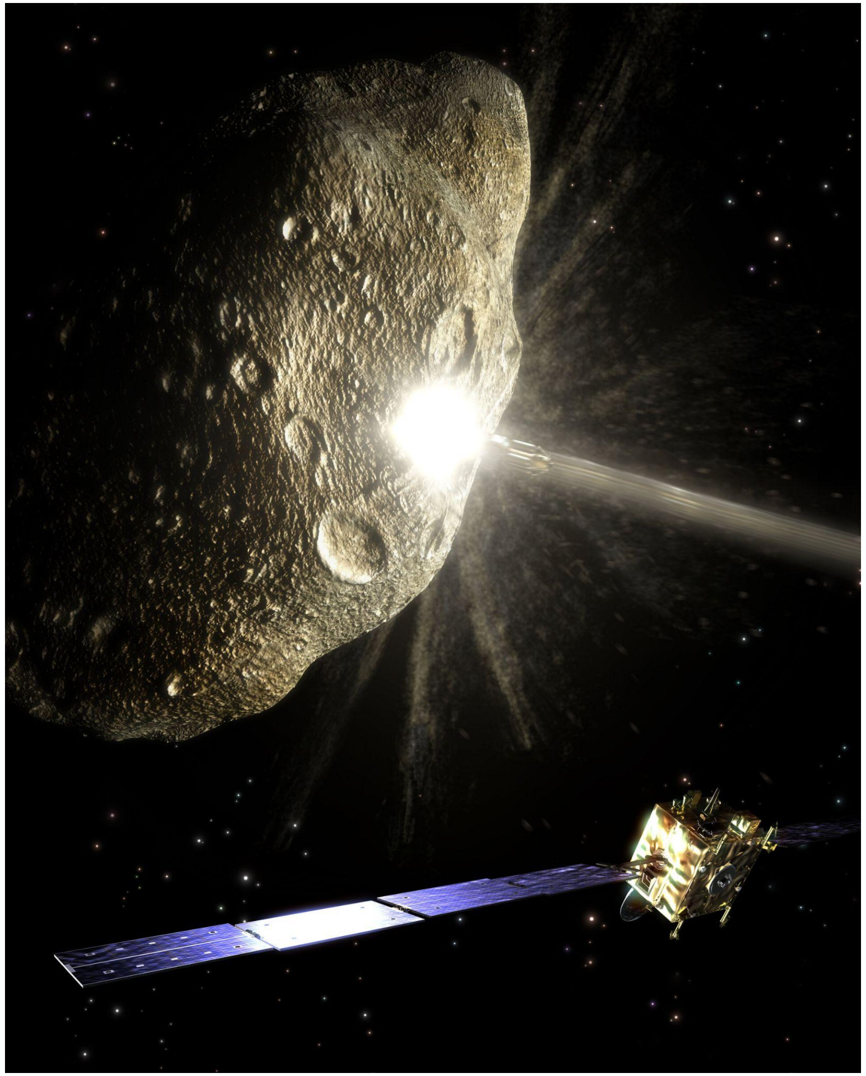
"... it will likely be a one time exercise between Dario and few of his friends in academia, cannot harm"

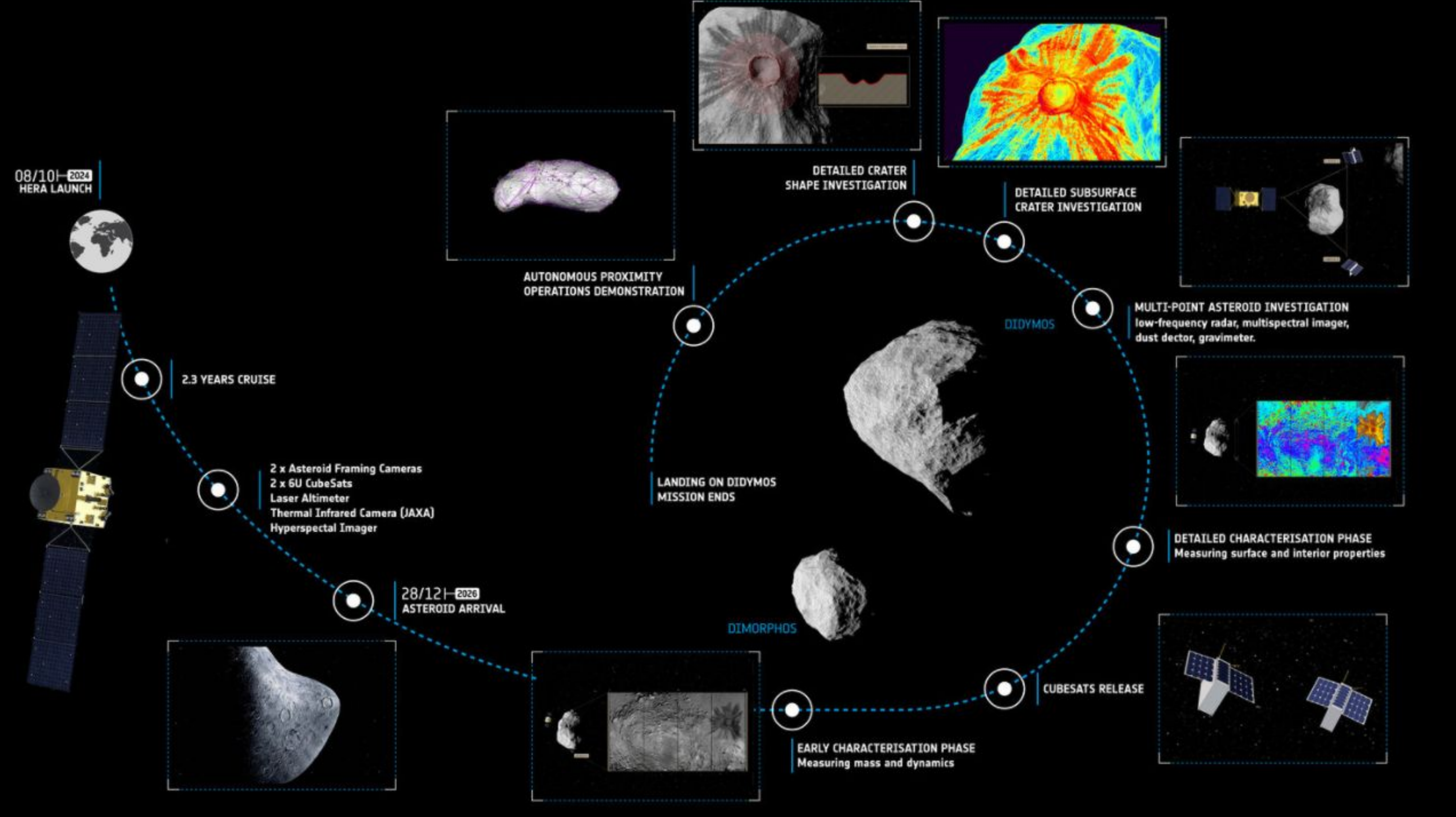
… alea iacta est

2005:
"Don Quijote is currently under study by **ESA's Advanced Concepts Team** (ACT). Two target asteroids (2002 AT4 and 1989 ML) have been selected.
The current scenario envisages two spacecraft in separate interplanetary trajectories. One spacecraft (Hidalgo) will impact an asteroid; the other (Sancho) will arrive earlier at the target asteroid, rendezvous and orbit the asteroid for several months, observing it before and after the impact to detect any changes in its orbit."

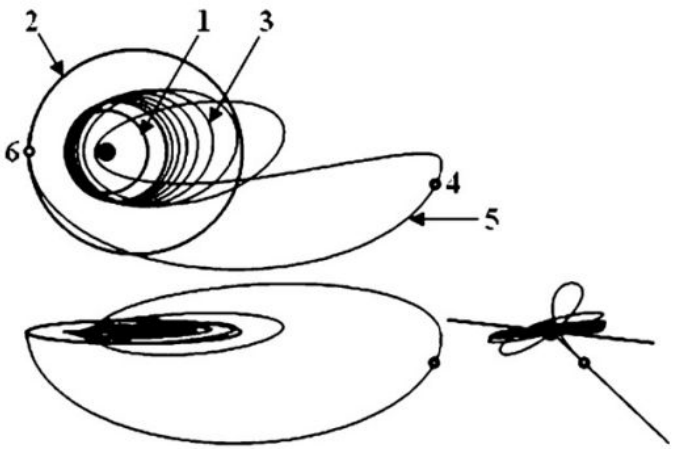
2021:
"The European Hera mission will follow NASA's DART asteroid-deflecting spacecraft to the binary space rock Didymos and detail the aftermath of DART's collision with the smaller of the two asteroids, Dimorphos. It will even attempt to peek inside the asteroid duo in a scientific first.

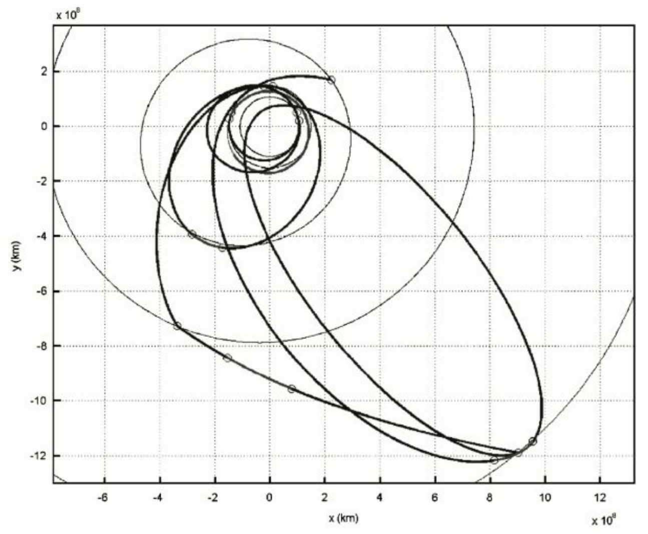
According to the European Space Agency's (ESA) original plans, Hera would have witnessed DART's suicidal encounter with Didymos' moon Dimorphos in 2022 firsthand. But initial hesitation among ESA's member states led to funding delays. As a result, this investigator spacecraft will only arrive at the scene more than two years after the cataclysmic impact"

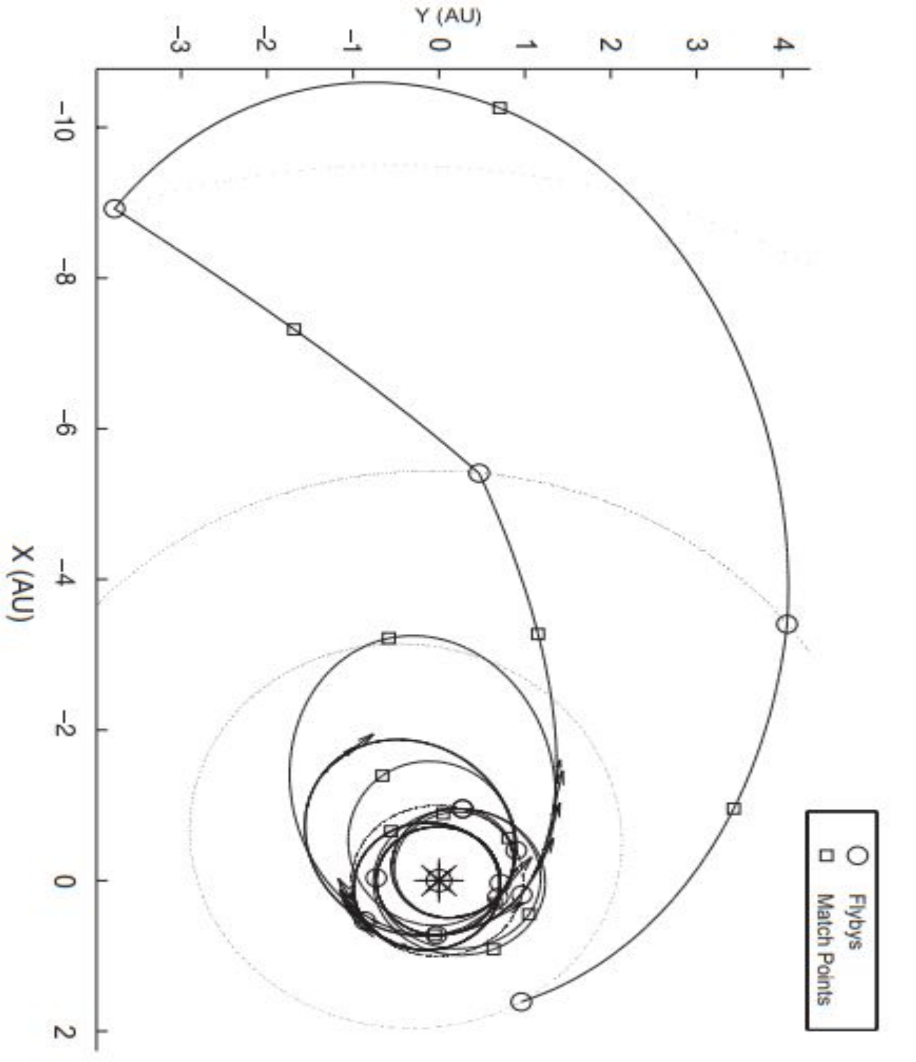


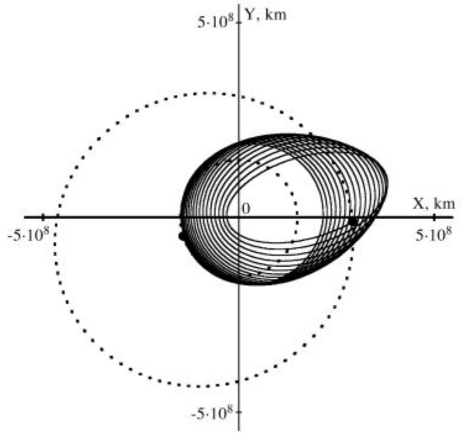

08/10 2024
HERA LAUNCH
2.3 YEARS CRUISE
2 x Asteroid Framing Cameras
2 x 6U CubeSats
Laser Altimeter
Thermal Infrared Camera (JAXA)
Hyperspectal Imager
28/12 2026
ASTEROID ARRIVAL
AUTONOMOUS PROXIMITY
OPERATIONS DEMONSTRATION
DETAILED CRATER
SHAPE INVESTIGATION
DETAILED SUBSURFACE
CRATER INVESTIGATION
MULTI-POINT ASTEROID INVESTIGATION
low-frequency radar, multispectral imager,
dust dector, gravimeter.
DIDYMOS
LANDING ON DIDYMOS
MISSION ENDS
DETAILED CHARACTERISATION PHASE
Measuring surface and interior properties
DIMORPHOS
CUBESATS RELEASE
EARLY CHARACTERISATION PHASE
Measuring mass and dynamics

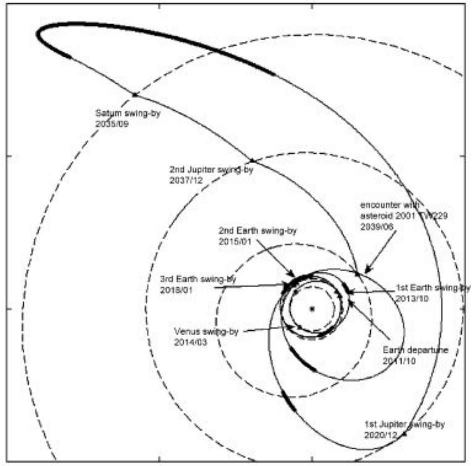
Exploration-exploitation

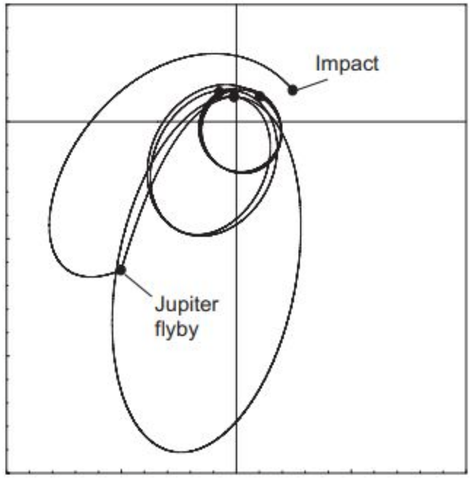










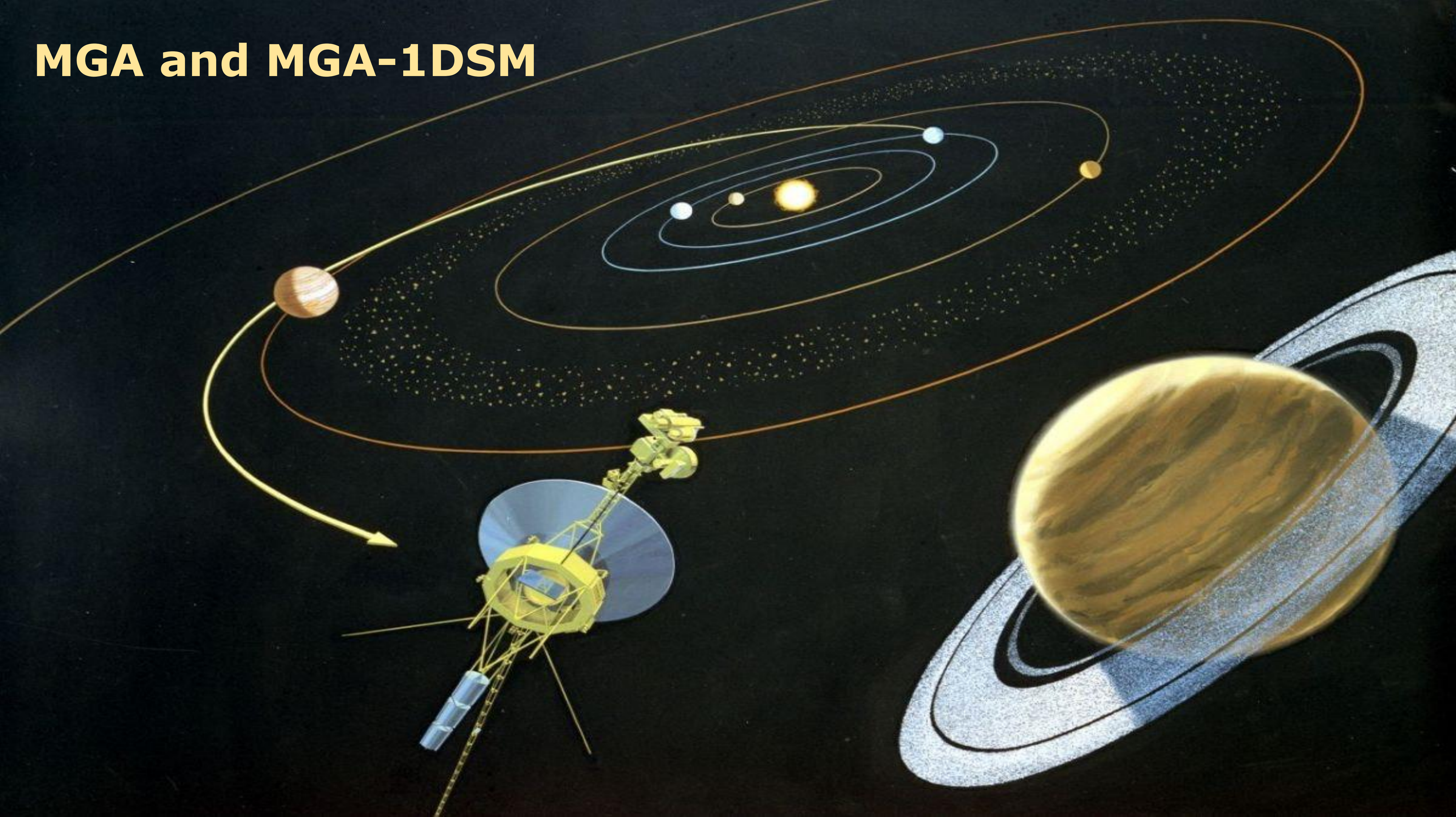


The GTOC series is born

"To organise the first international competition to find the global optimal of an interplanetary trajectory was a risky idea. We saw it, a bit romantically perhaps, as a sort of "sailing challenge", with our galaxy as the racing waters and mathematical tools as the competing boats. In keeping with this idea, we hoped each successive winner would become the host (and referee) for the next event. The competition was opened to the widest international community including industry, academia and research groups. Still it was far from certain that any of these specialists and researchers would be willing to devote their (usually scarce) free time to such a contest. As it turned out, luck was indeed on the side of those who dare"

