Google Cloud

Autopilot: workload autoscaling at Google

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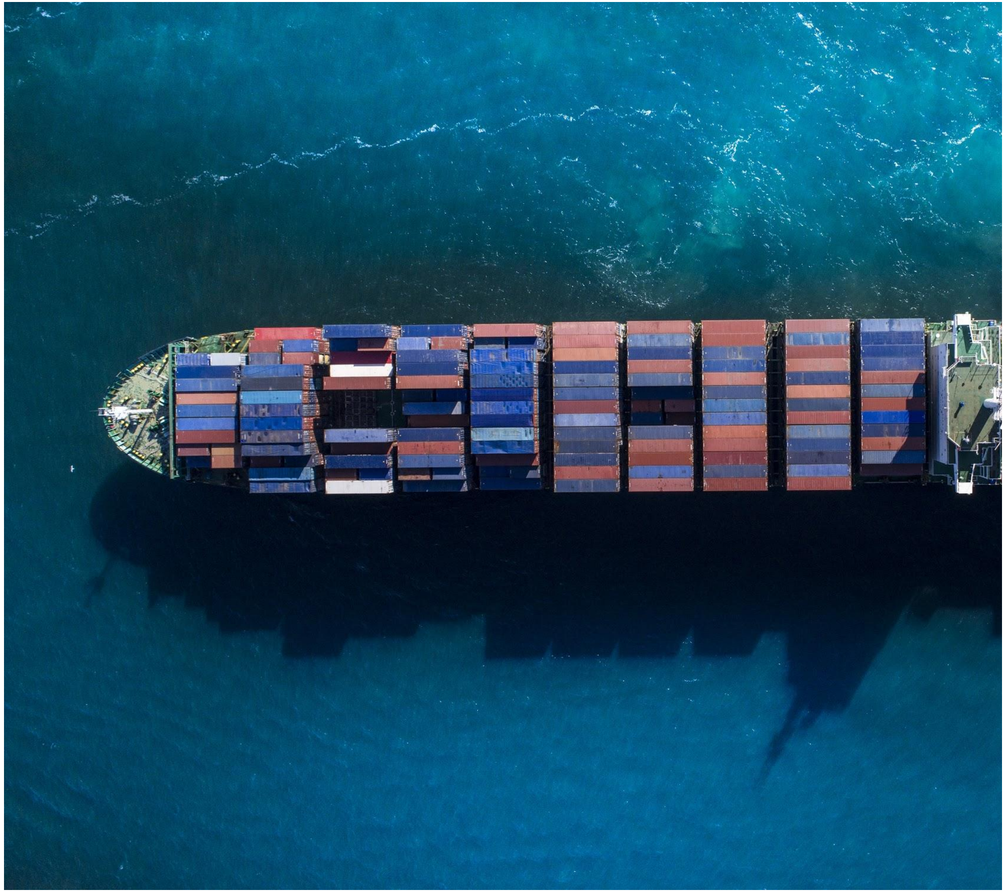
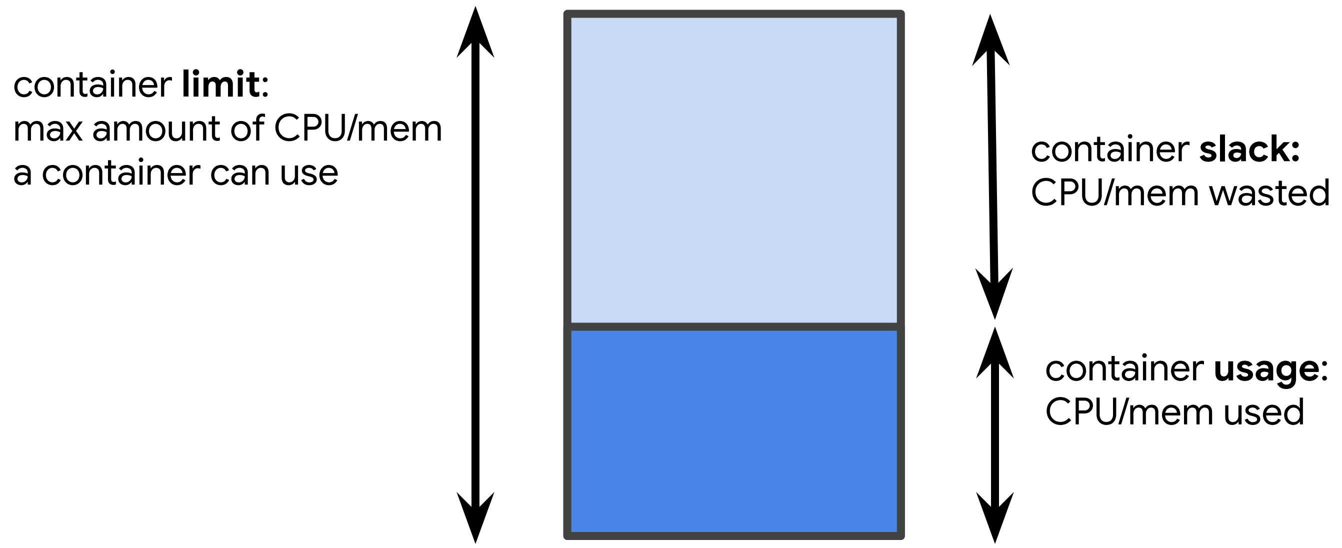
Google runs in containers

In any given week, we launch over two billion containers across Google.



Resource limits are crucial to isolate workloads



Borg, our scheduler, packs containers to machines by resource limits.

