SmartOS: Towards Automated Learning and User-Adaptive Resource Allocation in Operating Systems

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Operating systems

At 2018, 92% of households in US -> at least one computer [1]

Even more now!



Frustrated users

The time lost due to the frustrating experiences ranged from 30.5% to 45.9% of time spent on the computer. [2]

Frustration causes [2]

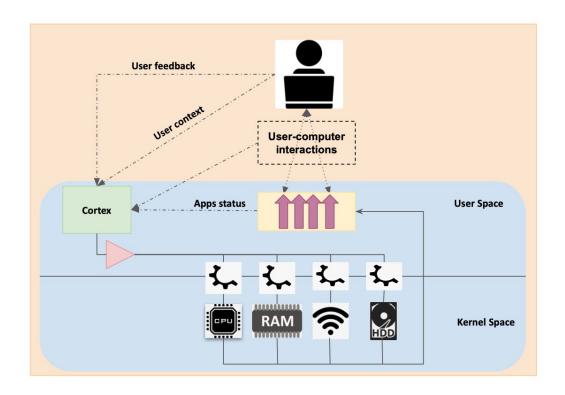
- Error messages
- Dropped network connections
- Long download times
- Hard-to-find features



What can be done?

- Give more resources (CPU, memory, network bandwidth, Disk I/O, etc.) to the applications that matter MORE!
 - Manually By user: Not all users are computer experts! It's time consuming and a frustrating job!
 - Automatically By OS
- What applications matter more? Is it always the foreground?
 - Editing a doc in Microsoft Office Word, while listening to music on youtube in Google Chrome, upgrading some software in the background and monitoring the stock widget on top of your desktop
- Based on the context, different users care more about some applications more than the others!
- How we can find the important applications?

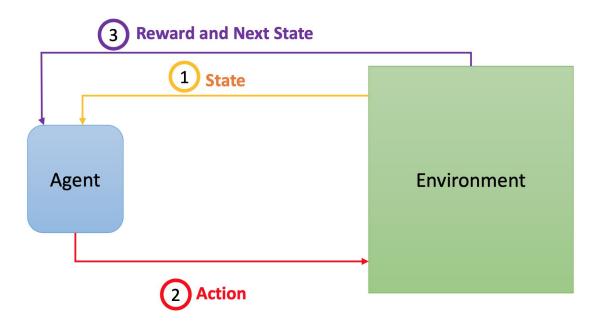
The solution



Cortex

- Heuristic based: Needs knowledge beforehand! Static! User preferences are changing constantly!
- Supervised/Unsupervised Machine Learning:
 - One time learning: Static! User preferences are changing constantly!
 - Cyclic learning/eval/deploy: What is the correct frequency to do learning? What happens if the user preferences differ from learned model faster than the learning frequency?

Reinforcement Learning



Prototype

Reinforcement learning

State:

| CPU | Memory | Network | Disk I/O | Fg | Audio/video |
|-----|--------|---------|----------|-----|-------------|
| 0/1 | 0/1 | 0/1 | 0/1 | 0/1 | 0/1 |

Action:

| CPU | Memory | Network | Disk I/O |
|-----|--------|---------|----------|
| 0/1 | 0/1 | 0/1 | 0/1 |

Reward:

Synthetic, +1 for the action leading to best performance and 0 otherwise

Resource Allocation

- **CPU**: Nice value
 - High prio: -20
 - o Normal Prio: o
- **Memory:** OOM Adjacent score and Cgroup memory swappiness
 - High prio: -1000 for score and o for swappiness
 - Normal prio: o for score and 60 for swappiness
- I/O: I/O nice
 - High prio: o real-time class
 - Normal prio: 4 idle class (default)
- Network bandwidth: Cgroup network I/O prio map
 - High prio: 10
 - Normal prio: o

Evaluation

Heuristics

- **Linux:** default linux CFS scheduler
- **Fg only:** high priority for foreground application for all resources
- **Fg + video/audio:** high priority for foreground and video/audio applications for all resources
- **Fg + dependent:** high priority for the foreground application and all other applications that foreground performance depends on.
 - o predefined directed acyclic graph to store dependencies between applications

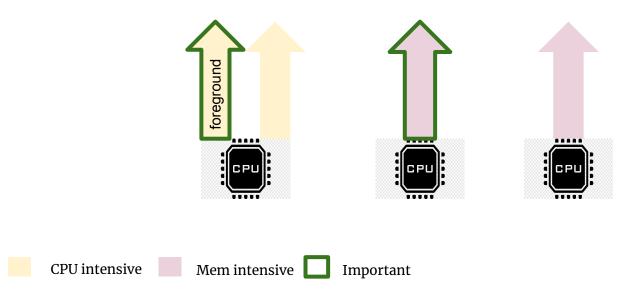
Heuristics

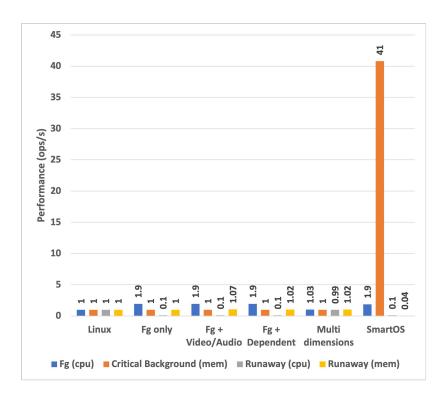
• Multi-dimension:

- Uses a predefined map that stores the essential resources per application's performance
- High prio for the foreground application in all resources necessary to its performance
- Assign the remaining resources to the important applications to the user
- Important applications are stored in a hash map defined by asking the user in the beginning.

Variation of Dimensions

• Ubuntu 20.04 virtual machine with 8 GB of memory, 4 processors, and 50 GB VDI disk drive.





For more scenarios please refer to the paper

SmartOS Dynamicity and Convergence

- 4 different scenarios
- 60 seconds on each scenario (extreme case)
- Ask for the feedback after each scenario and move to the next scenario

With less frequent change of applications, SmartOS is able to achieve convergence even sooner!

| RL Algorithm | Feedbacks |
|------------------|-----------|
| DQN | 52000 |
| QLearning | 28400 |
| Sarsa | 3680 |
| Double Qlearning | 2400 |
| A2C | 1600 |
| Monte Carlo | 400 |

SmartOS Overhead

- SmartOS adaptation to each user feedback takes:
 - o 0.218 ms total execution time
 - o 0.21 ms pure CPU time
 - So less compared to human adaptation time which is in order of seconds
- Required memory for cortex 21.3 MB
- Negligible overhead!

Discussion and Future Work

Real world scenarios

- Human study
- Adding implicit user feedback
- Continuous state and action vector
- More complex user context

SmartOS failures

o In case of failure return back to Linux CFS

Cross platform

- Place the cortex in the cloud
- Work with multiple devices
- Learn across users

Conclusion

- Learning based operating system
- Adjusting resource allocation based on user preferences
- Works better than heuristics
- Monte carlo achieves convergence sooner than other RL algorithms
- Overhead is negligible (order of tenth ms)

Thank you!

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Any Questions?

Resources

- https://www.census.gov/newsroom/press-releases/2021/computer-internet-use.html
- https://www.researchgate.net/publication/2834775 Understanding Computer User F rustration Measuring and Modeling the Disruption from Poor Designs