Now we "**only**" had to participate and learn

MGA and MGA-1DSM

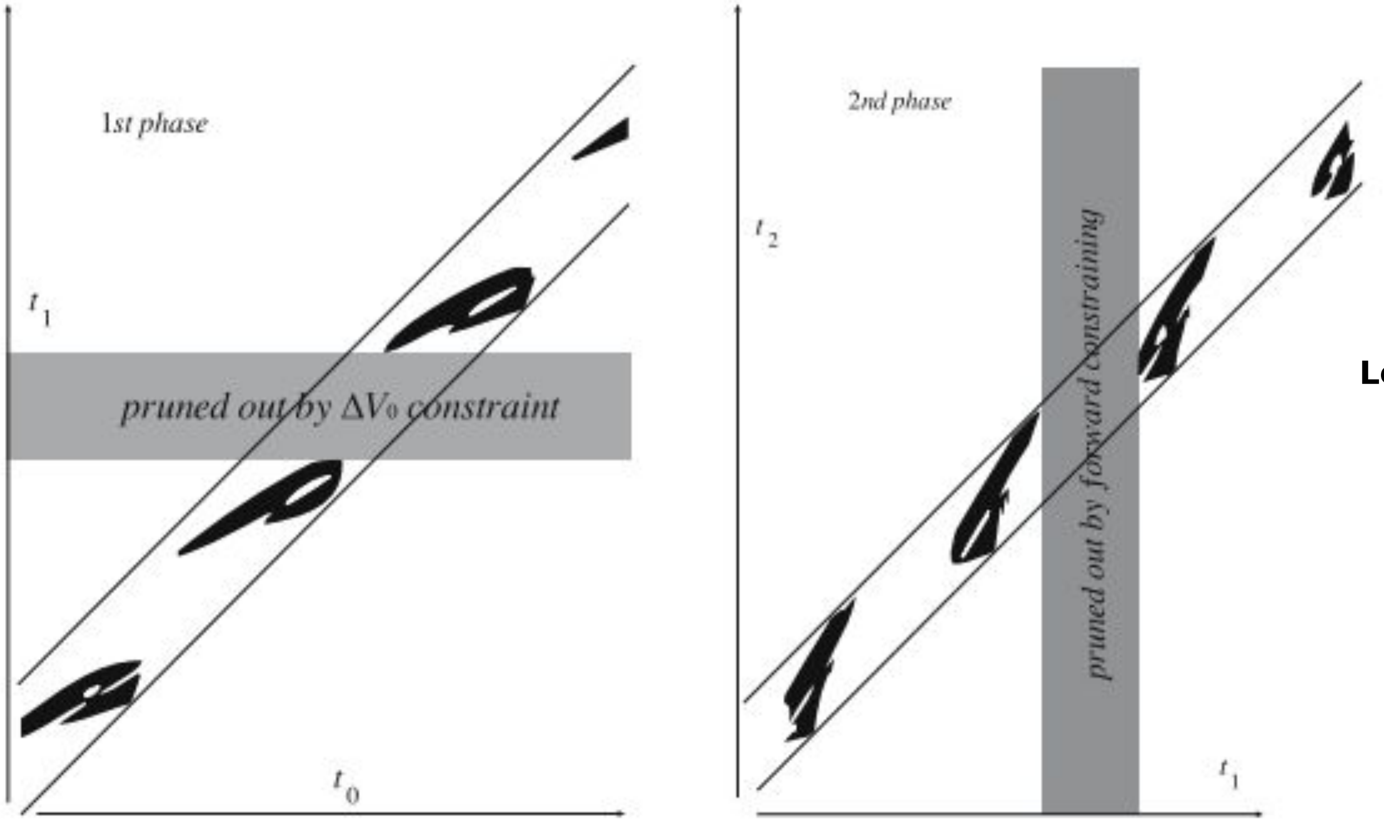


MGA, MGA1DSM and MGA-LT

$$
\begin{aligned}
&\min f(x_1, x_2, \ldots x_n) \\
&g_1(x_1, x_2, \ldots x_n) = 0 \\
&g_2(x_1, x_2, \ldots x_n) < 0 \\
&\ldots \\
&g_m(x_1, x_2, \ldots x_n) > 0
\end{aligned}
$$

with no initial guess

GASP (MGA)



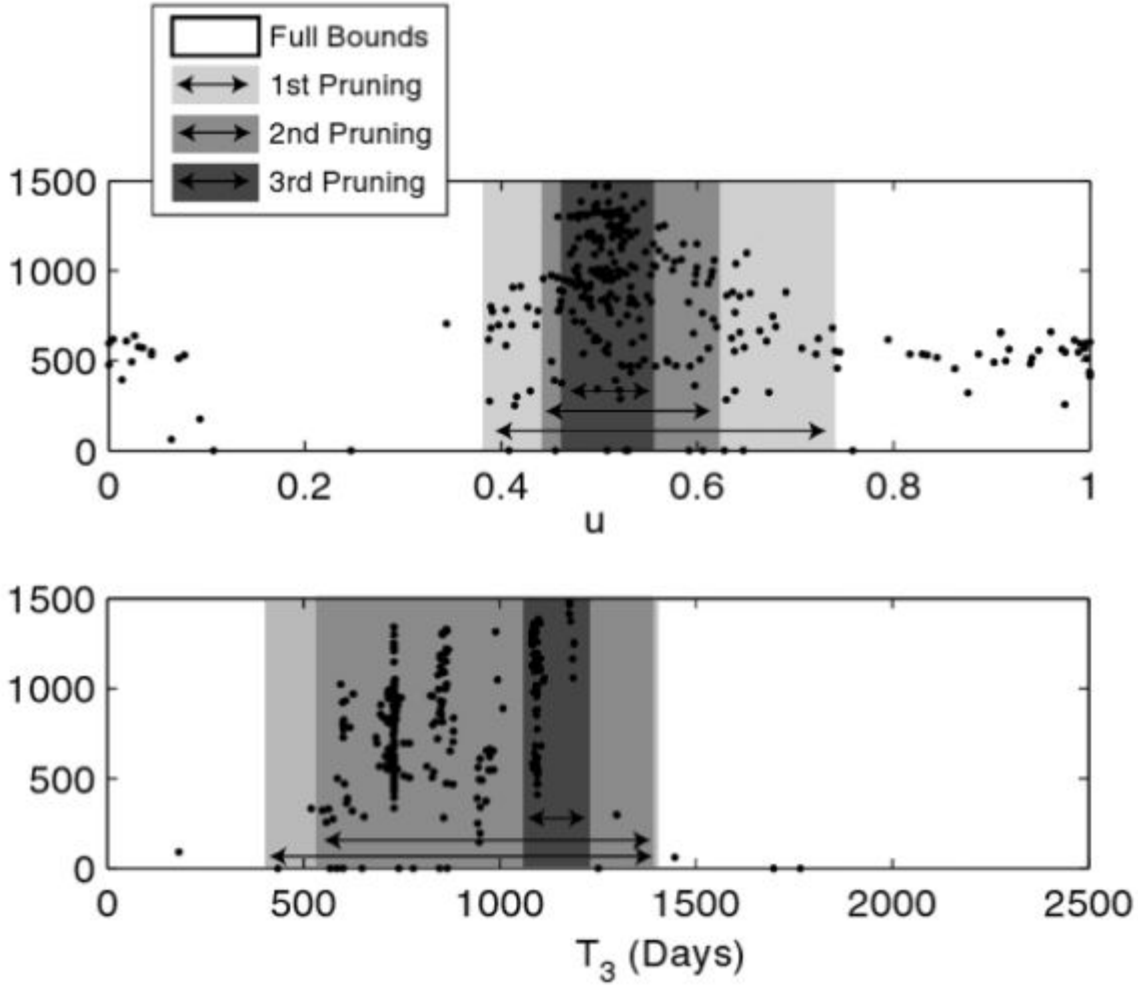
Lesson learned:

- Most of the search space is infeasible
- Precompute trajectory legs, then patch
- N dimensional problem -> N times 2D problems (incremental approach)

GASP (MGA-1DSM)

Lesson learned:

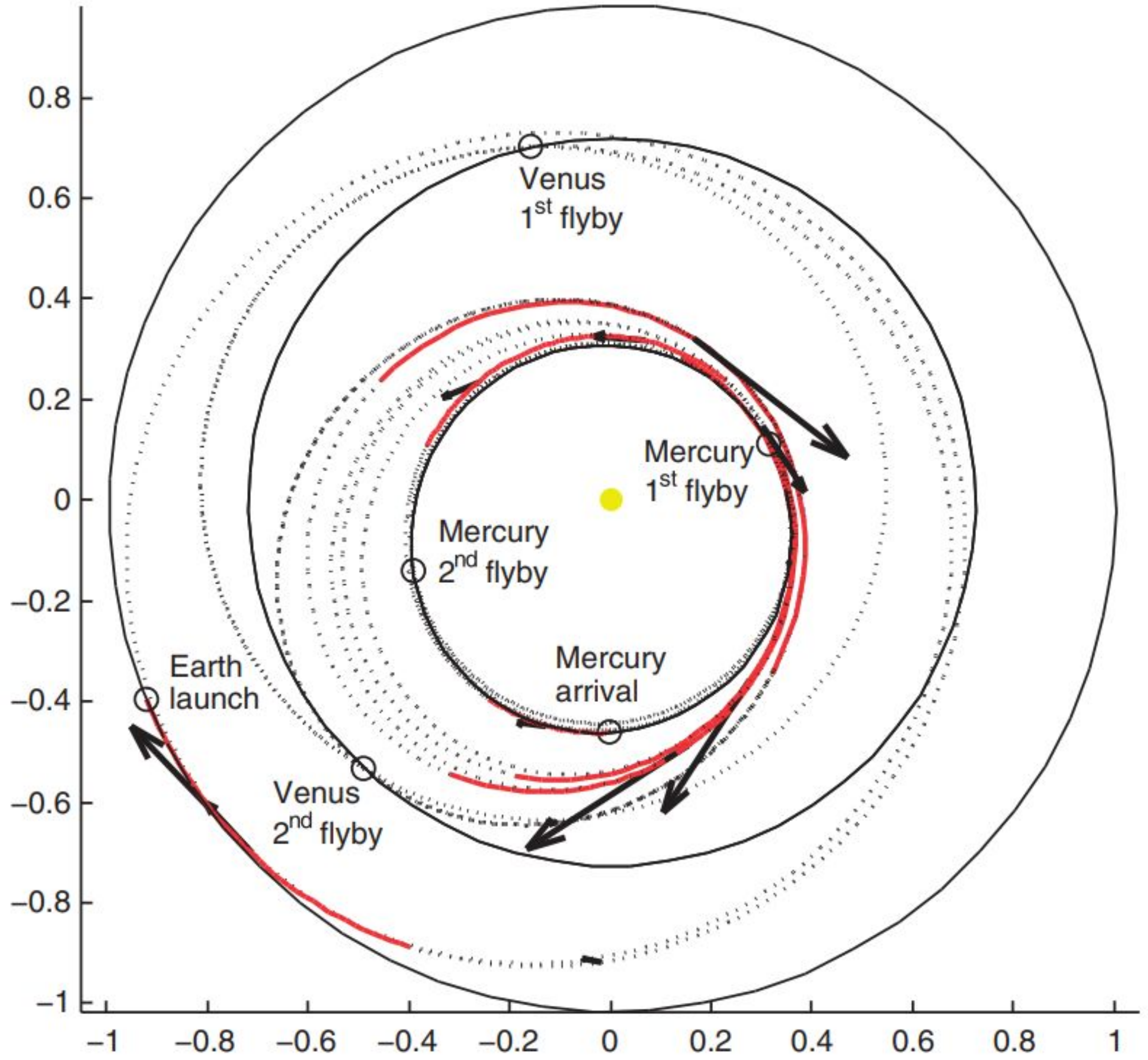
- Failed optimization runs contain useful information.
- Smart restarts are essential for evolutionary success.
- Up to <10 flybys, resonances being tricky.
- Parallelization via island model.



MBH (MGA-LT)

Lesson learned:

- MBH strategy works with LT legs and non linear constraints.
- < 5 fly-bys .
- Up to <10 flybys, resonances being tricky.
- Computationally intensive

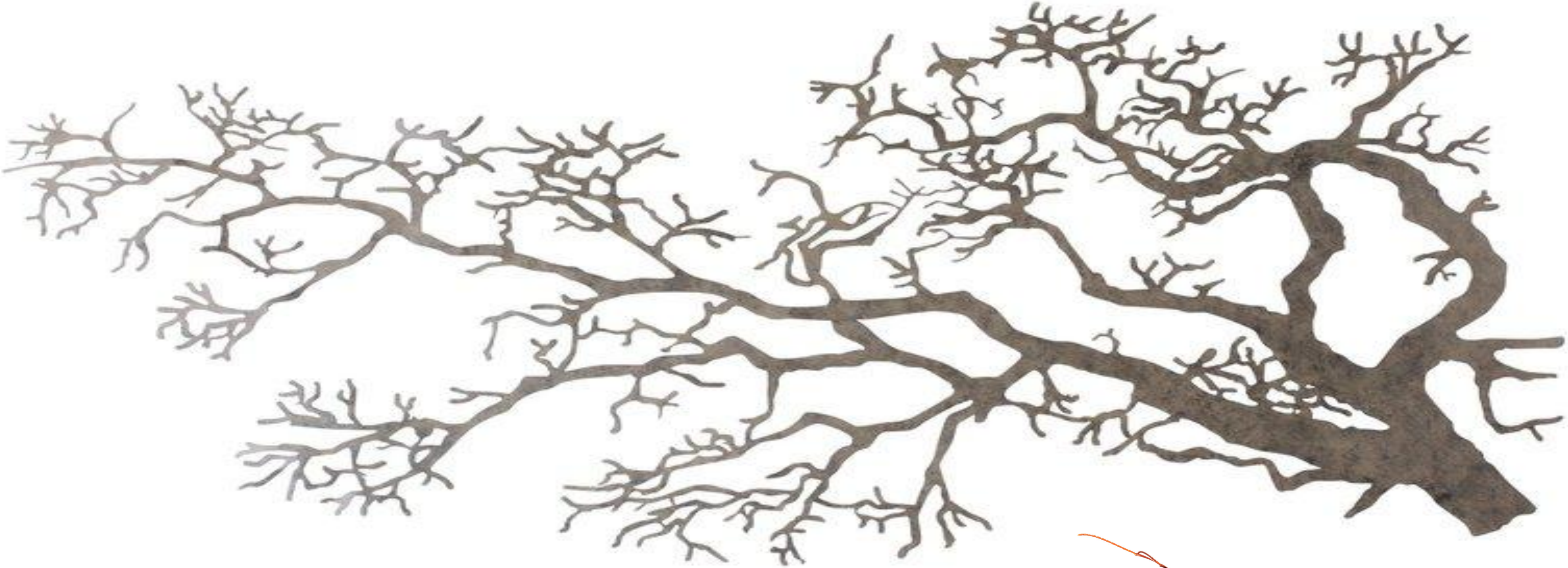


The TSP approach (towards GTOC9)

Consider a Traveling Salesman Problem with...