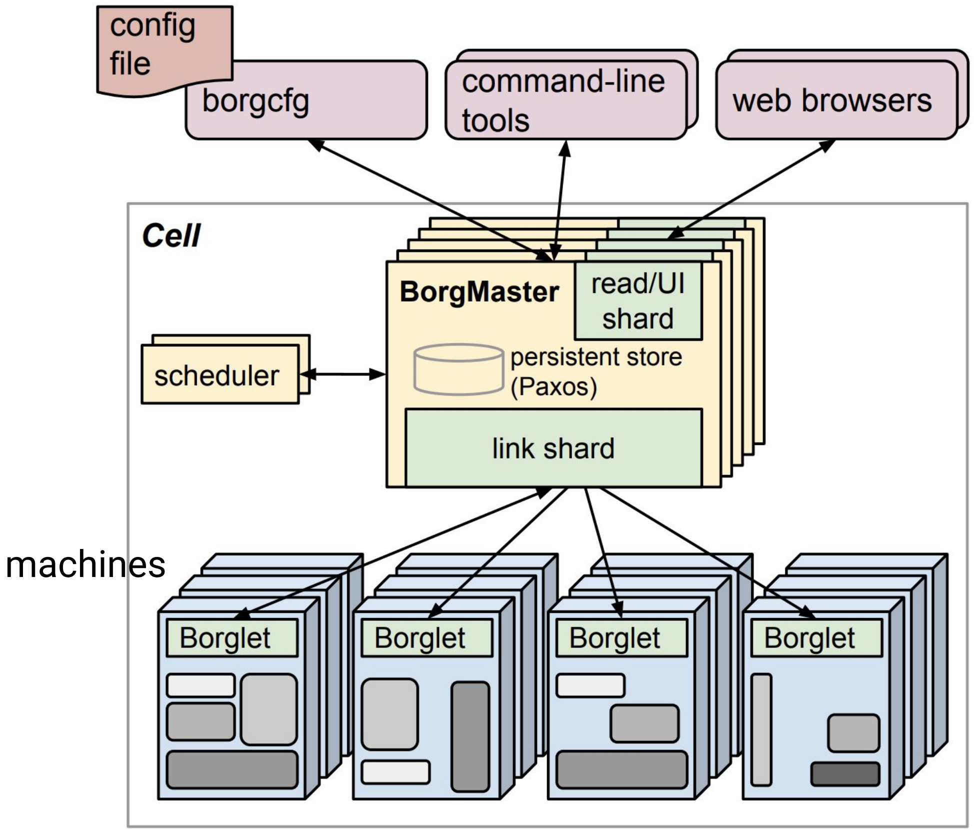
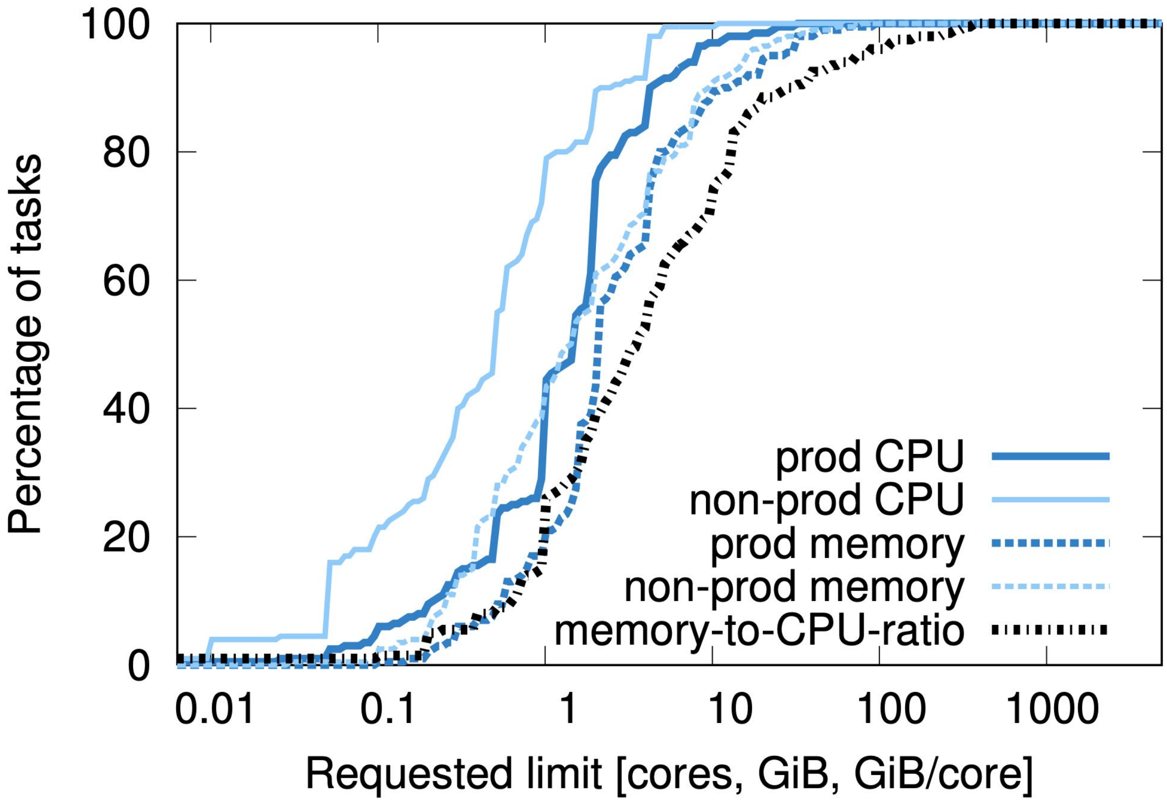


image source: http://dx.doi.org/10.1145/2741948.2741964 [Verma et al., EuroSys'15]

Limits are fine-grained:
CPU in milli-cores
memory in bytes



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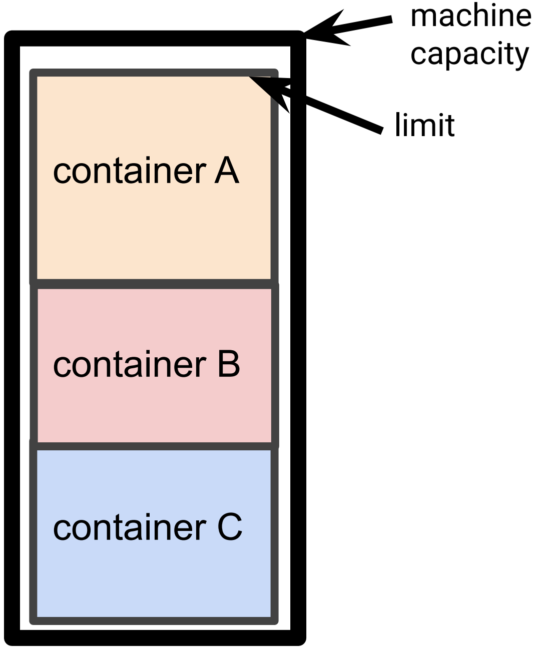
We pack containers to machines by limits.

So, precise limits are crucial for efficiency and reliability.



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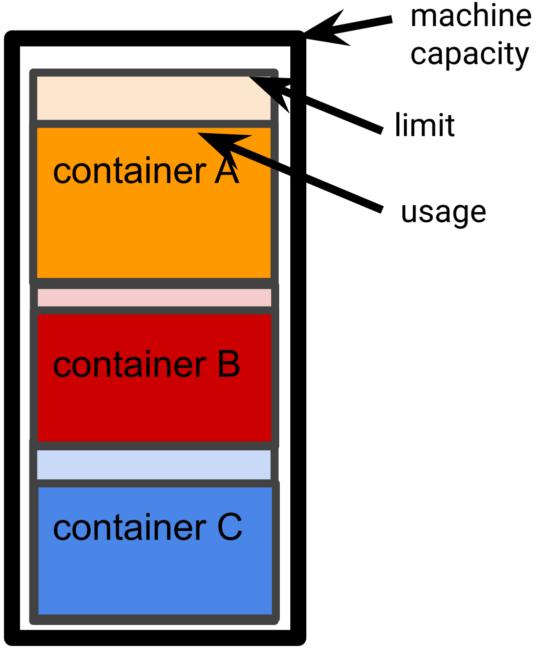

precise
limits

good!

