

#### Virtual Machine Allocation with Lifetime Predictions

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# Motivation

- Allocation decisions have a direct impact on resource efficiency
- Inefficient placement might result in fragmentation and unnecessary over-provisioning
- Improvements of 1% in packing efficiency can lead to cost savings of hundreds of millions of dollars (Hadary et al., 2020)

**Goal:** Increase Azure's packing efficiency with lifetime-aware algorithms

**Problem:** *Dynamic* multi-dimensional bin packing problem



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lifetime



#### Example



#### Example



### VM lifetime characterization

- How are lifetimes in our system?
- $\cdot$  High variance of lifetimes
  - $\cdot$  Median: 16 minutes
  - $\cdot$  Average: +1 day
- · Lifetime temporal patterns
  - Feasibility of VM lifetime prediction





# Our contributions

- 1. Lifetime-aware algorithm
- 2. ML model for VM lifetime predictions
- 3. System to support it on real-time

Idea: "Prioritize putting jobs with similar lifetimes together"

• Lifetime ranges are partitioned into classes (where class 0 contains the smallest lifetimes)

- If the request is predicted **class 0**:
  - assign to any node using Best Fit
- If the request is predicted class j:
  - assign to a class j node (if exists), using Best Fit, else,
  - assign to any node using Best Fit
- Dynamically updates lifetime classification of nodes
  - · Predicted remaining lifetime
- Theoretical indication that LA is **robust to prediction errors**



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# **Predicting lifetime**

#### **Challenges:**

- $\cdot$  Small feature set
- $\cdot$  Fast inference time
- Missing data (loss or pruning)
- $\cdot\,$  Skewed and long-tailed lifetime distribution

#### Features:

- VM centric (VM type, OS, request time)
- Customer centric (temporal distribution)

LightGBM model Binary classification Short/long threshold

### System architecture

**Challenge:** How to predict on real time without causing delays?



#### **Real-world production results**

- Initial version (ML model + algorithm) in production
- 20 Million daily prediction requests
  - · 200+ datacenters
  - $\cdot$  60+ regions
- $\cdot$  60% cache hit on inference results
- 99.2% predictions within time budget
  Limit of 30ms
- · ML model on production achieves expected performance

#### **Experiments**



**Packing Density:** Measures the average number of allocated cores on non-empty machines

#### Conclusion

We designed and implemented:

- Lifetime-aware packing algorithm robust to prediction errors
- **ML model** for VM lifetime predictions
- **System infrastructure** to support ML predictions in the critical path

> Packing improvements expected to save hundreds of millions of dollars per year

General methodology for resource management:

- 1. Produce data-driven intelligence (ML training, simulations) offline, slower time-scale
- 2. Utilize the intelligence at real-time ("inference")
- 3. Applies to other scenarios, e.g., admission control (OSDI'23)

#### References

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