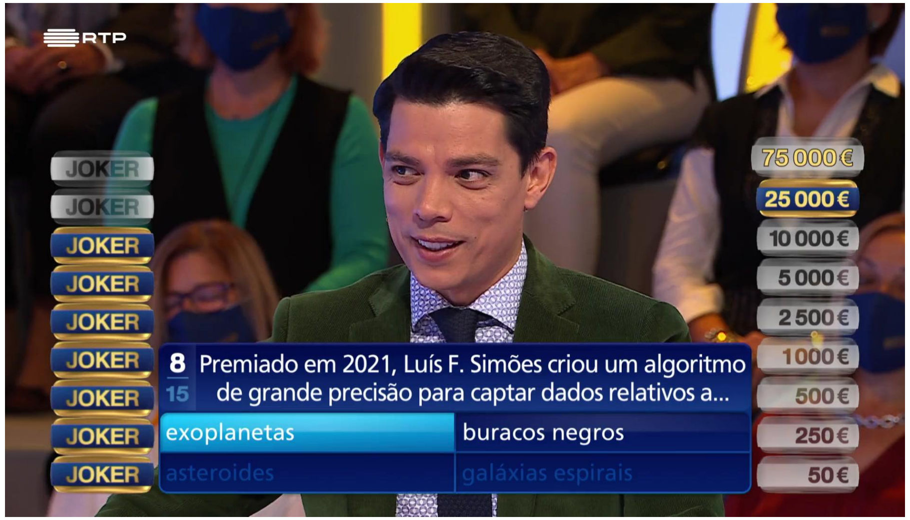
- Limited fuel capacity *and* working hours, but salesman still needs to sell at as many cities as possible;
- No GPS device to guide him on the road (no clear notion of distances);
- Many roads lead to chosen destination. The driving itself also needs planning;
- While driving towards cities, roads may turn out to be temporarily blocked;
- ... and cities are moving around *!*

tree searches, and ants

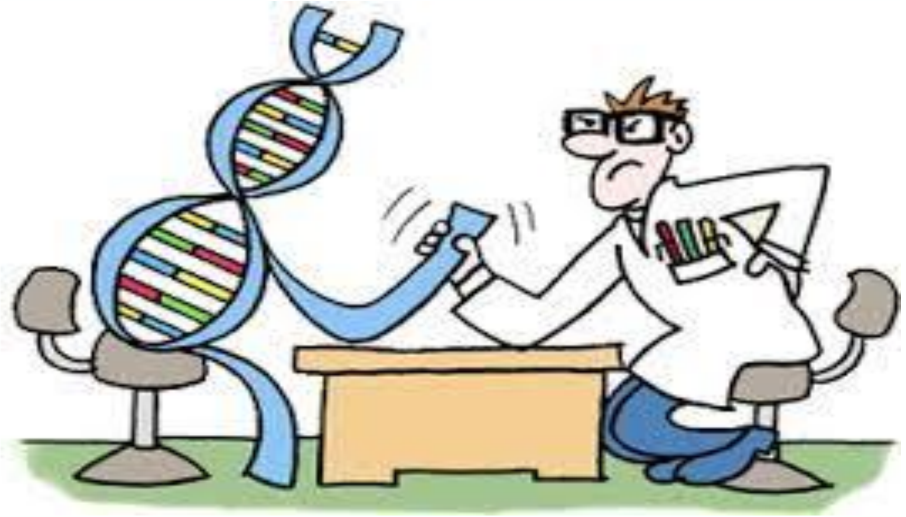


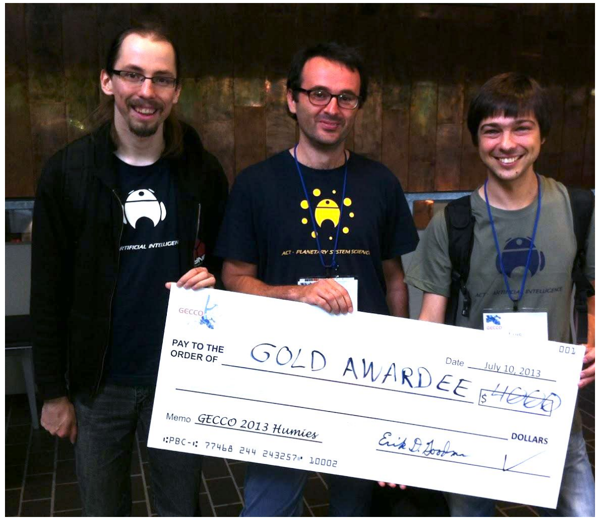
Lazy Race Tree Search (LRTS), Beam P-ACO

- Beam Search emerged as the approach of choice in early GTOC competitions.
- In many GTOCs, 1st or 2nd place always went to a team that used some variant of Beam Search.
- The multiobjective nature of the search problematic -> greedy heuristics an issue.

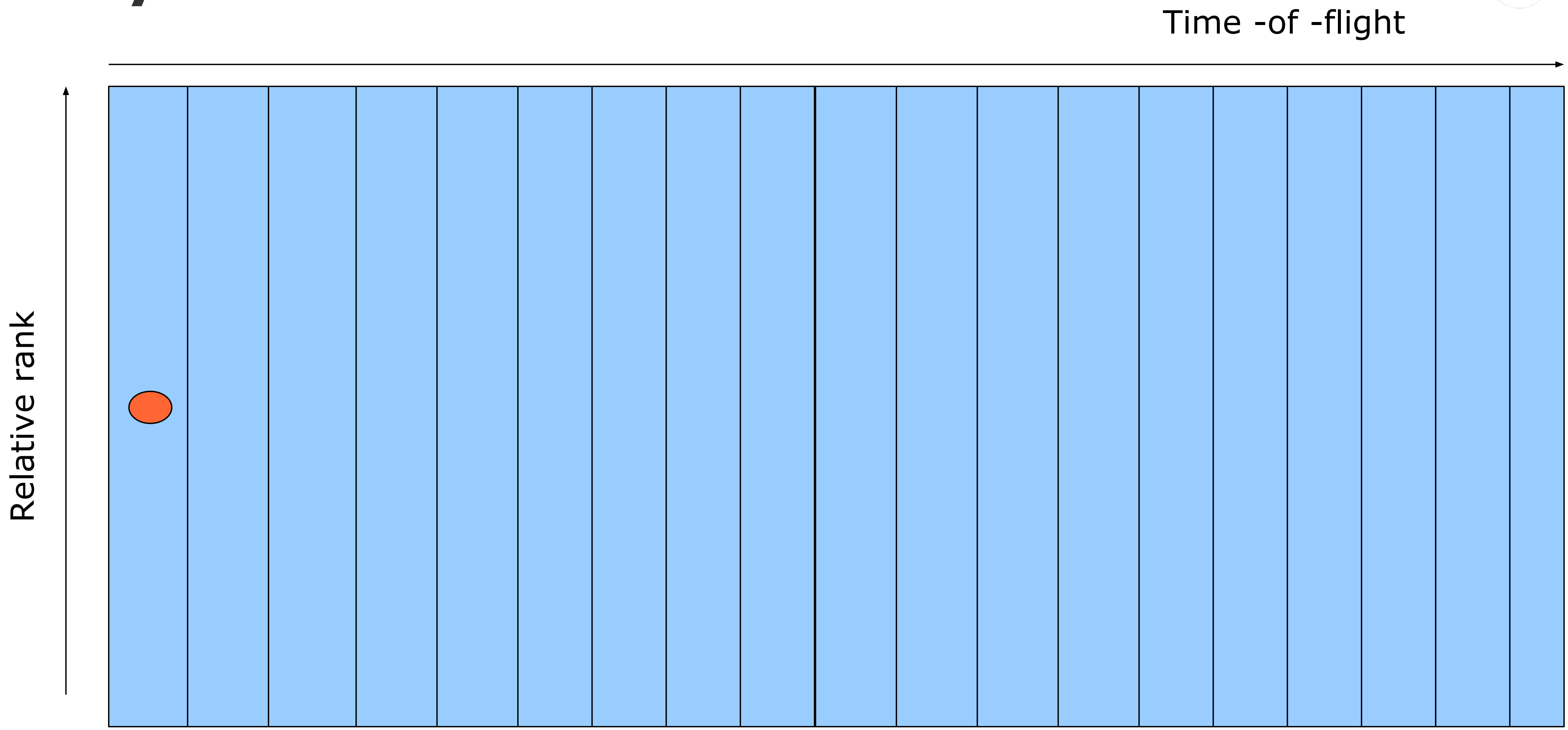


- LRTS (GTOC6) -> dealing intrinsically with DV, DT.
- Beam P-ACO (GTOC9) -> improving the basic beam search
- MCTS -> special mention