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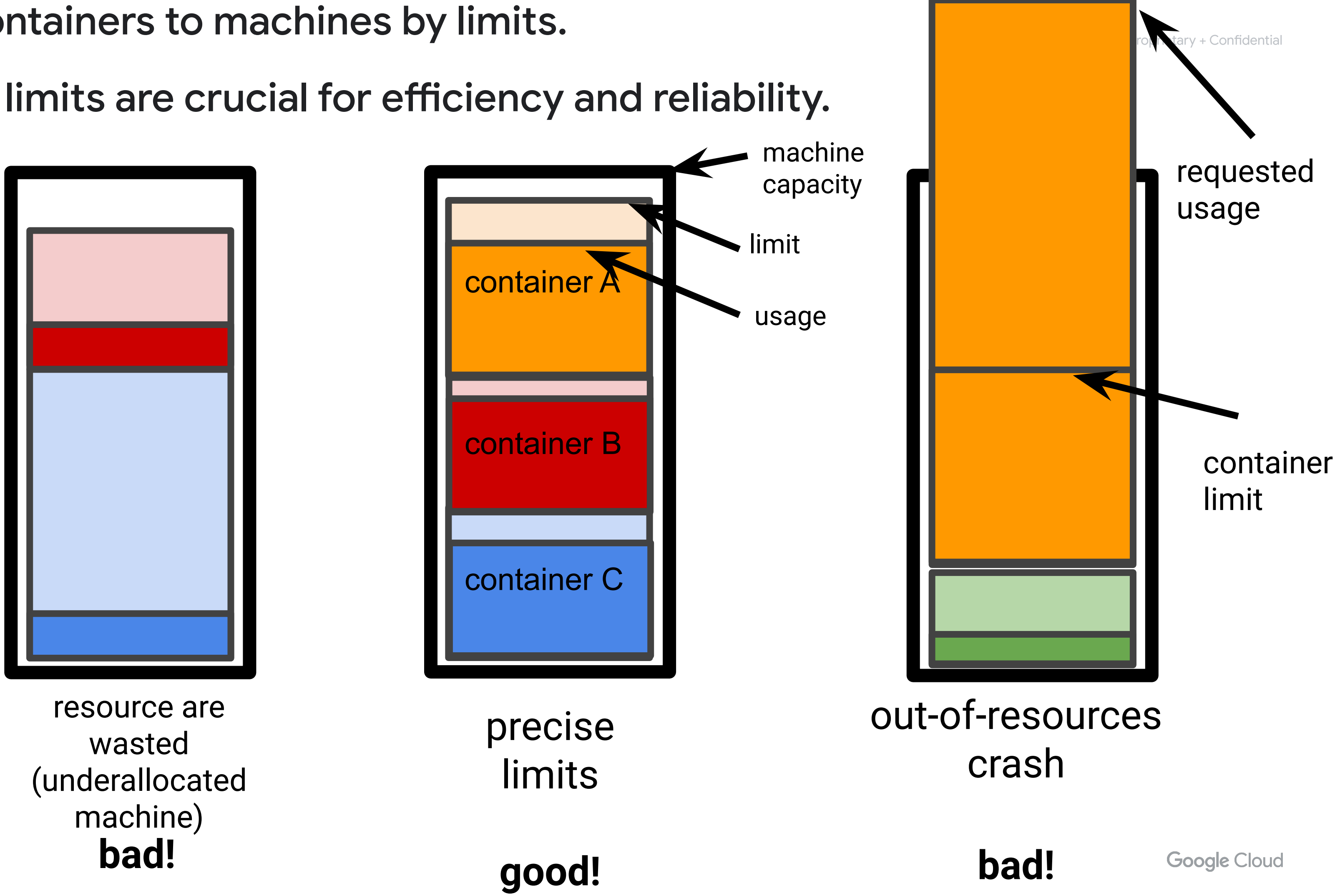
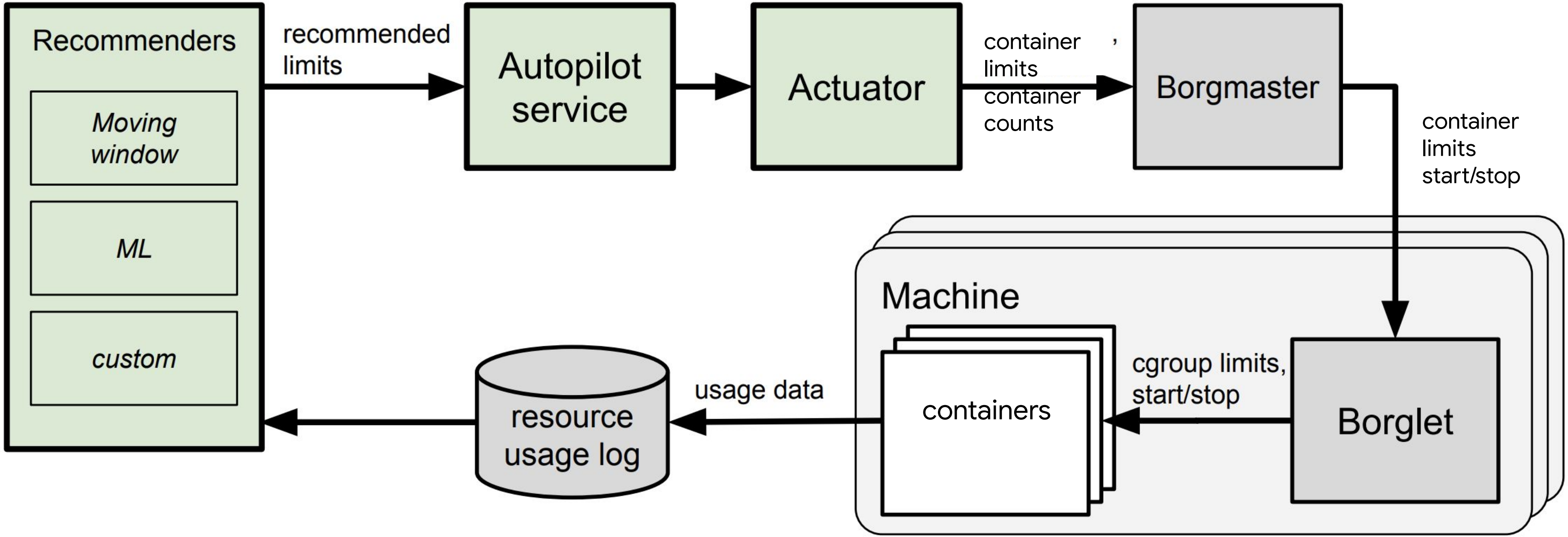


Autopilot acts as a **controller** for Borg limits.



Autopilot continuously adjusts resource limits:

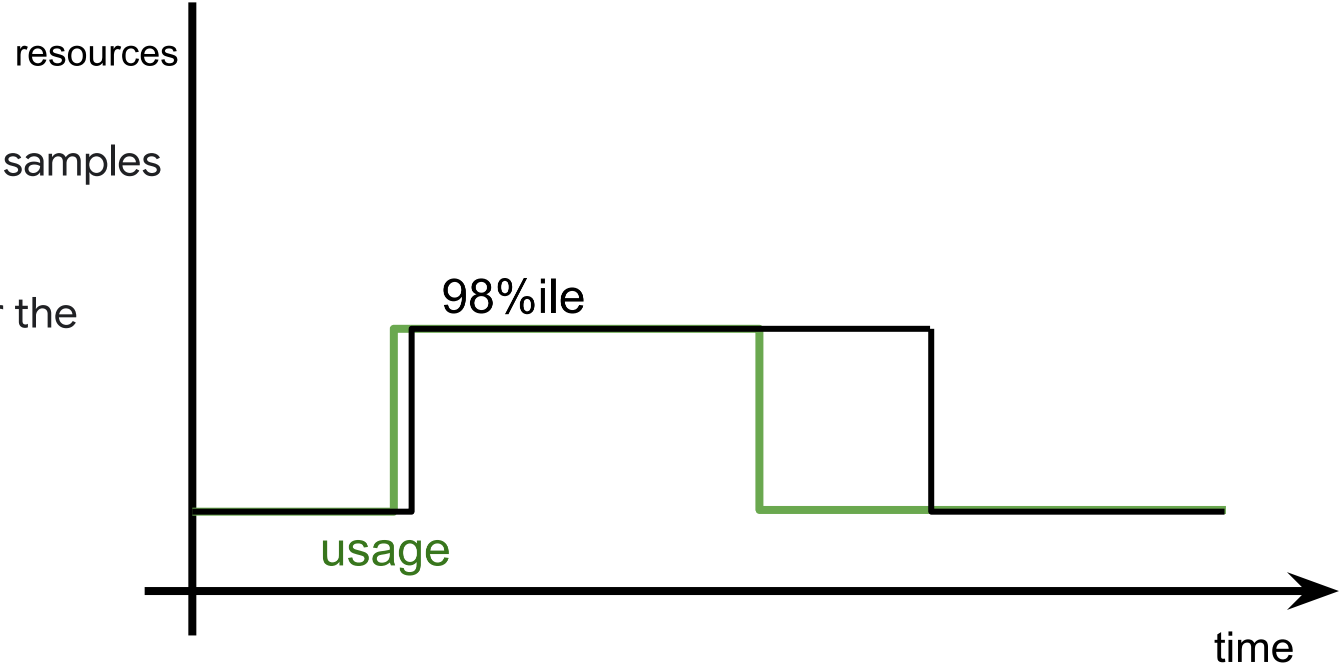
CPU/Mem limits for containers (vertical scaling),

number of replicas (horizontal scaling).

Autopilot Recommenders

Moving window recommenders

- Exponentially-decaying samples (half-life of 48 hours)
- Compute statistics over the samples, e.g. 95%ile
- add a safety margin



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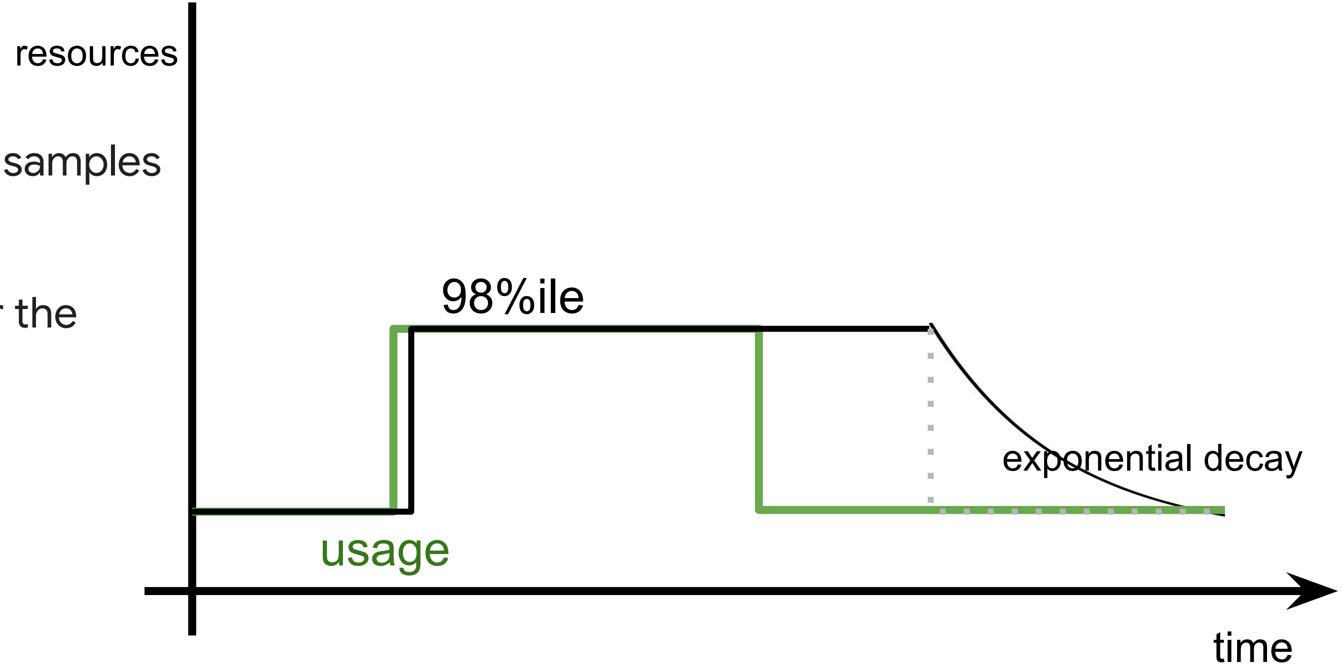