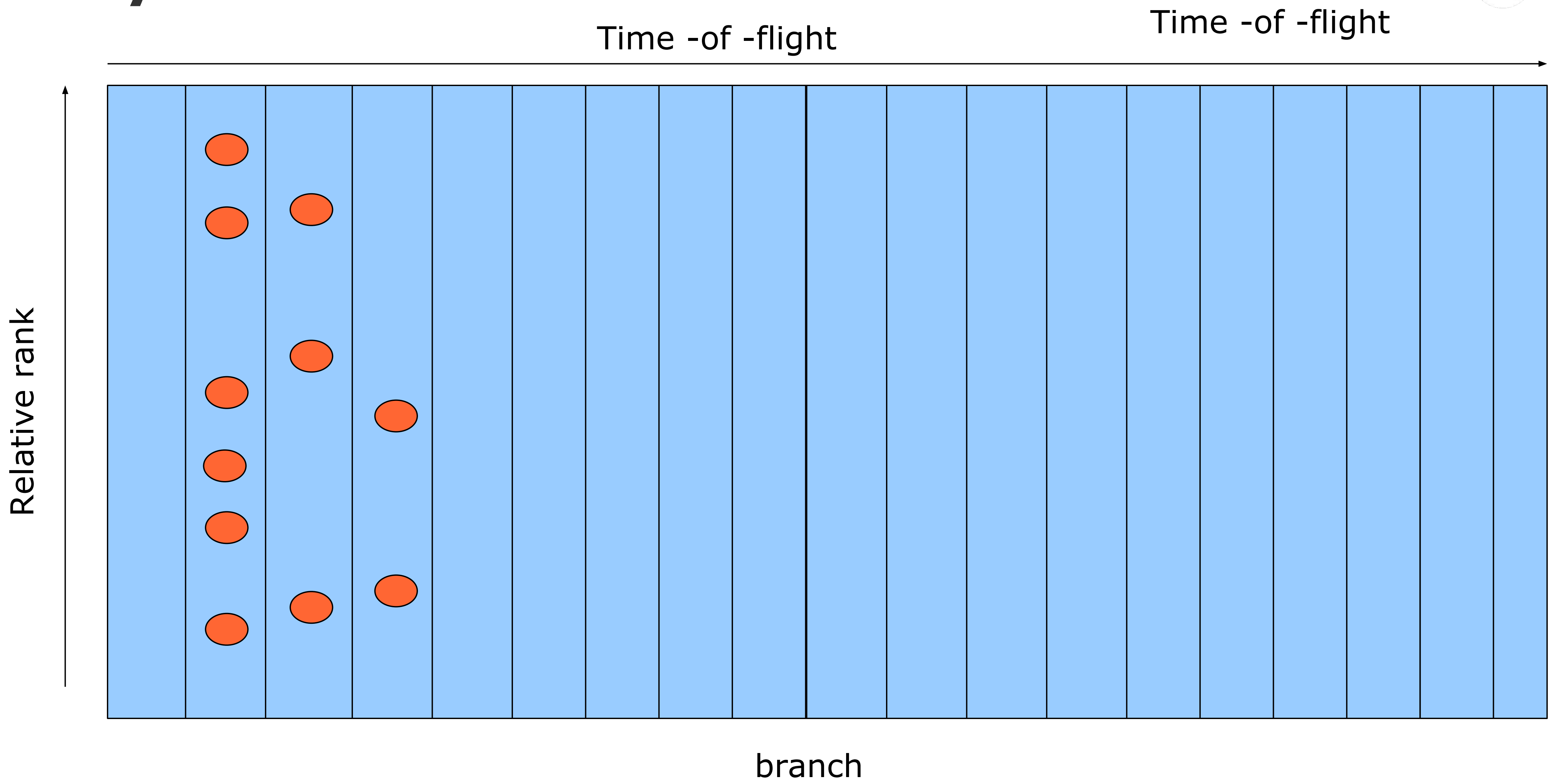




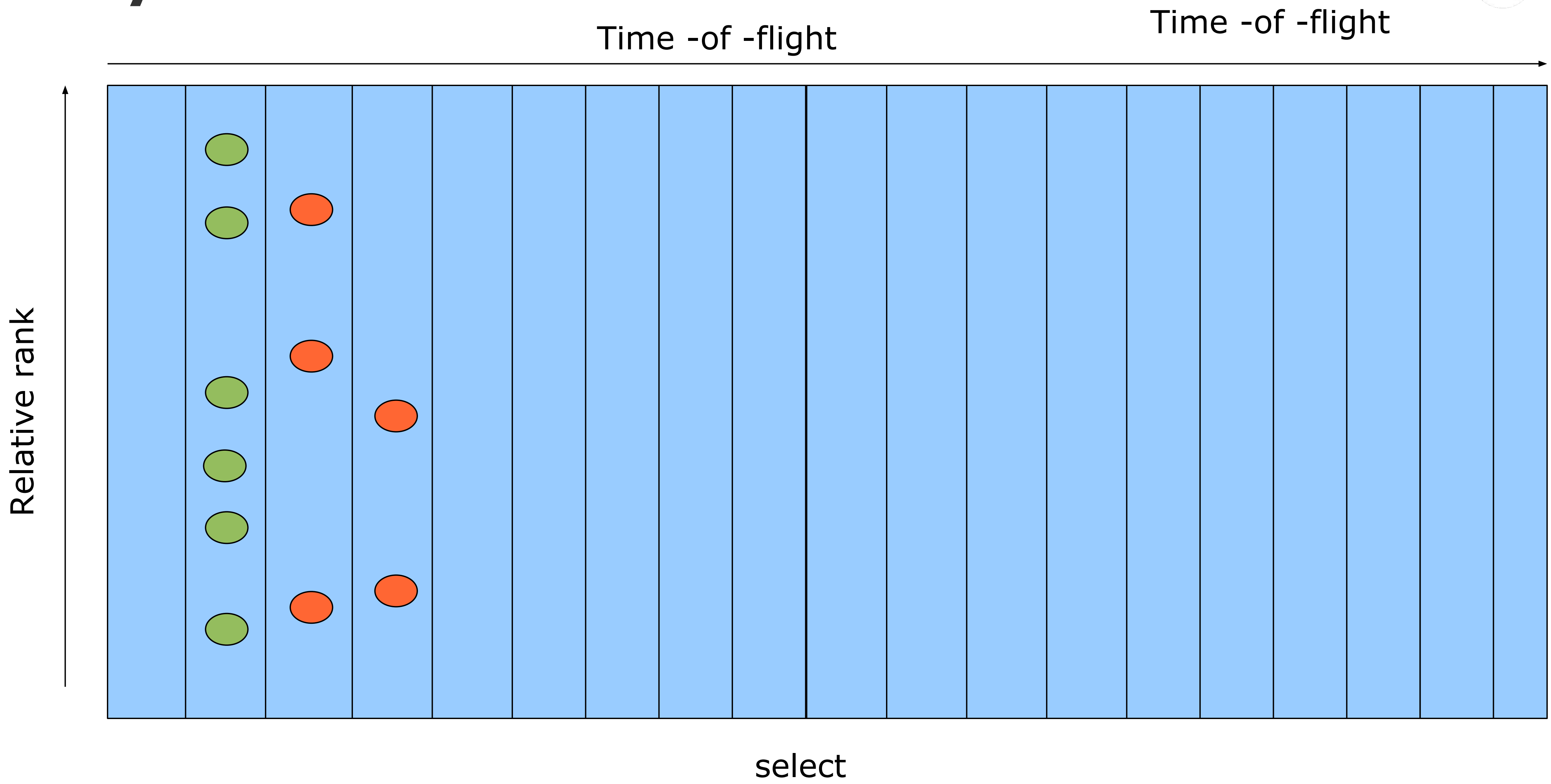
Lazy Race Tree Search



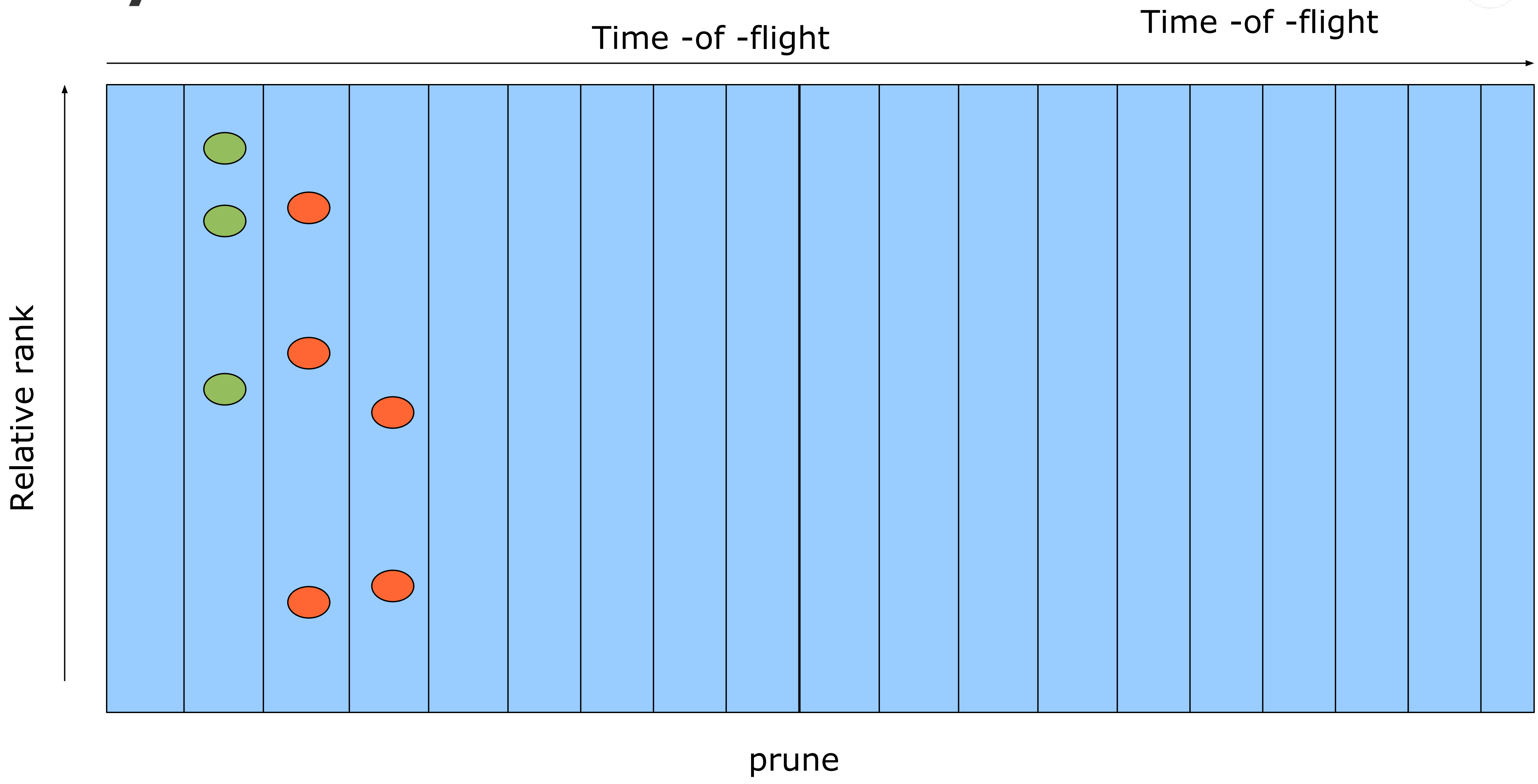
Lazy Race Tree Search



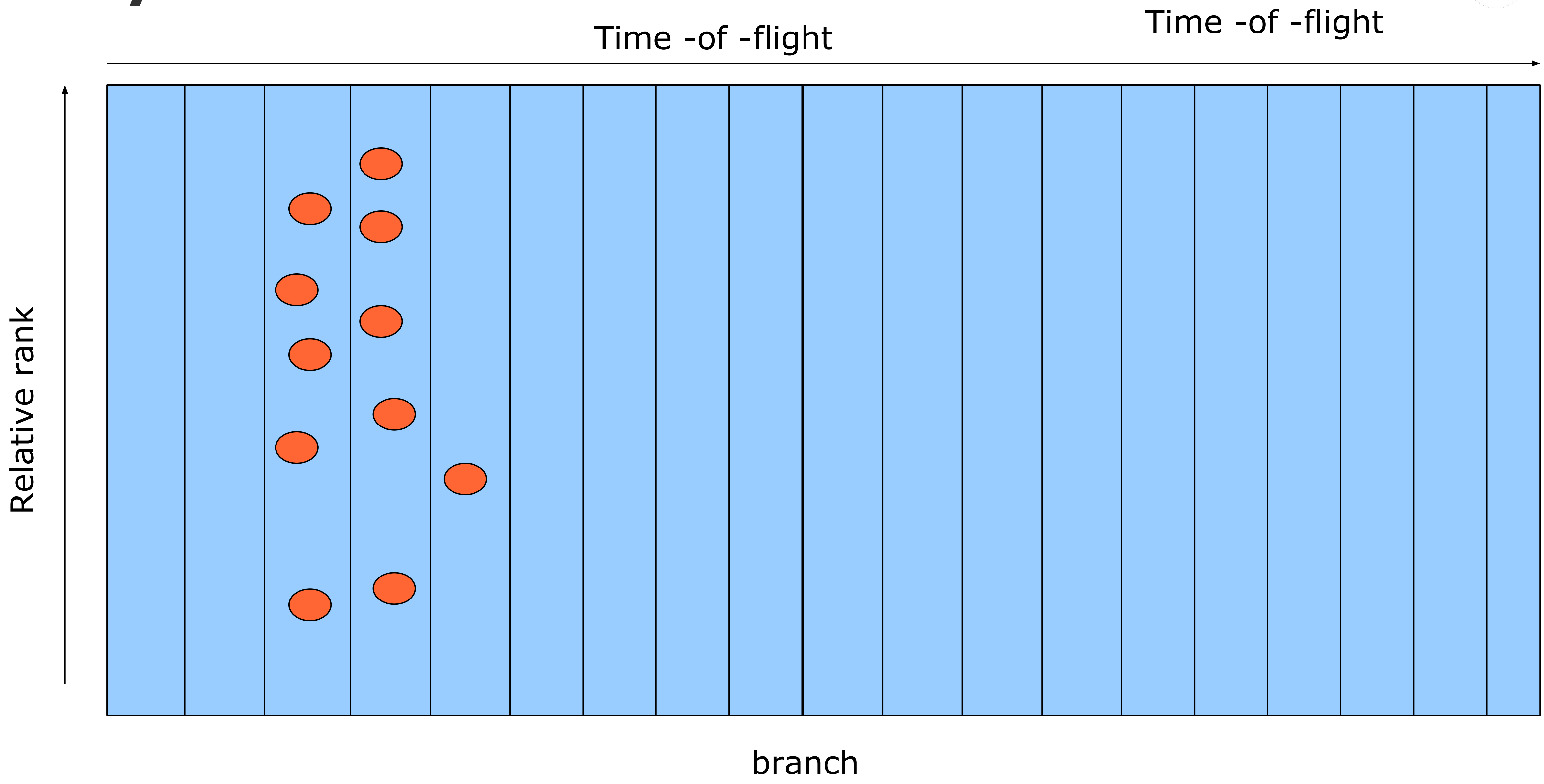
Lazy Race Tree Search



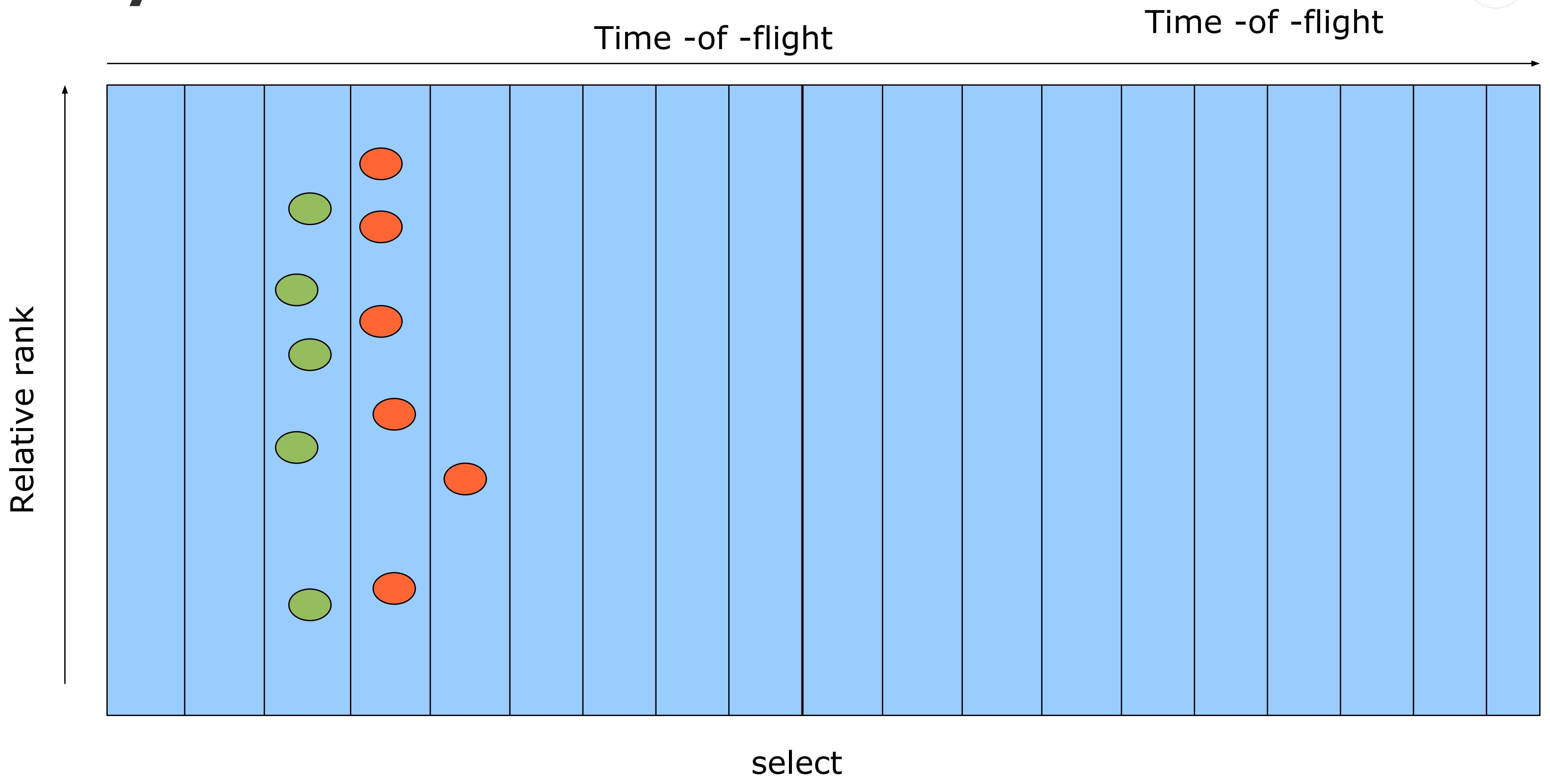
Lazy Race Tree Search



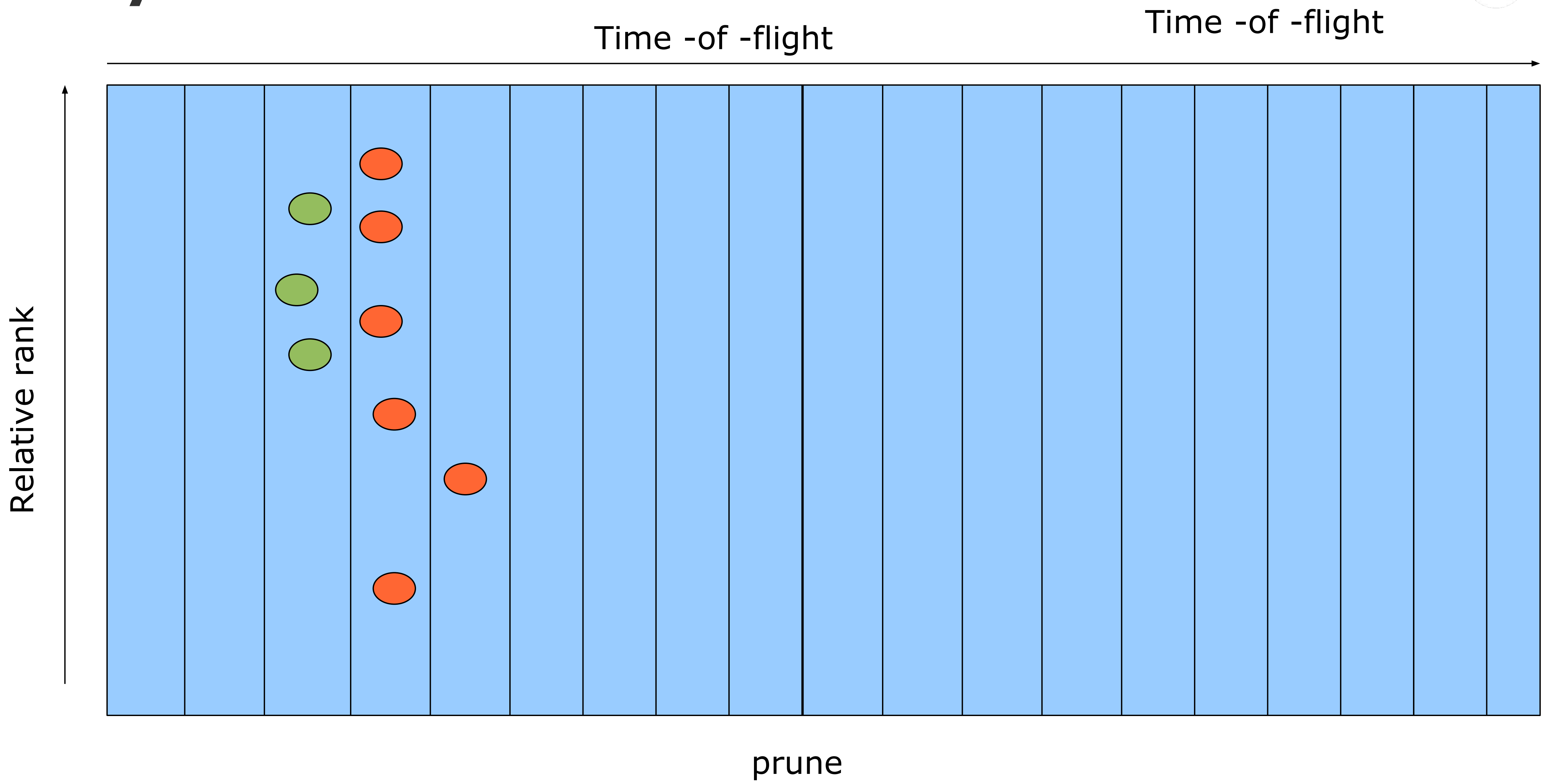
Lazy Race Tree Search



Lazy Race Tree Search



Lazy Race Tree Search



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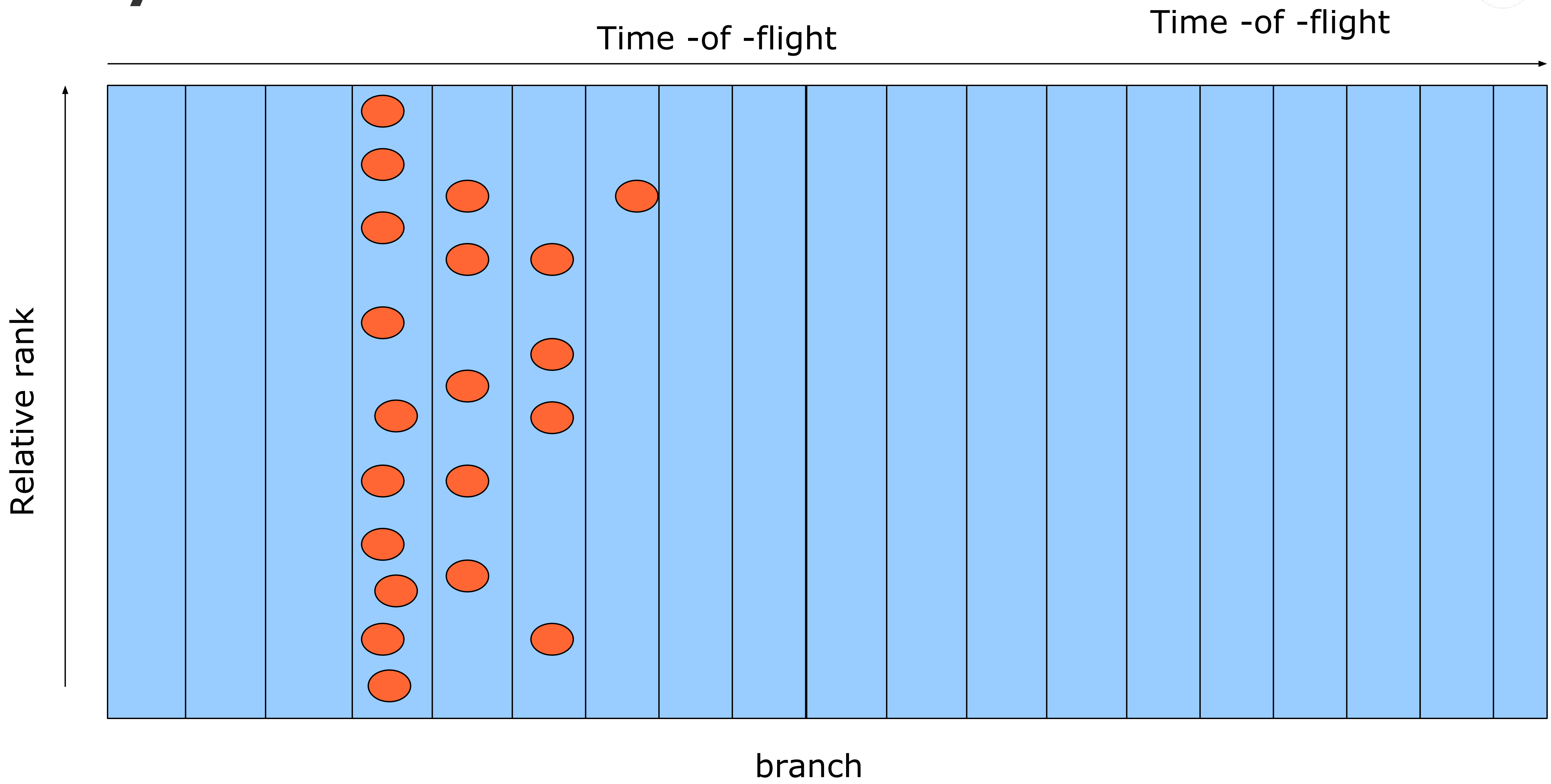
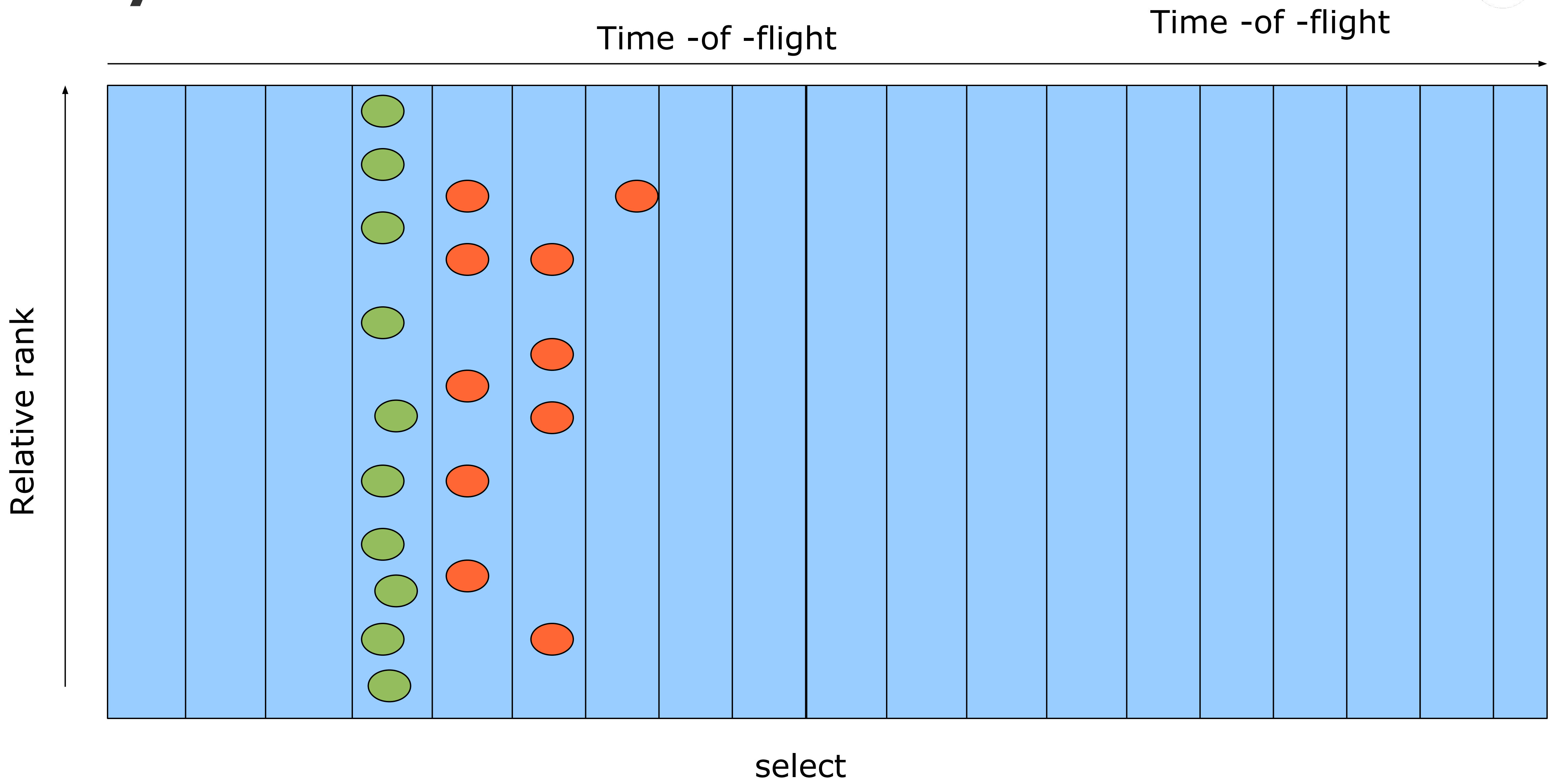


Lazy Race Tree Search



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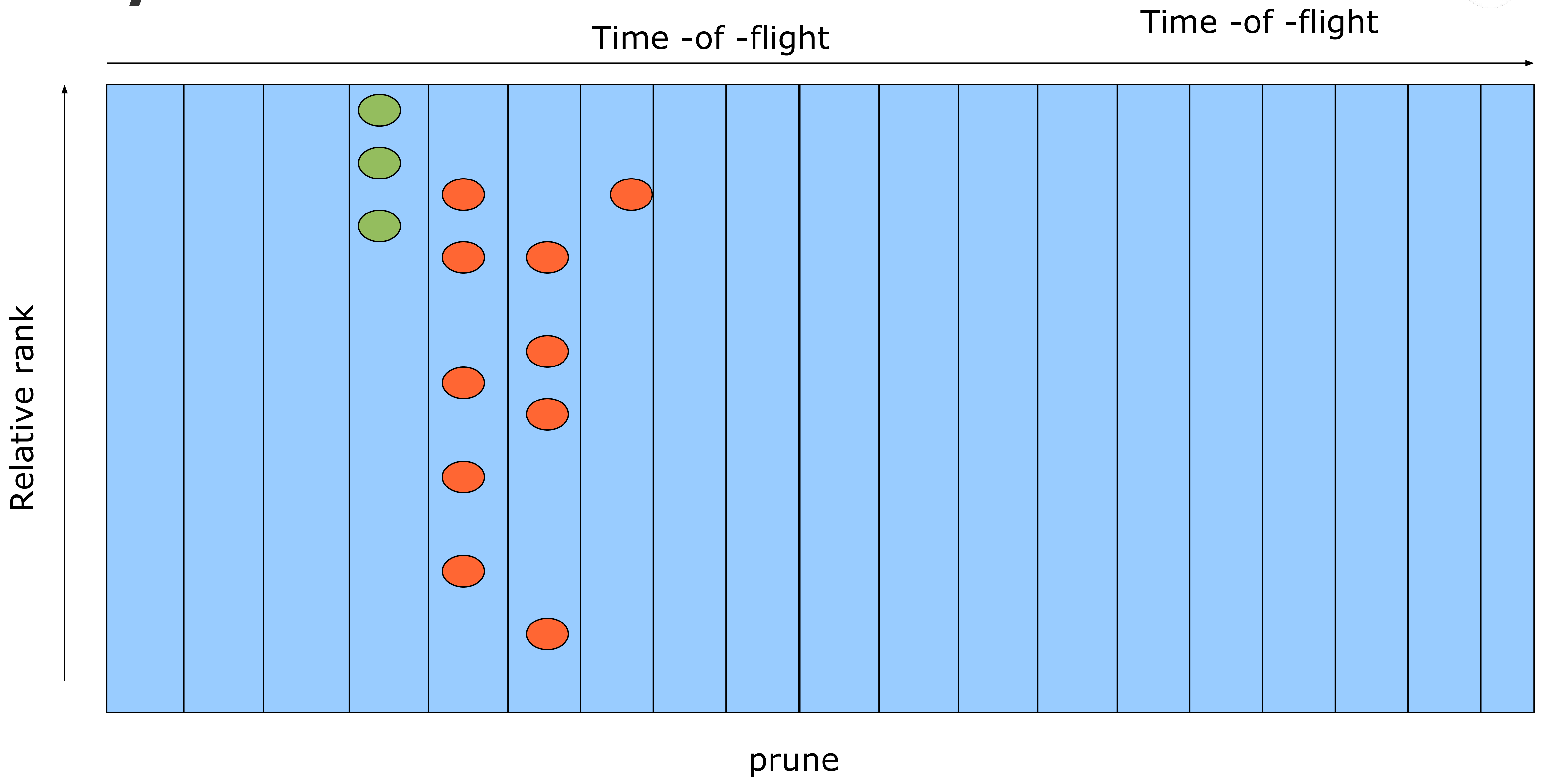
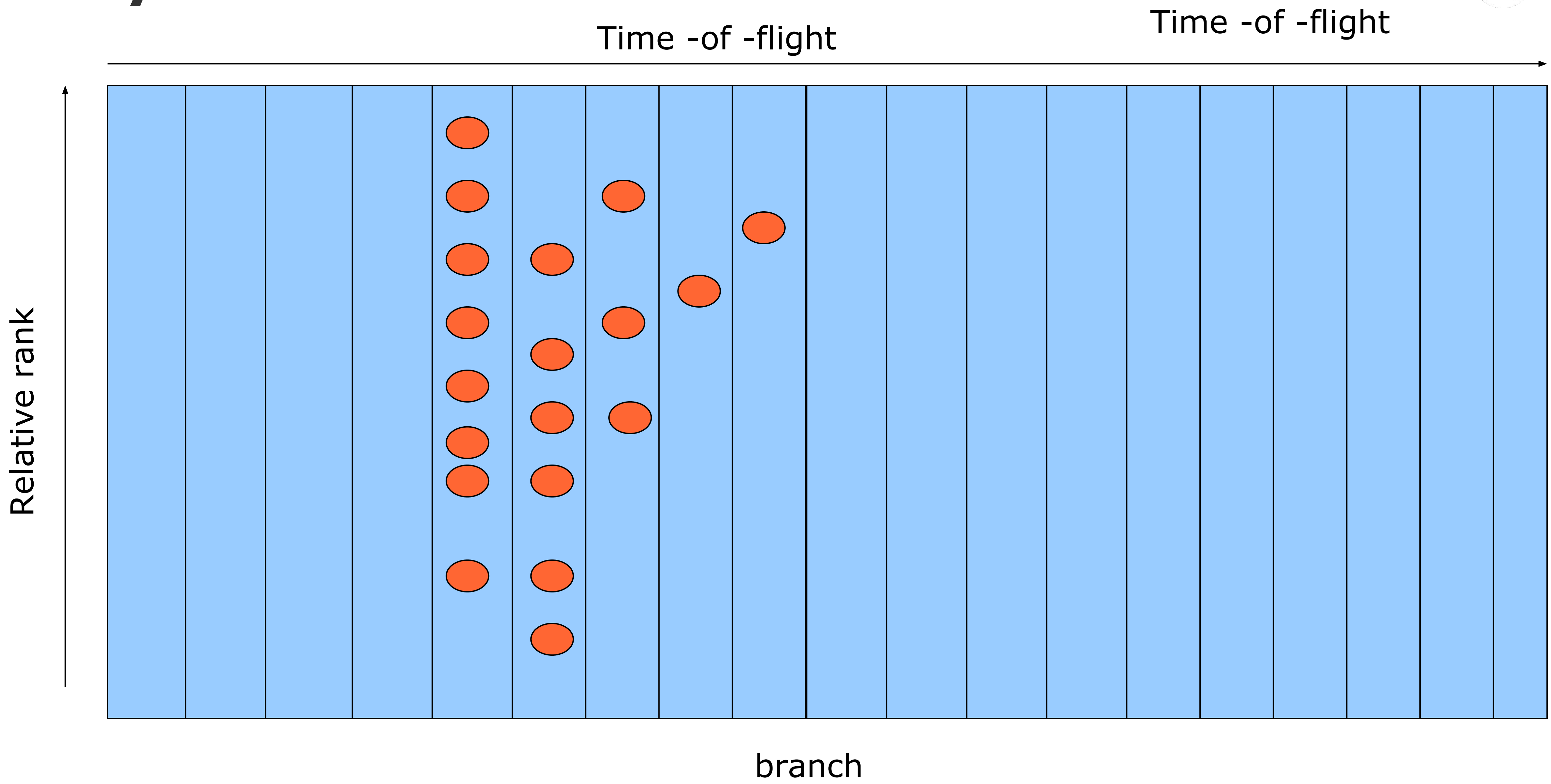
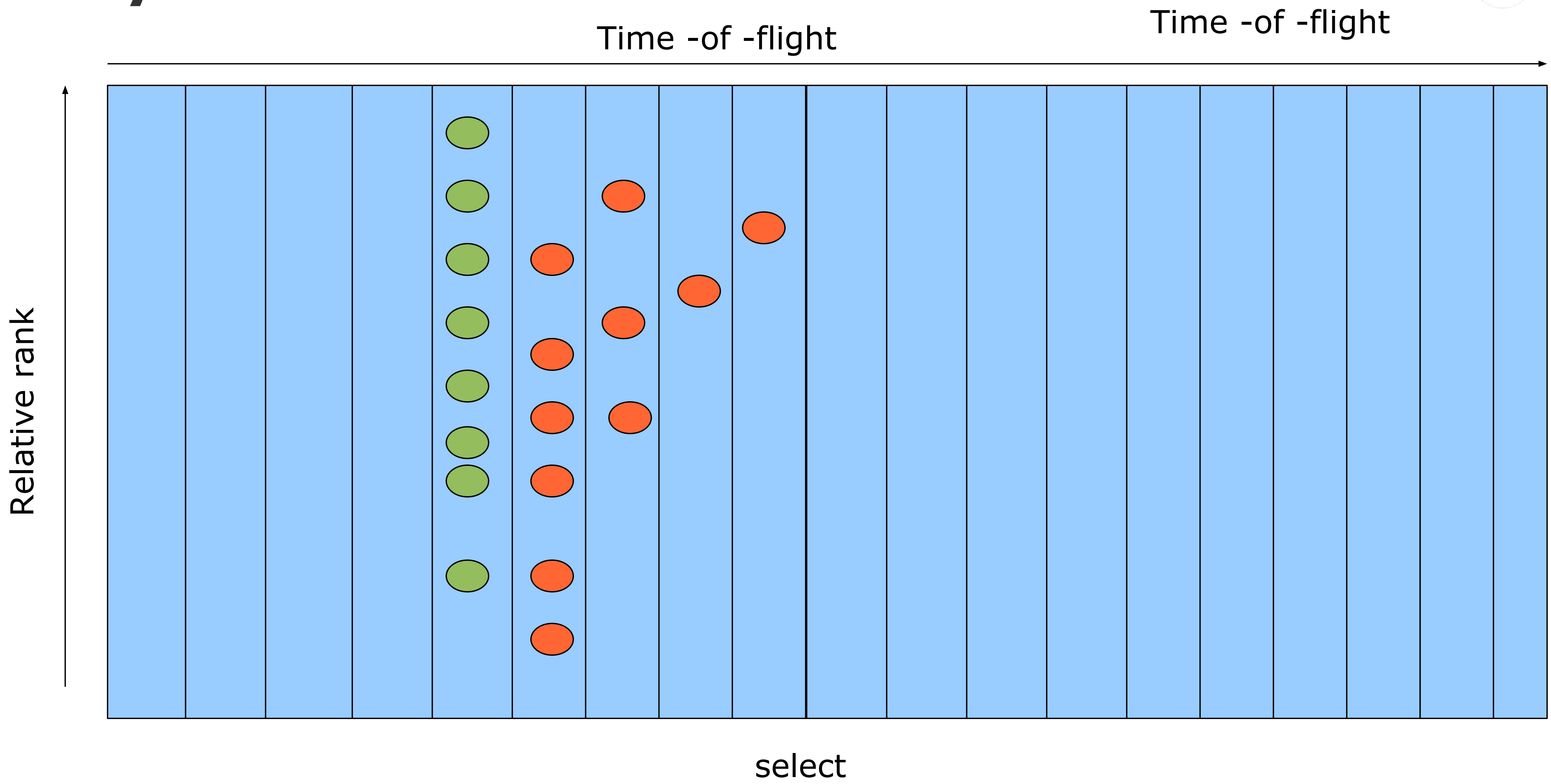