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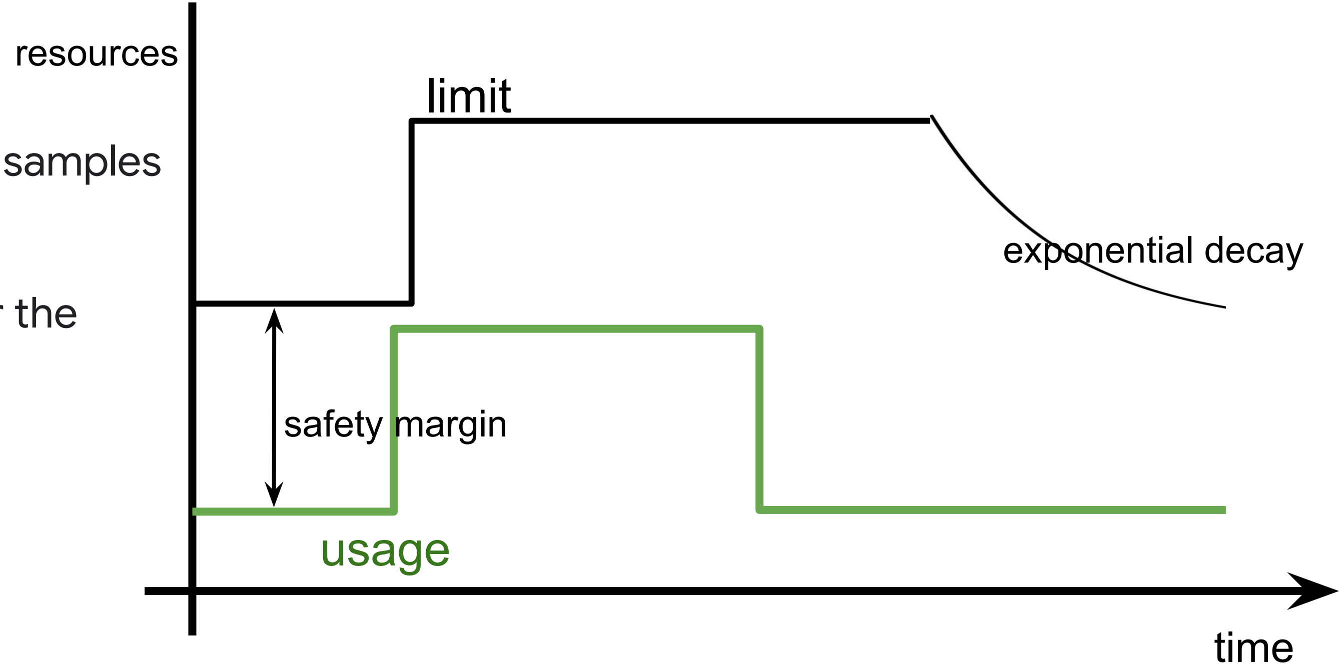
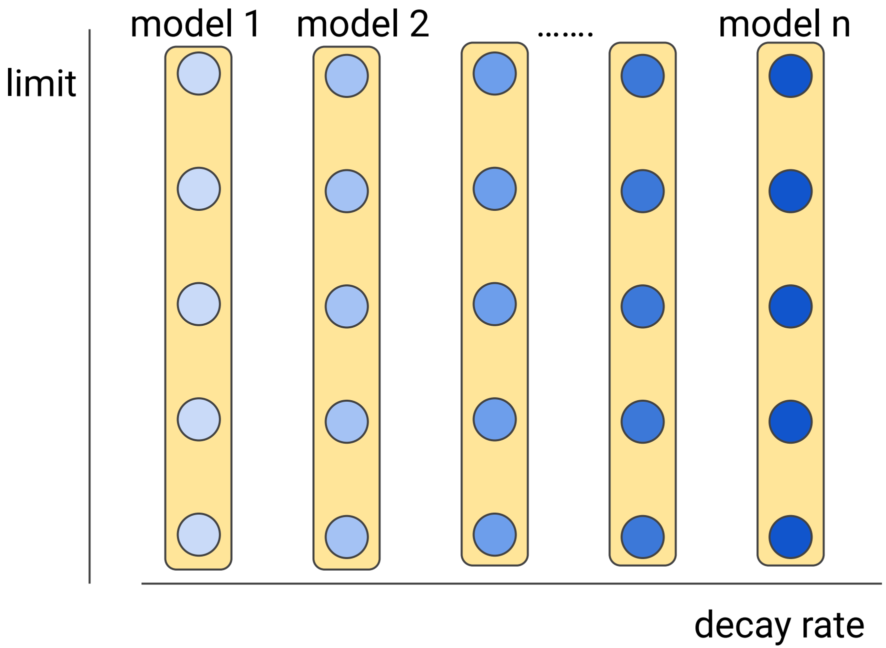


Machine learning recommenders

- Each model is an arg-max algorithm picking a limit value
- Each model is parametrized by the decay rate and the safety margin.
- The recommender picks the model performing the best over a longer time period.



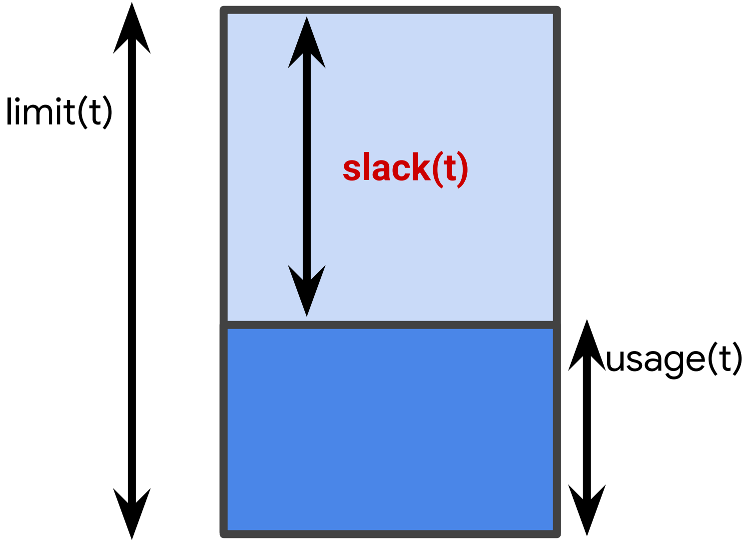
Evaluation:
Observational study of production jobs
Focus on memory

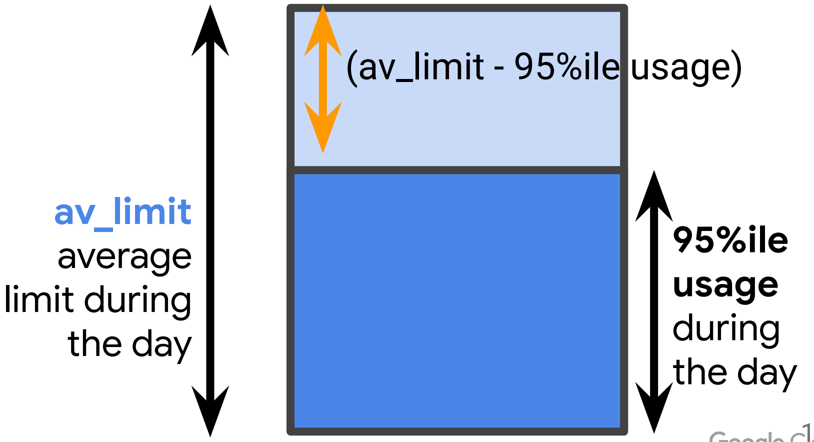
Autopilot efficiency - reduction of slack

absolute slack:
$\int \mathrm{slack}(t)\,dt = \int \mathrm{limit}(t)\,dt - \int \mathrm{usage}(t)\,dt$

unit: capacity of a single (largish) machine

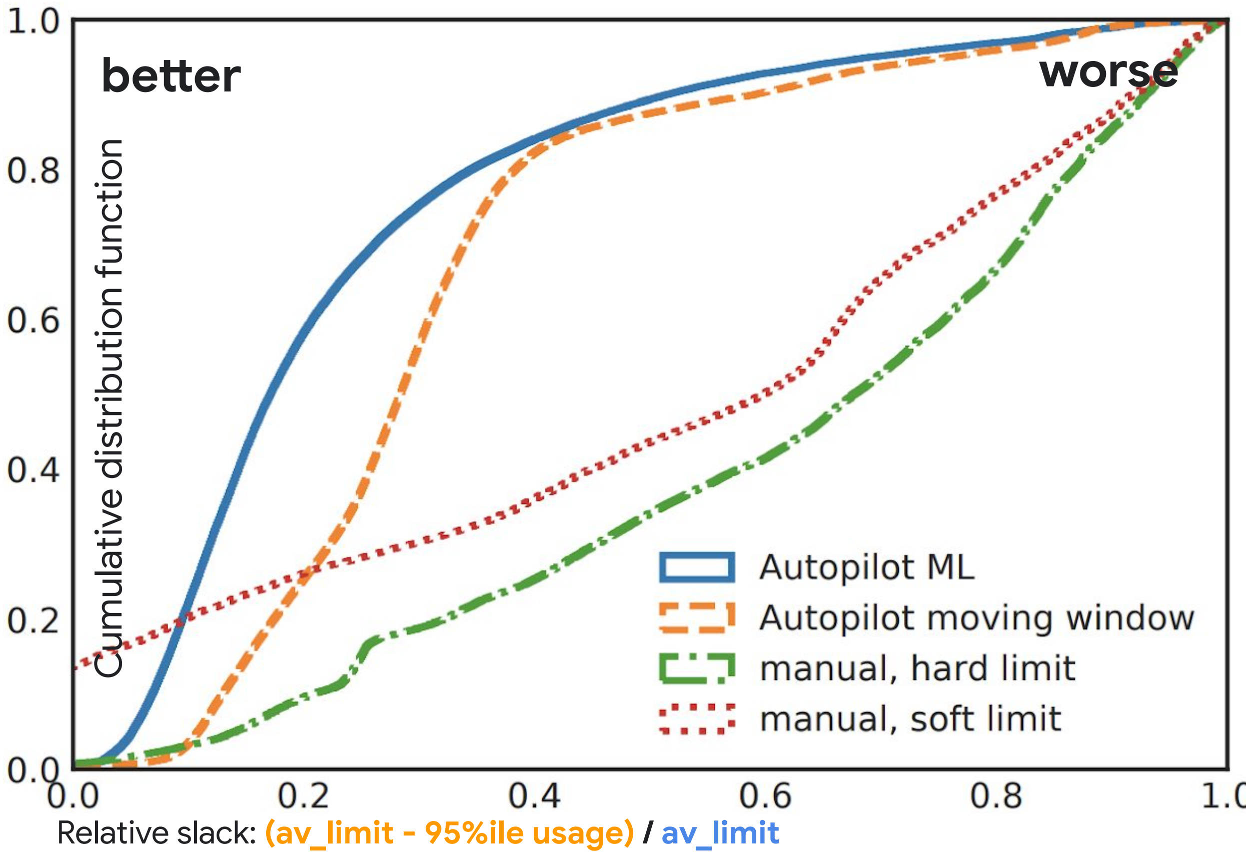
relative slack:
(av_limit - 95%ile usage) / **(av_limit)**

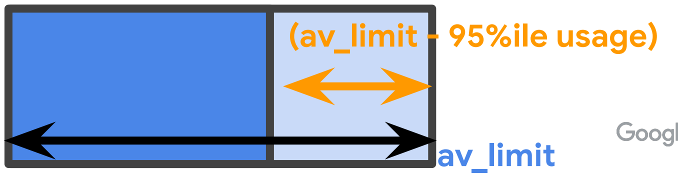




Autopiloted jobs have significantly smaller relative slack.

A random sample of 5000 jobs in each category.





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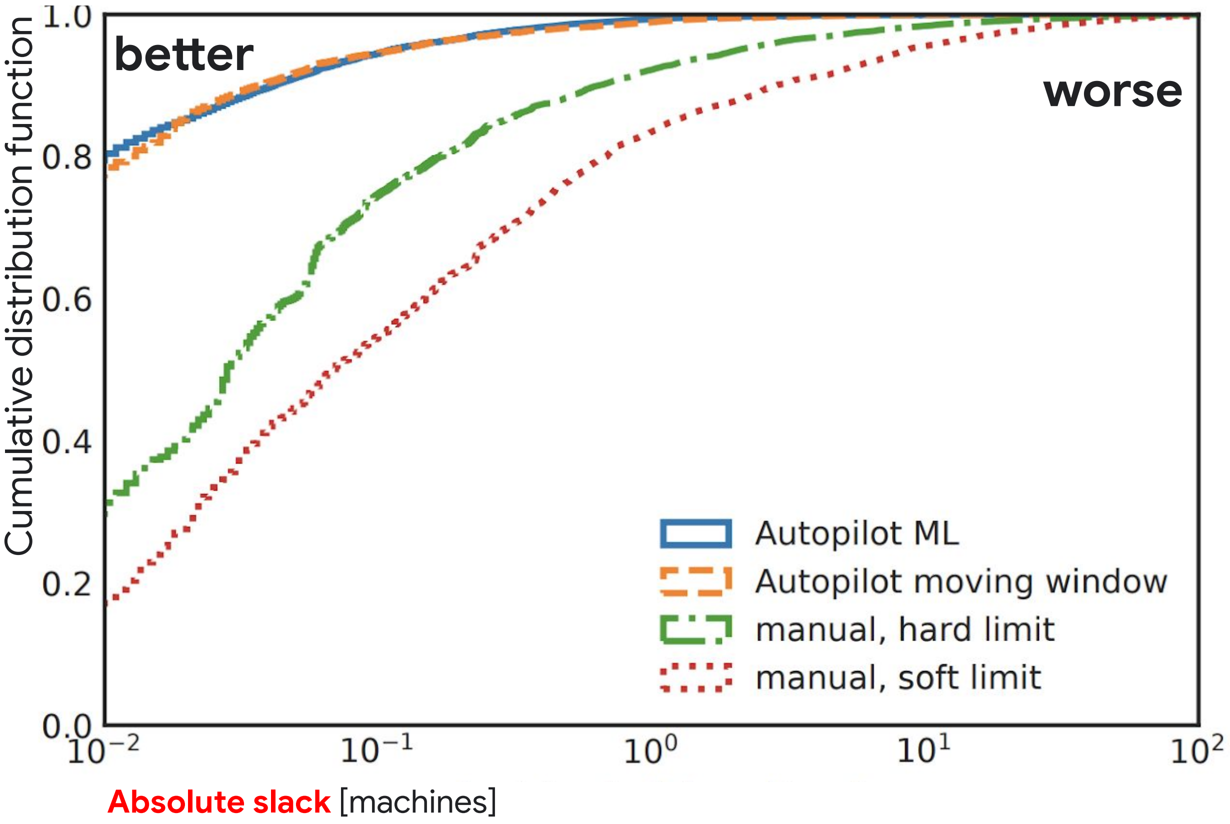
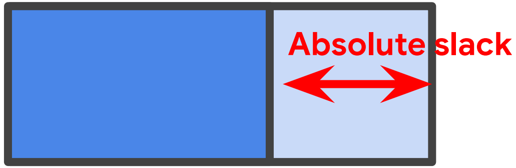
Autopiloted jobs save significant capacity.