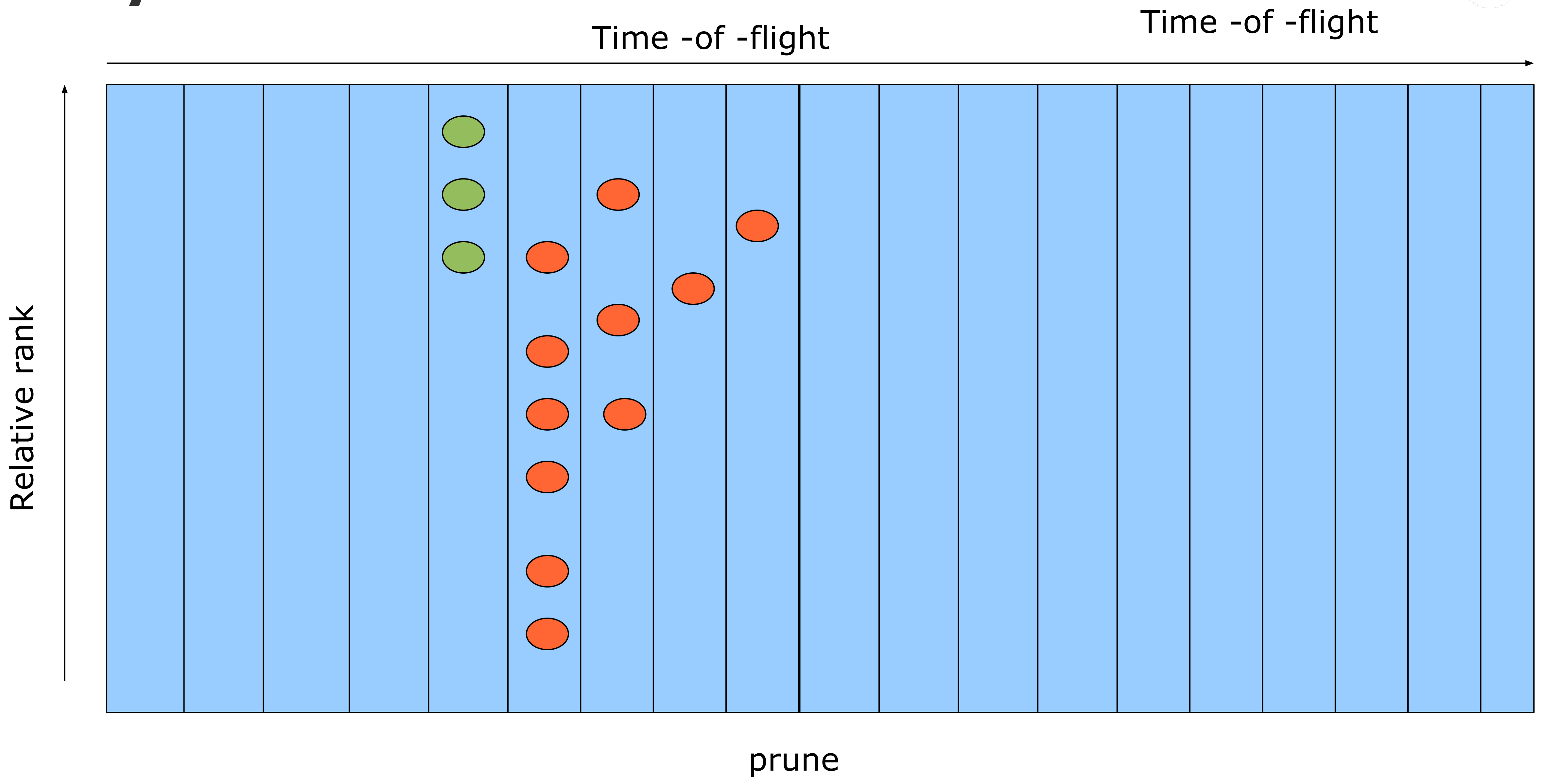
Lazy Race Tree Search



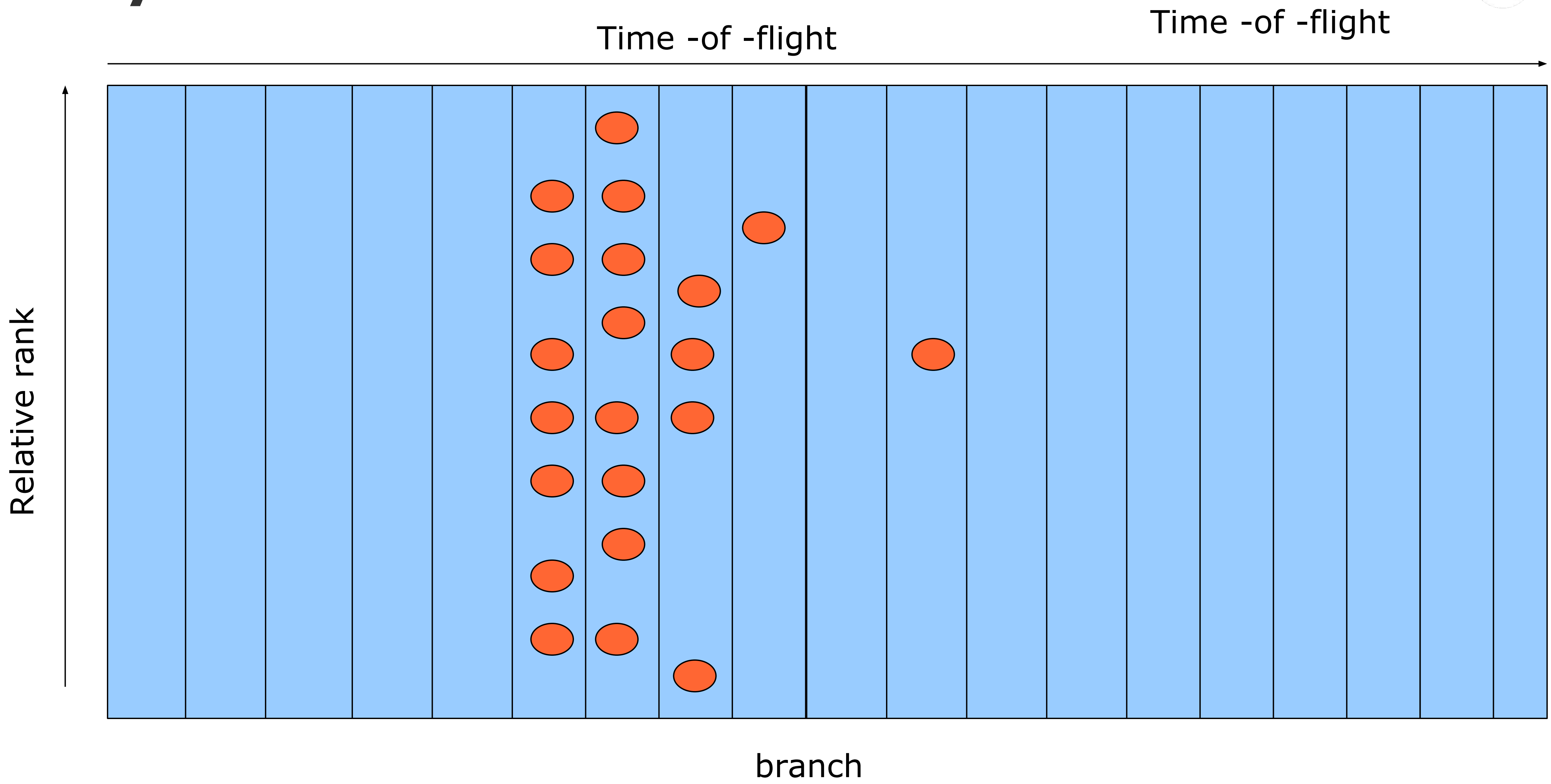
Lazy Race Tree Search



Lazy Race Tree Search



Lazy Race Tree Search



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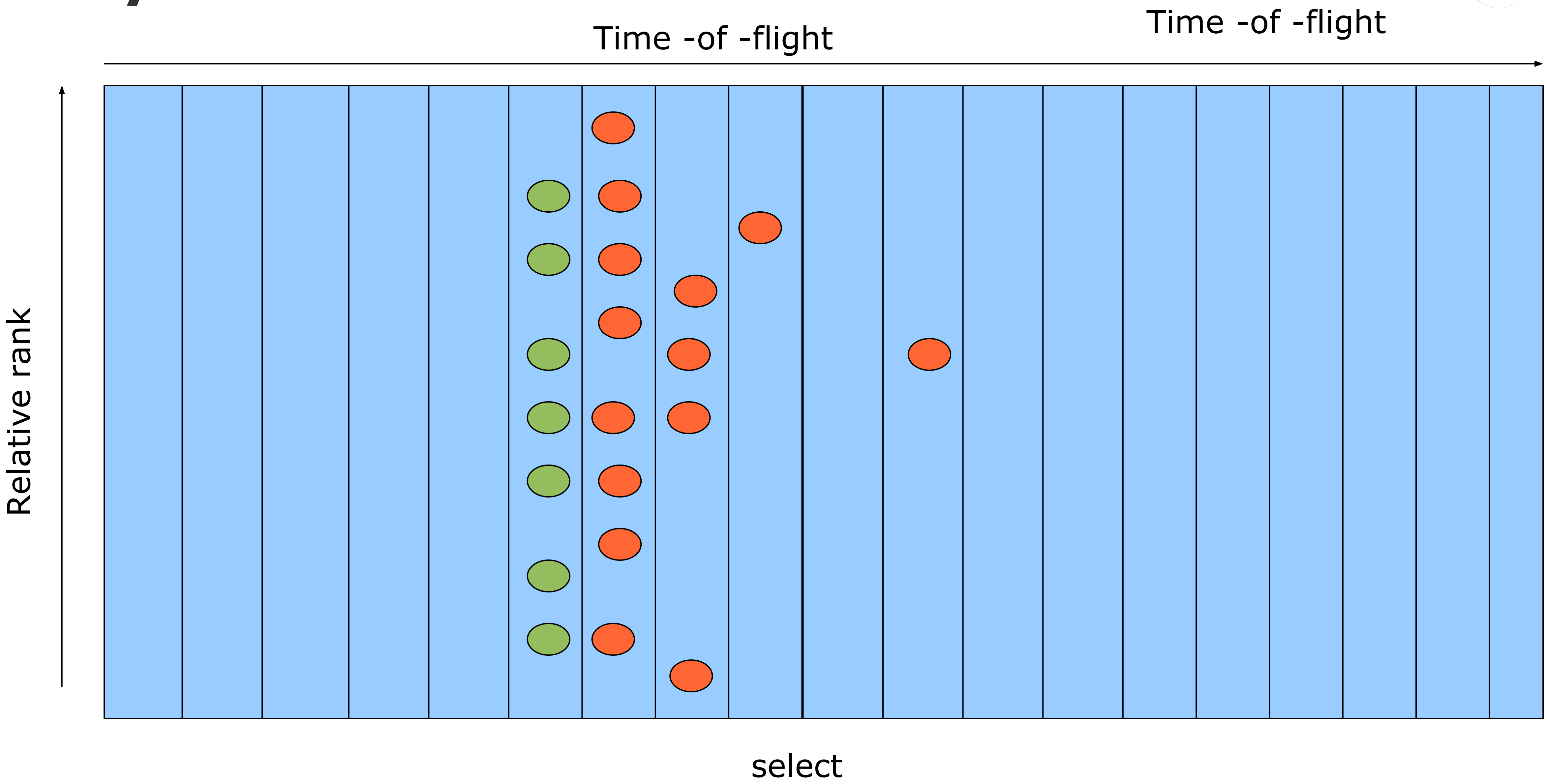
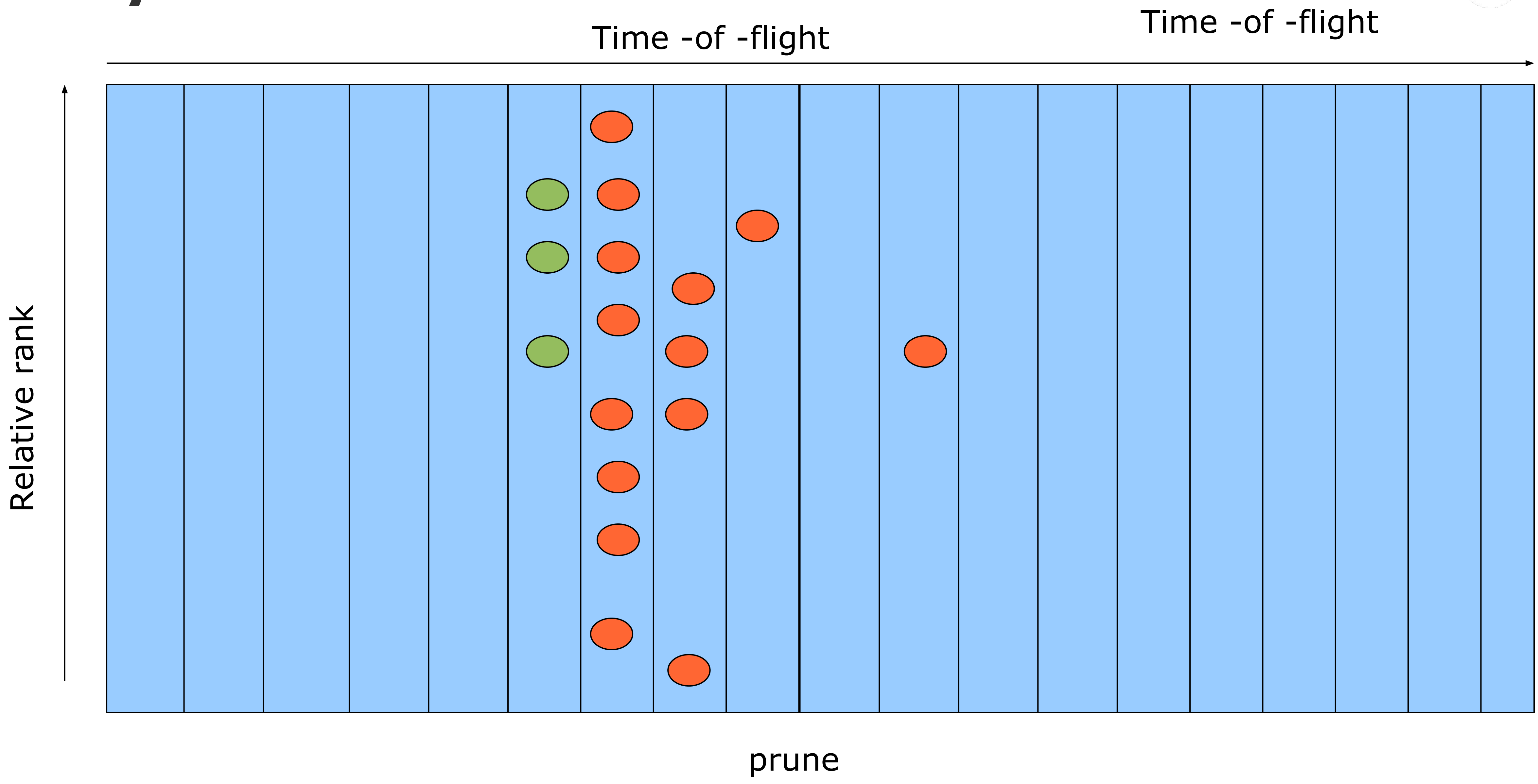


Lazy Race Tree Search



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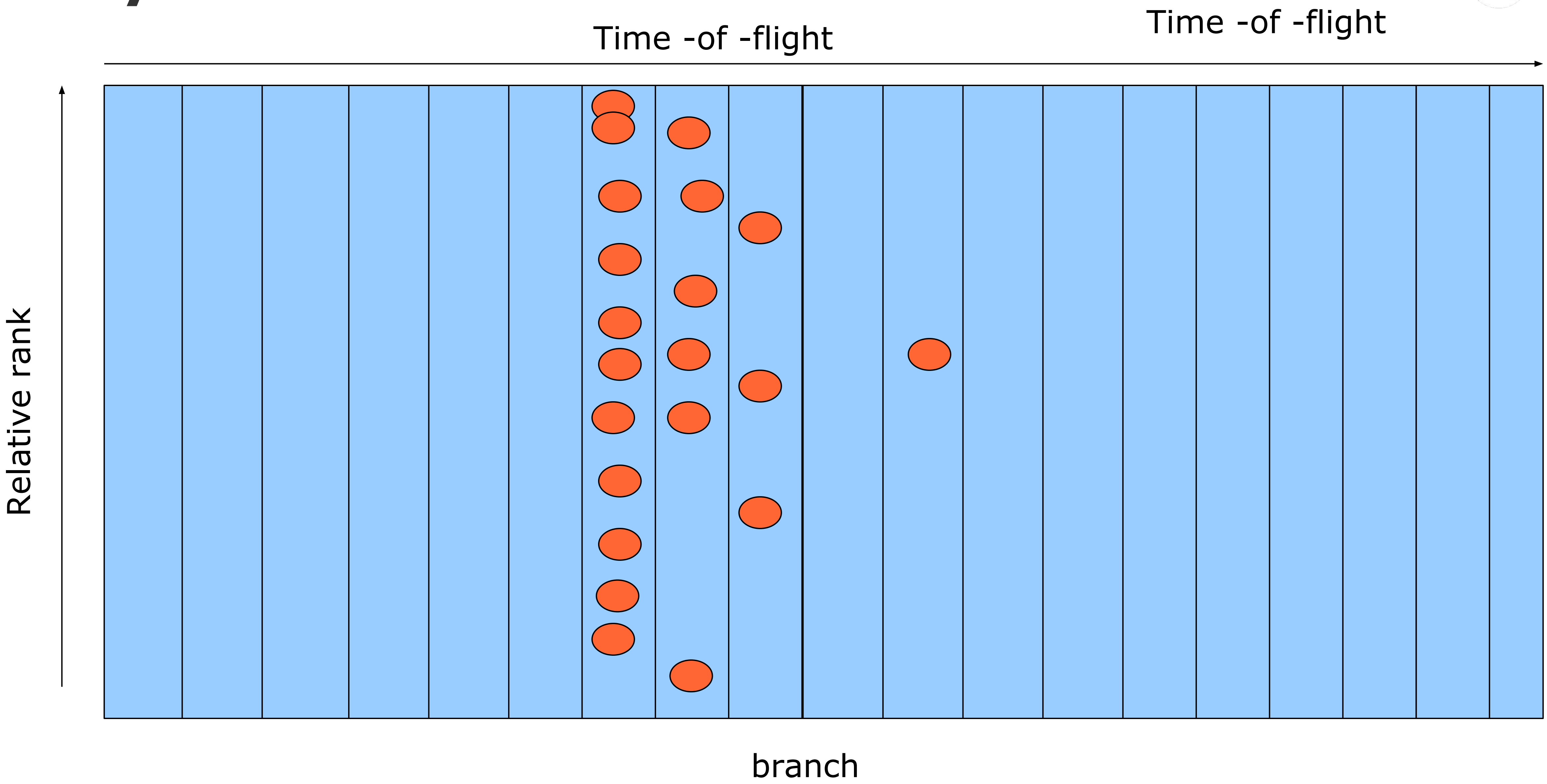