A random sample of 5000 jobs in each category.

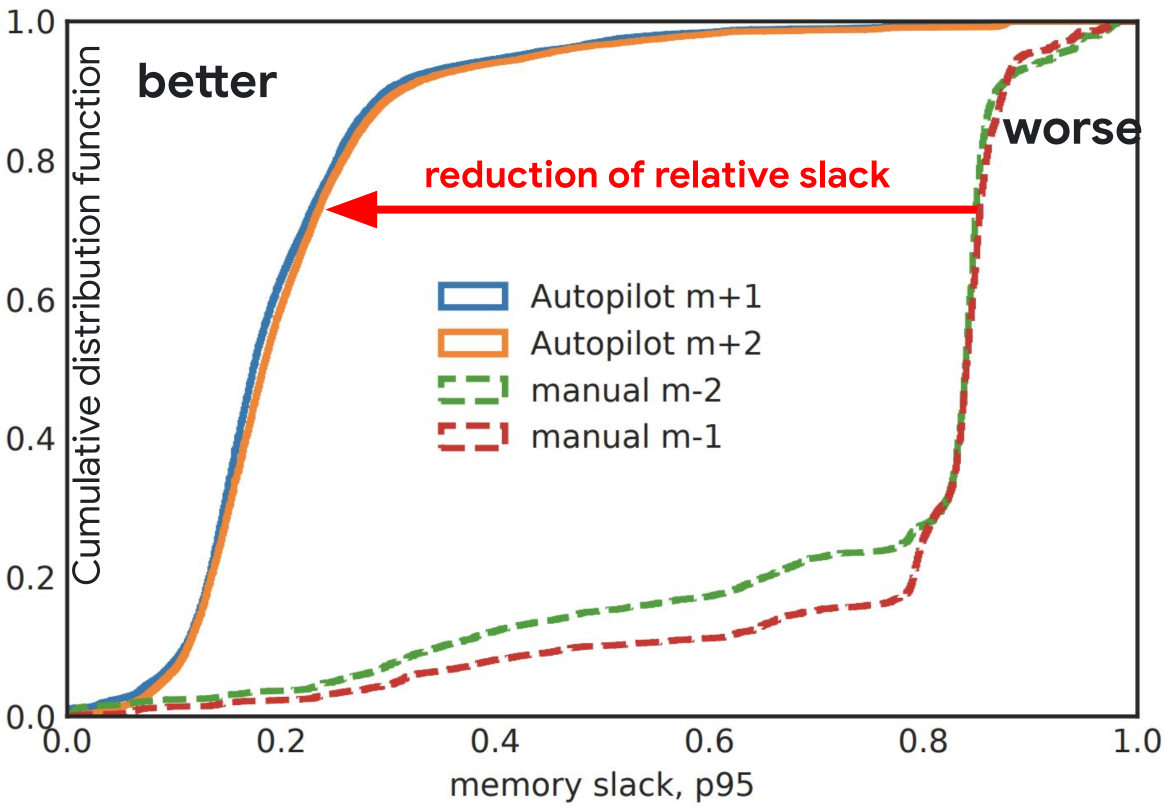




When jobs migrate to Autopilot, their slack is significantly reduced.

A random sample of 500 jobs that migrated to autopilot in a certain month, m0.

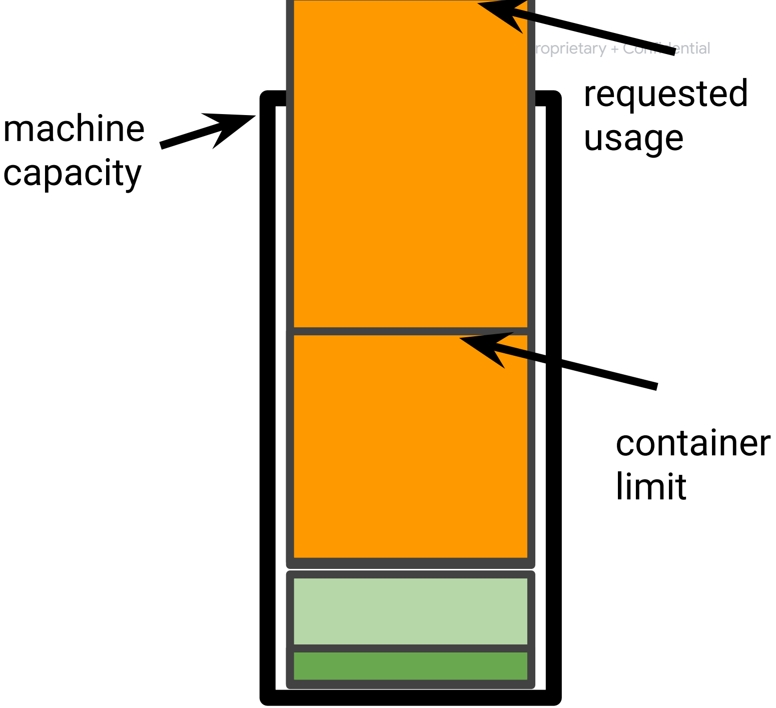
CDFs for slack for 2 months before and after migration



Autopilot Reliability:
how frequent are
out-of-memory errors.