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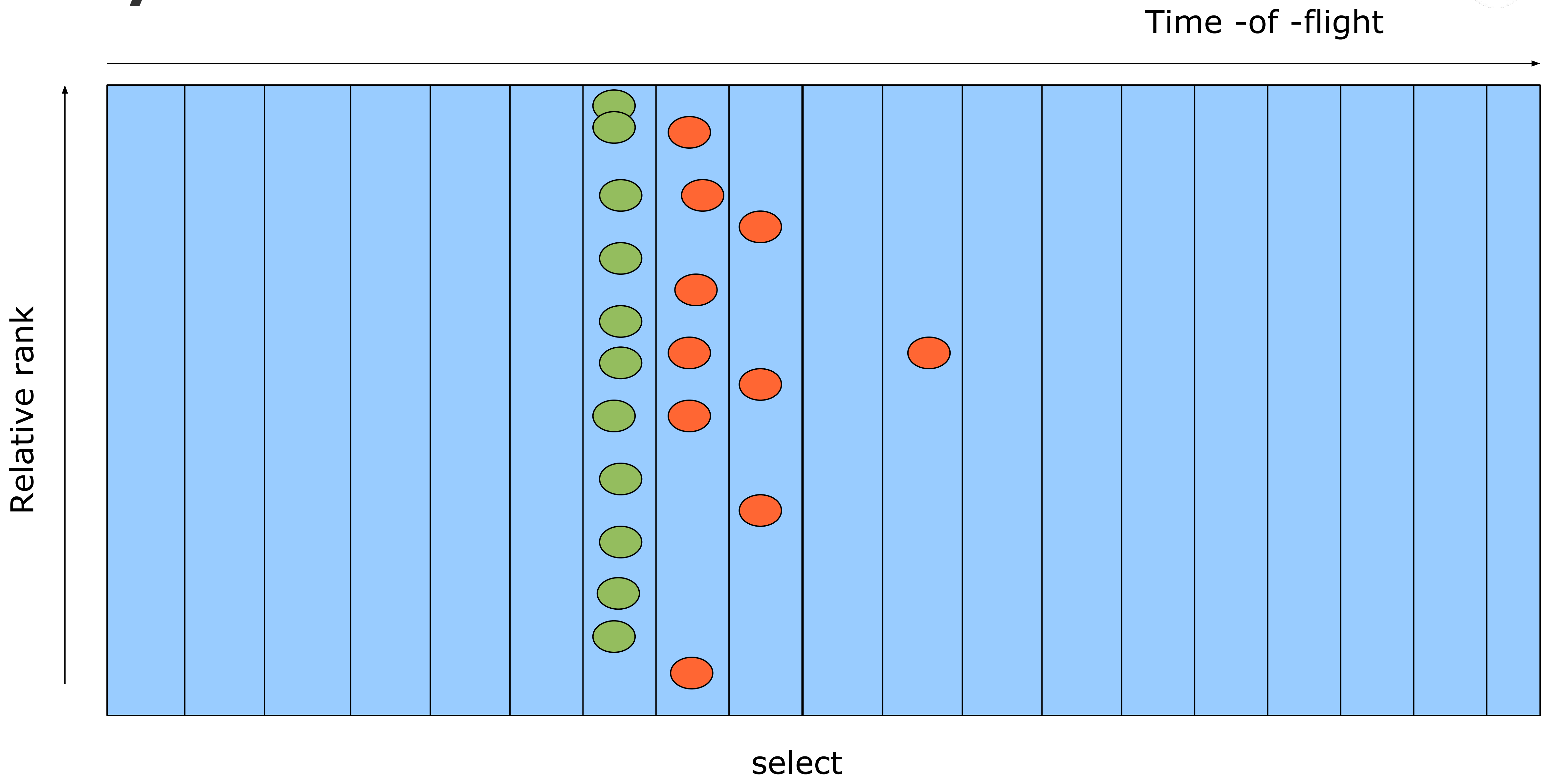
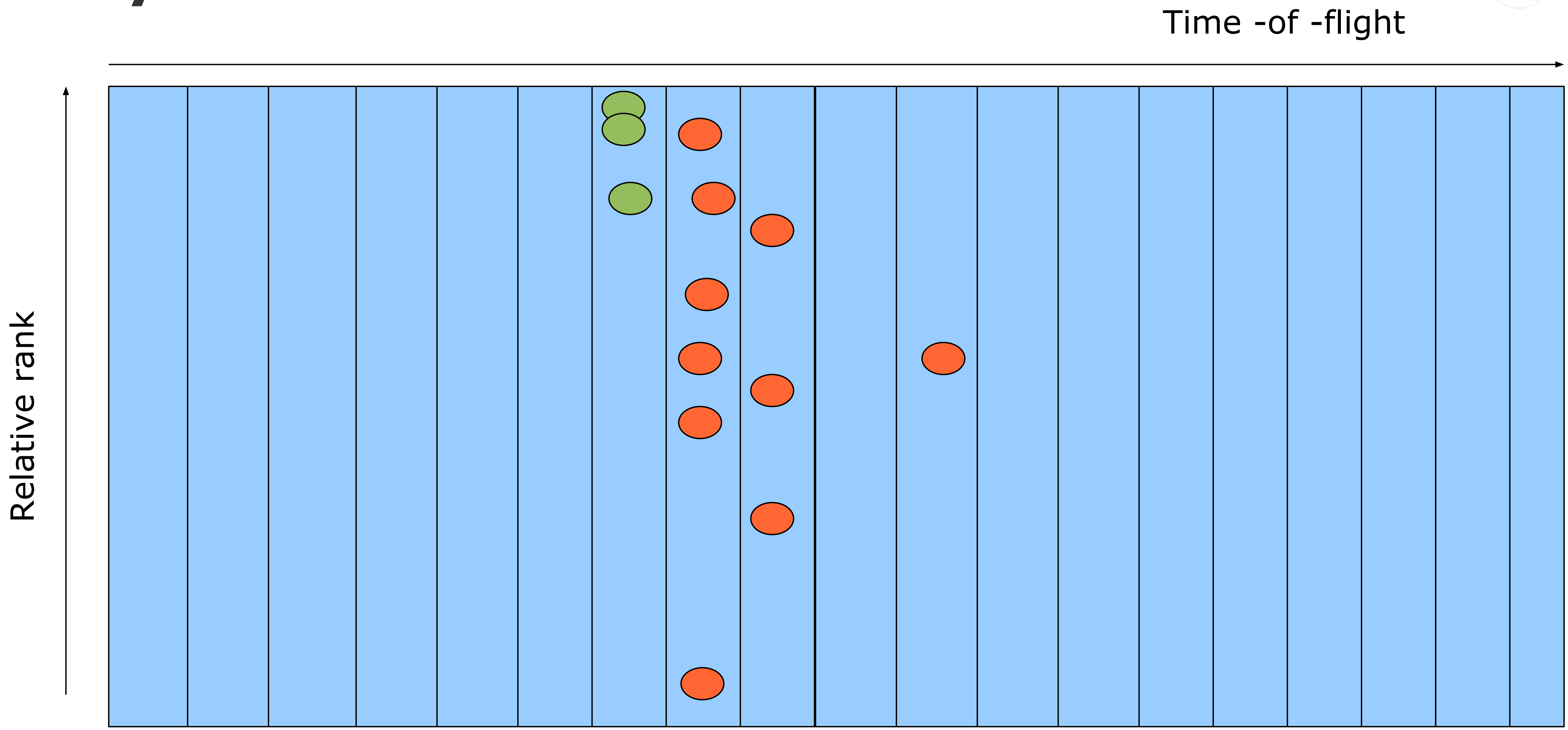
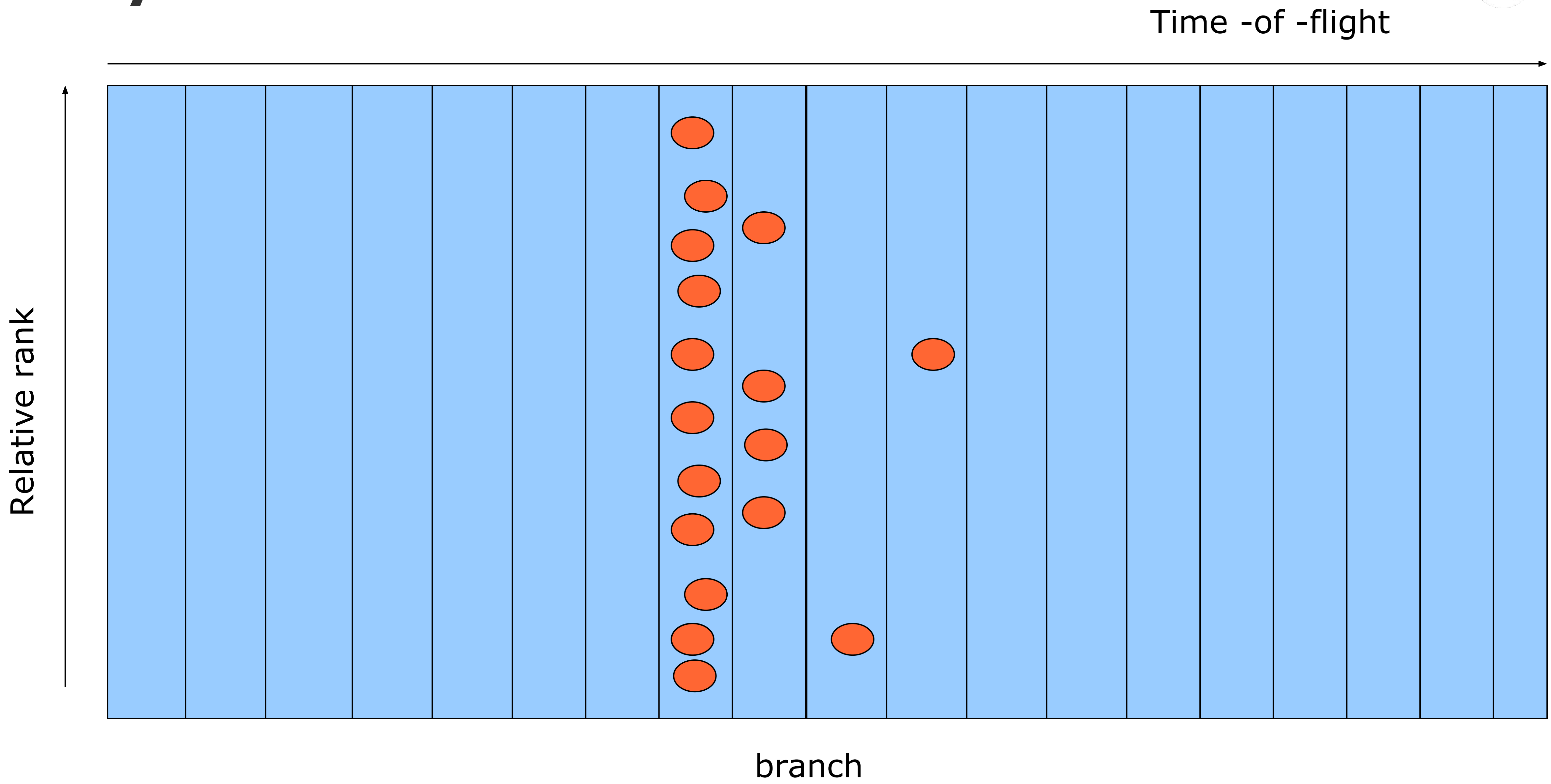


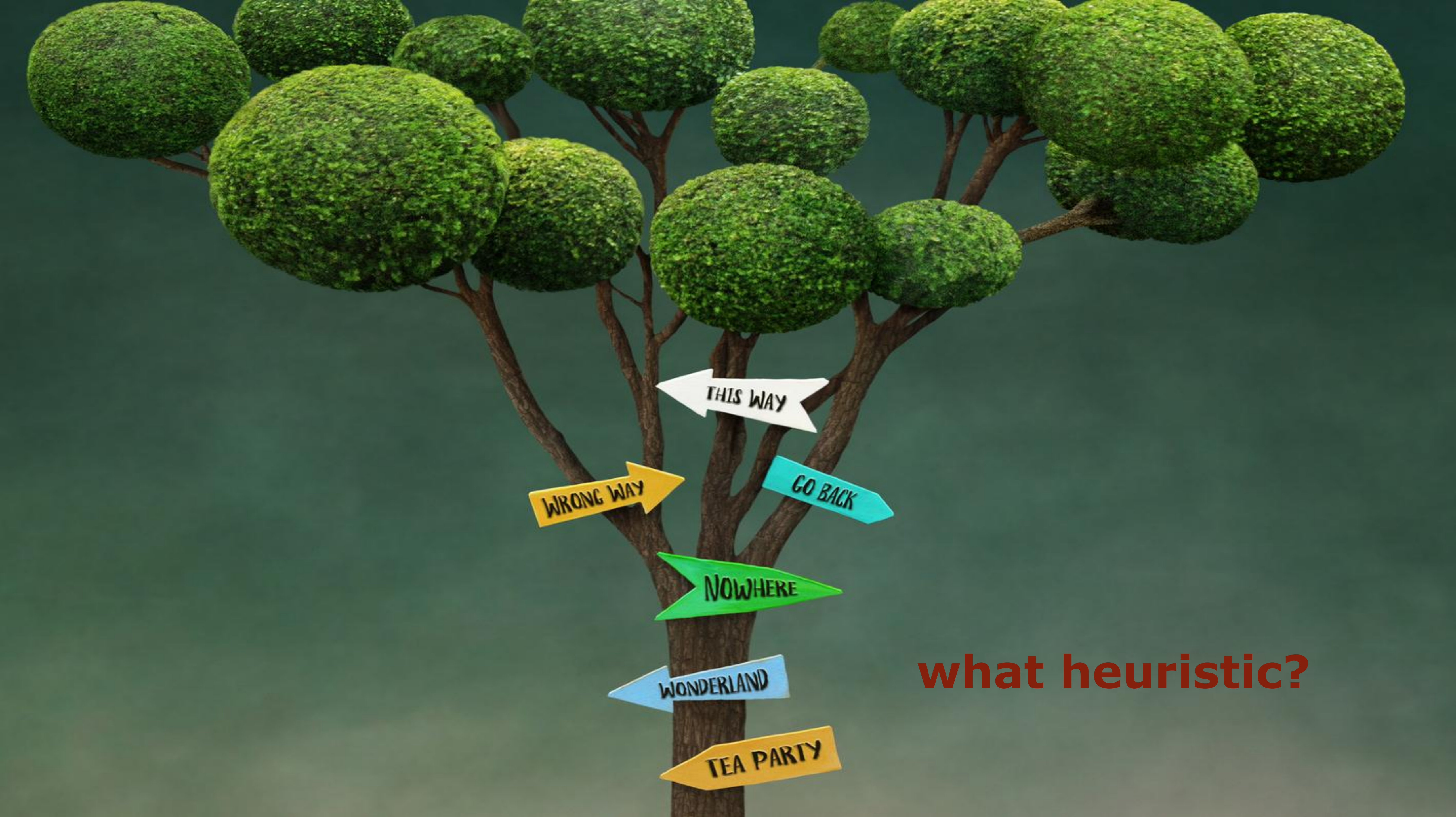
Lazy Race Tree Search



prune

Lazy Race Tree Search

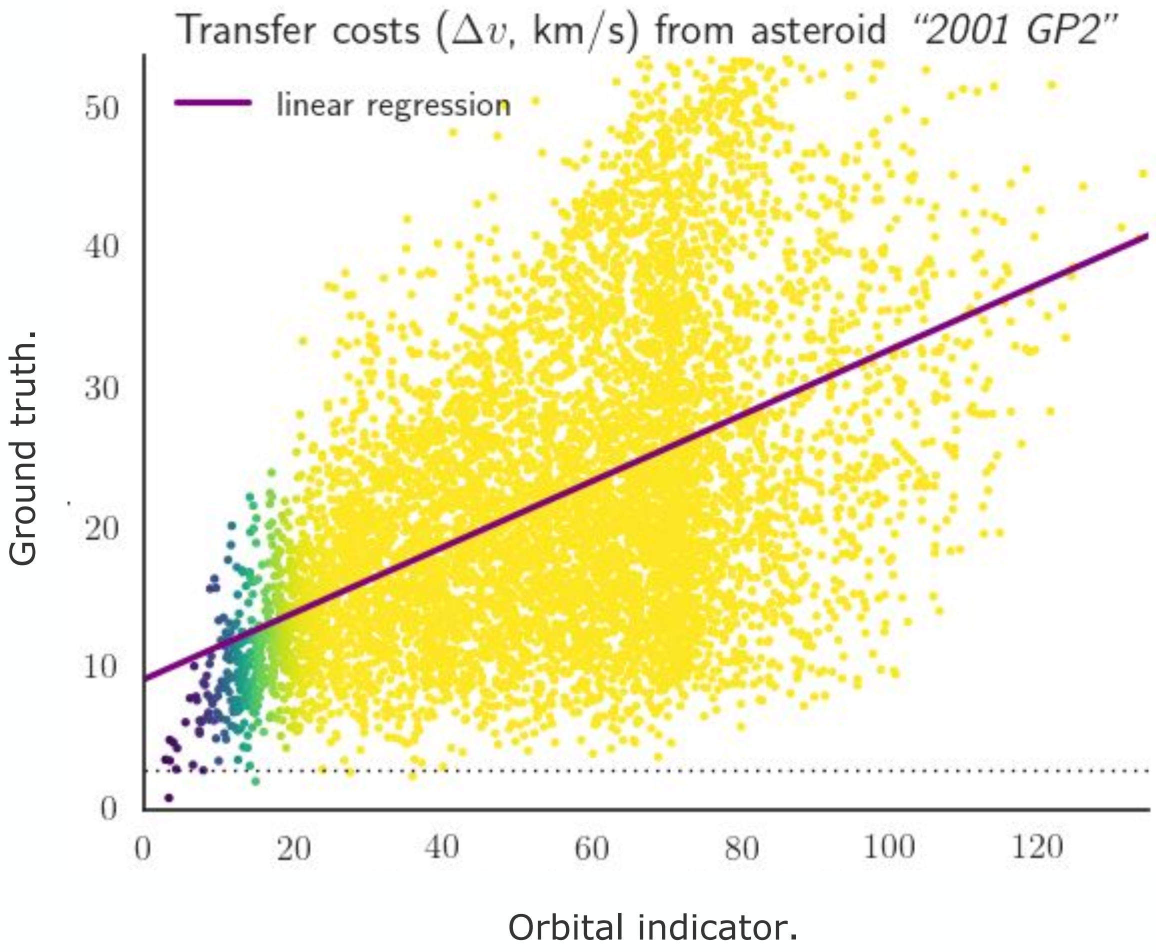




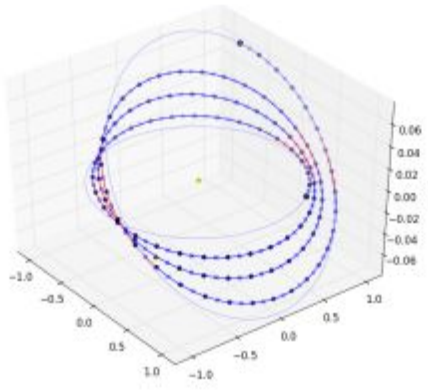
what heuristic?

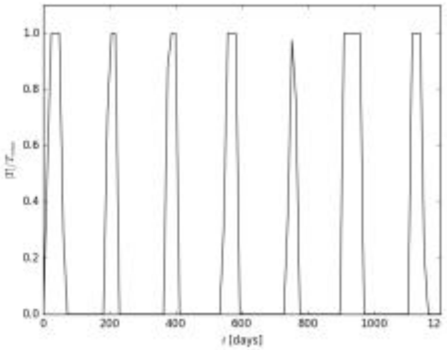
Example from GTOC5

We are loosing many good jump occasions!