We count terminations of containers.

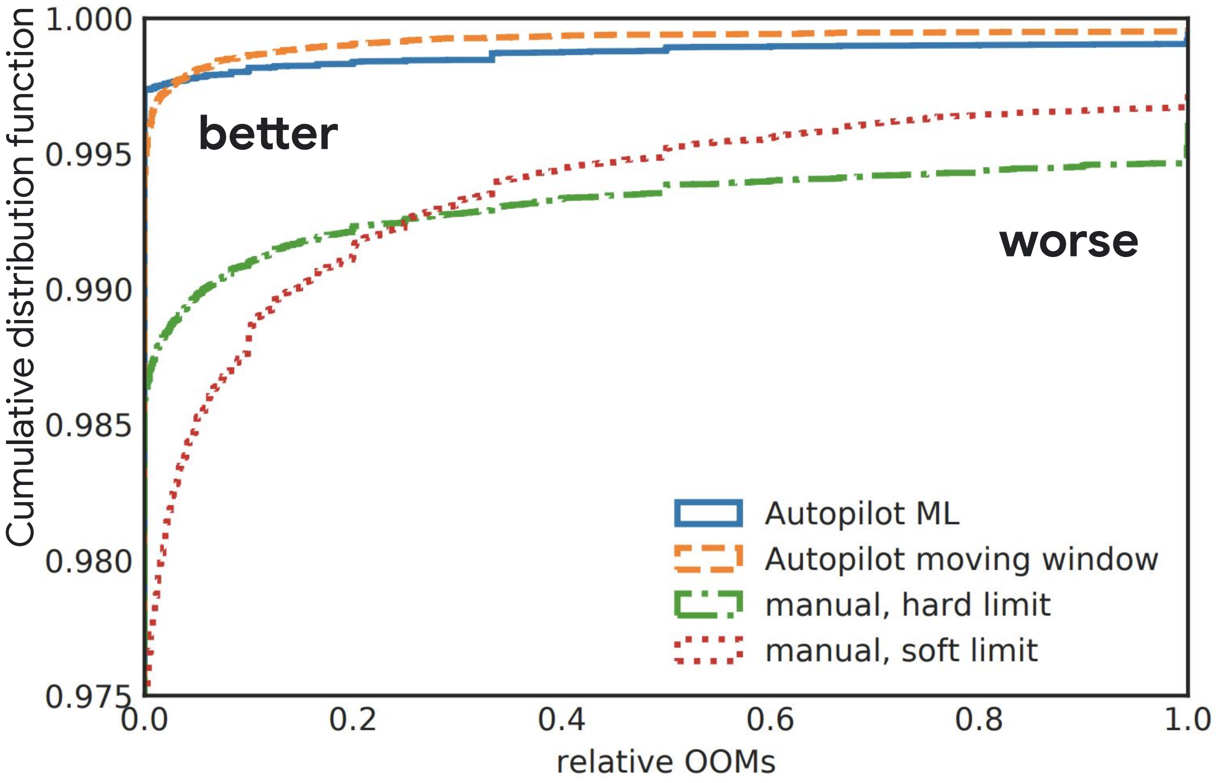
We weight the number of terminations by the average number of containers of a job.



out-of-resources crash

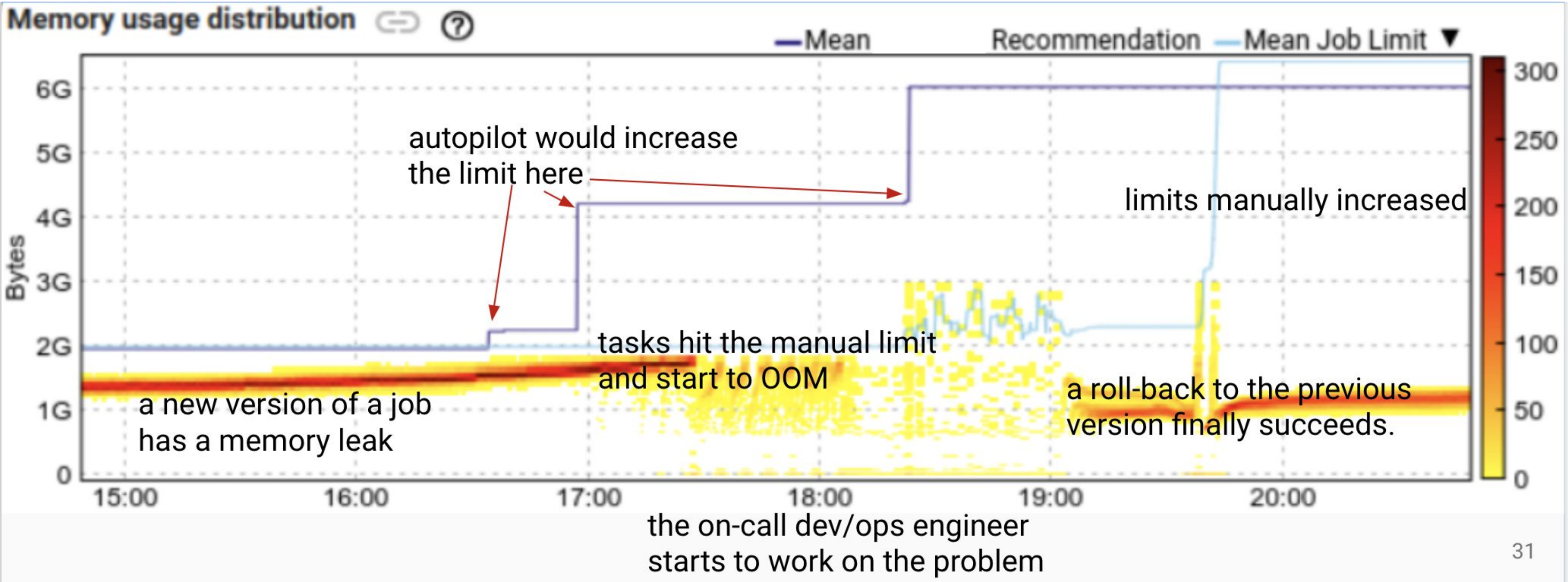
Autopilot reduces the frequency of out-of-memory events.

OOMs are rare: 99.5% of autopiloted jobs have no OOMs.



DevOps:
Autopiloted jobs account for over 48% of Google's fleet-wide resource usage.

Autopilot’s dynamic limits could help to keep the job running despite bugs.



Autopilot: workload autoscaling at Google

1. Efficient scheduling requires fine-grained control of jobs' limits
2. Humans are bad at setting the limits precisely.
3. Autopilot uses past usage to drive future limits
4. Autopilot reduces relative slack by 2x

...and it reduces the number of jobs severely impacted by OOMs 10x