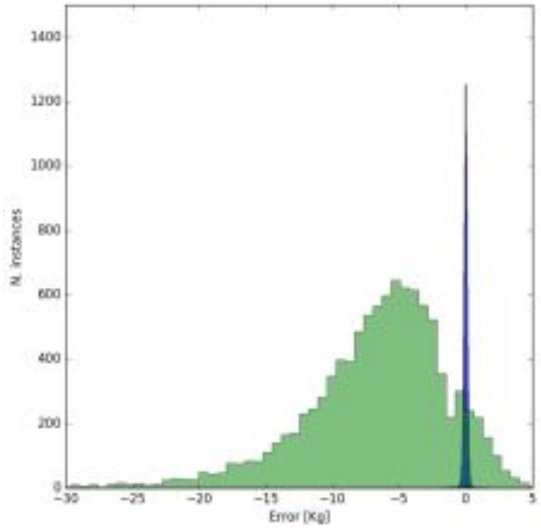


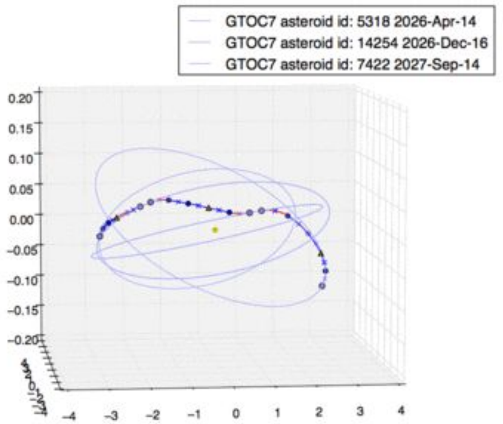
Learning the heuristic



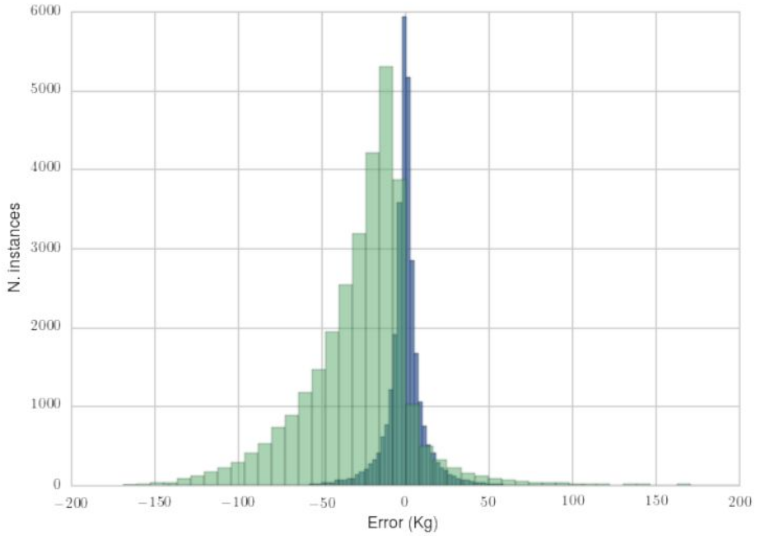


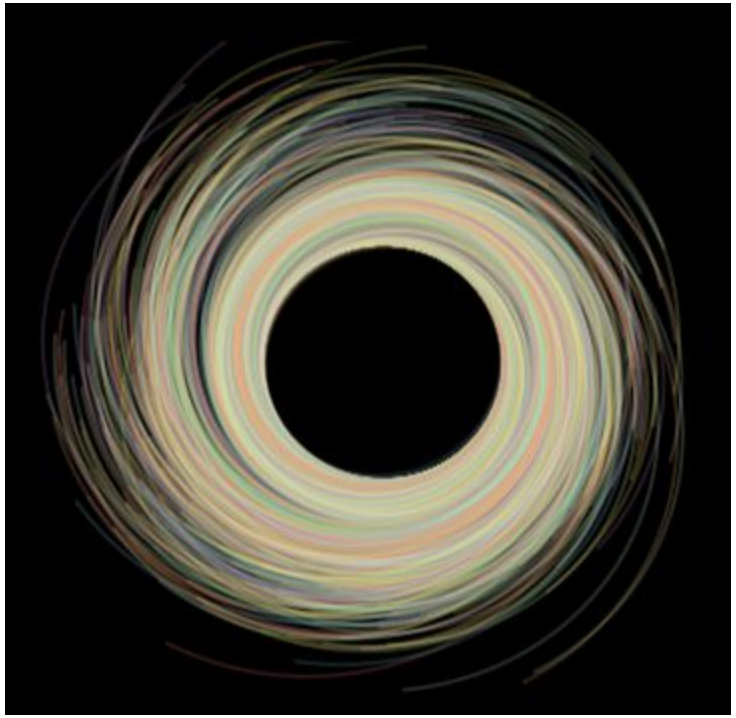
ML: SEP - 40000 asteroids at ~ 1AU



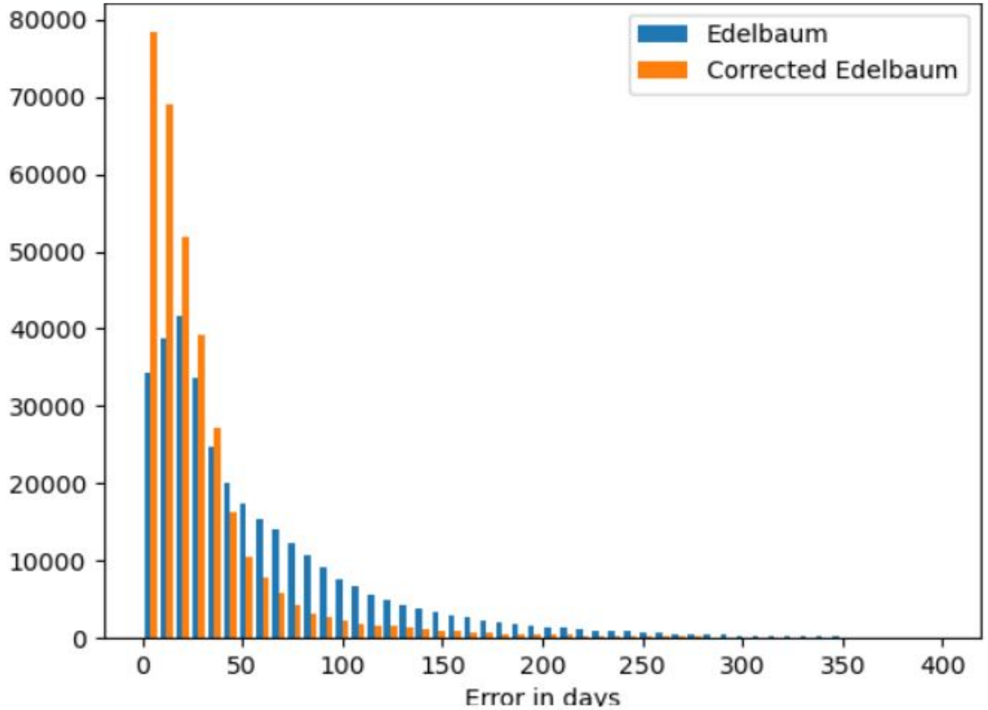


ML: GTOC7 jumps





ML: GTOC11 spirals



ML vs. analytical

ML

Generic methodology. 👍

~~Database creation.~~ 👍

No need for problem knowledge 👍

Analytical

Better when possible. 👍

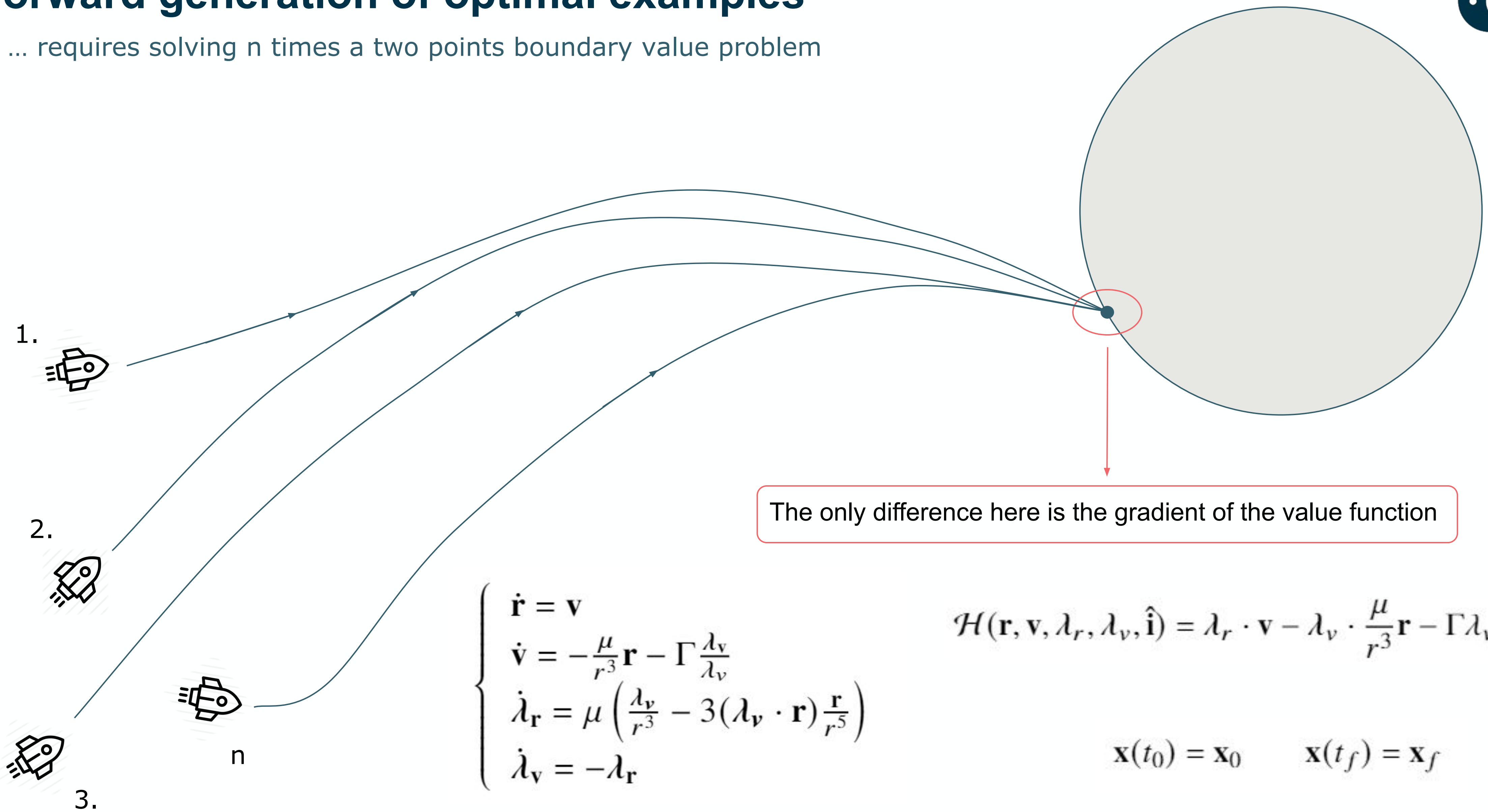
Often relies on (unrealistic) hypothesis. 👎

Use of problem knowledge 👍

… or a combination of the two!

Forward generation of optimal examples

… requires solving n times a two points boundary value problem



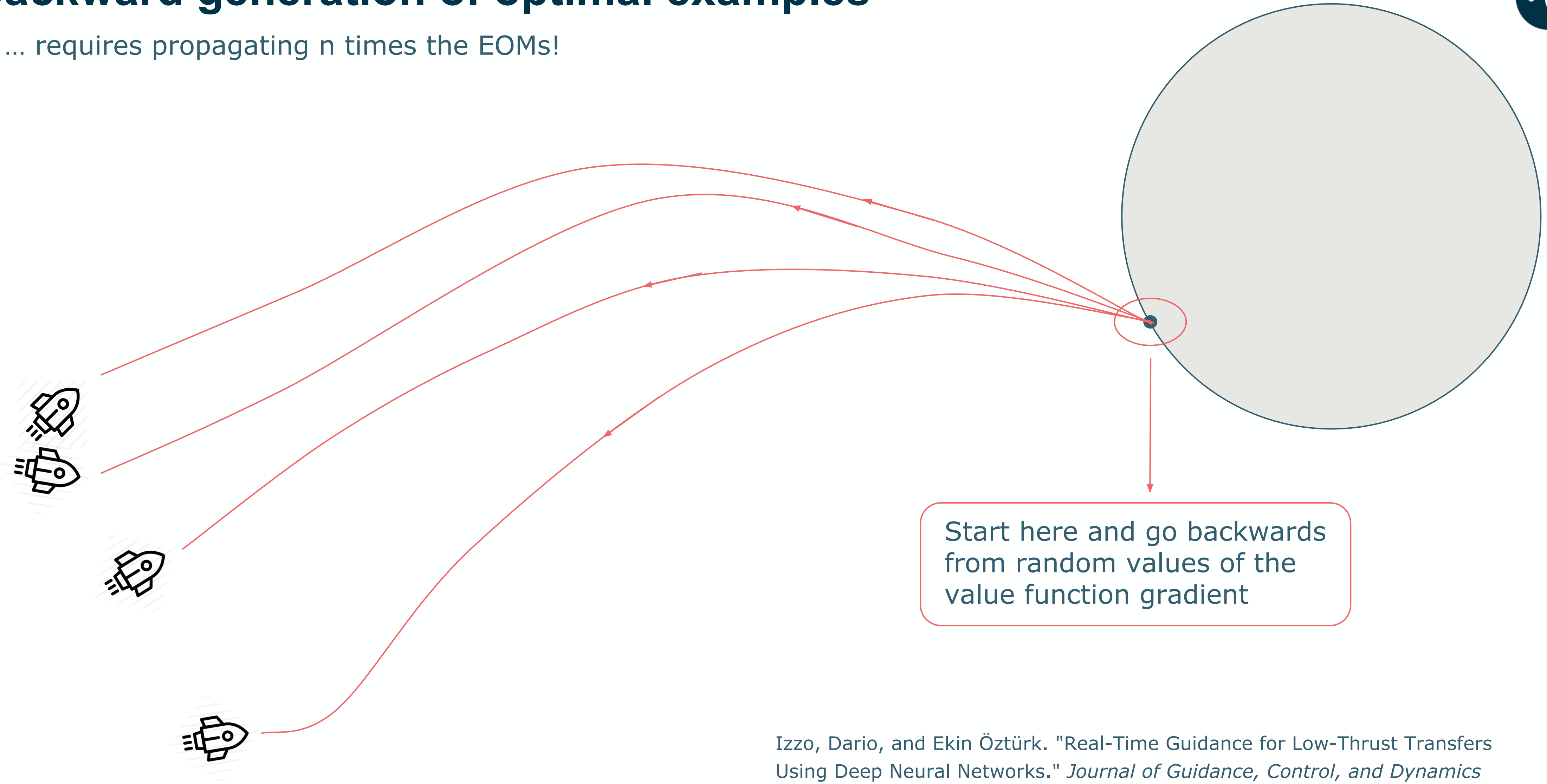
$$\begin{cases} \dot{\mathbf{r}} = \mathbf{v} \\ \dot{\mathbf{v}} = -\frac{\mu}{r^3}\mathbf{r} - \Gamma\frac{\boldsymbol{\lambda}_v}{\lambda_v} \\ \dot{\boldsymbol{\lambda}}_\mathbf{r} = \mu\left(\frac{\boldsymbol{\lambda}_\mathbf{v}}{r^3} - 3(\boldsymbol{\lambda}_\mathbf{v}\cdot\mathbf{r})\frac{\mathbf{r}}{r^5}\right) \\ \dot{\boldsymbol{\lambda}}_\mathbf{v} = -\boldsymbol{\lambda}_\mathbf{r} \end{cases}$$

$$\mathcal{H}(\mathbf{r}, \mathbf{v}, \boldsymbol{\lambda}_r, \boldsymbol{\lambda}_v, \hat{\mathbf{i}}) = \boldsymbol{\lambda}_r \cdot \mathbf{v} - \boldsymbol{\lambda}_v \cdot \frac{\mu}{r^3}\mathbf{r} - \Gamma\lambda_v + 1 = 0$$

$$\mathbf{x}(t_0) = \mathbf{x}_0 \qquad \mathbf{x}(t_f) = \mathbf{x}_f$$

Backward generation of optimal examples

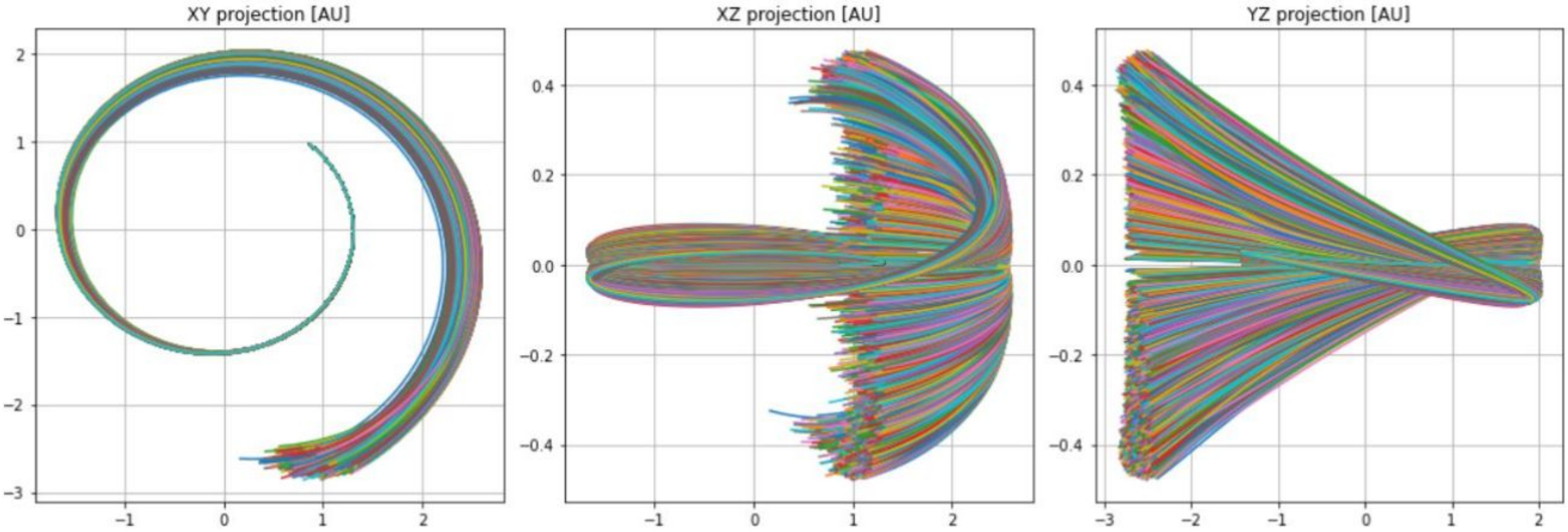
… requires propagating n times the EOMs!



Start here and go backwards from random values of the value function gradient

Izzo, Dario, and Ekin Öztürk. "Real-Time Guidance for Low-Thrust Transfers Using Deep Neural Networks." *Journal of Guidance, Control, and Dynamics* 44.2 (2021): 315-327.

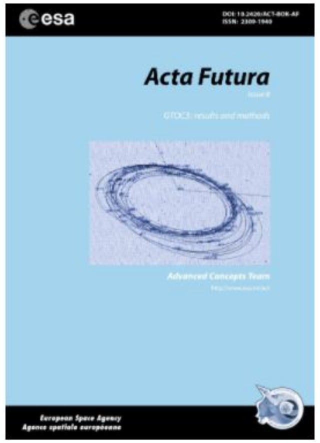
Backward generation of optimal samples

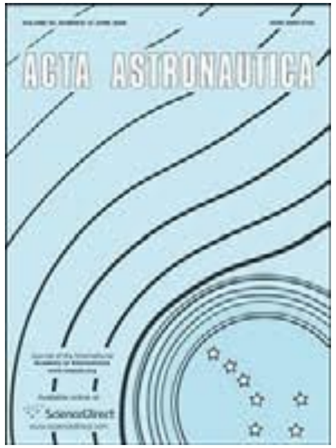


2 orders of magnitude speed up w.r.t single shooting

GTOC badges

- 3 special issues in peer-reviewed journals (plus one upcoming for GTOC11).
- > 100 scientific papers fully on GTOC problems
  … many more mentioning such problems.
- A similar event in China modelled after GTOC: the CTOC (btw … going to the gym works!).
- > 500 scientists ~30 different countries.





Thank YOU!

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MGA1DSM pruning:

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MGA-LT and MBH:

Yam CH, Lorenzo DD, Izzo D. Low-thrust trajectory design as a constrained global optimization problem. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering. 2011 Nov;225(11):1243-51.

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