On-demand, Spot, or Both: Dynamic Resource Allocation for Executing Batch Jobs in the Cloud

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Background

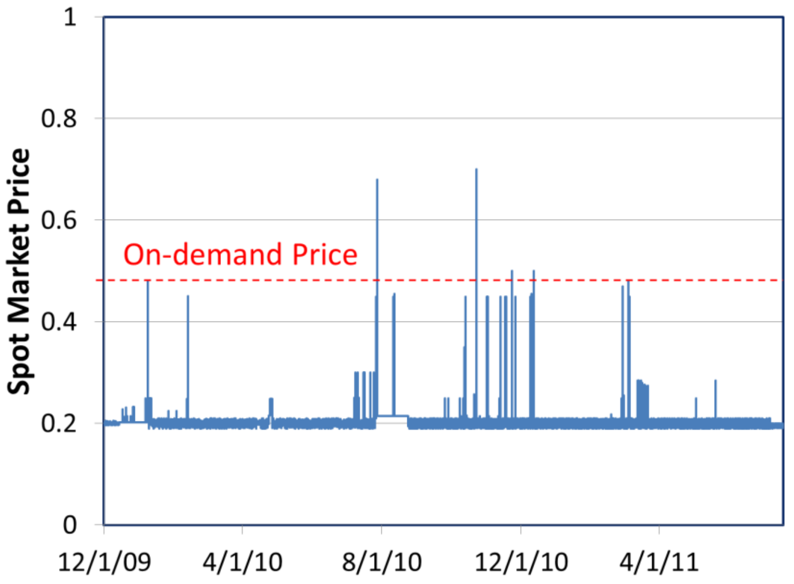
- Cloud is a growing business
- More purchasing options, more variety
- Which/when/where resource should I rent??
- Pricing calculators, auto-scale mechanisms exist, but not enough…
- Need to automatically adjust purchasing decisions as a function of dynamically evolving conditions/workloads.

Background

- This work: Automated resource allocation for batch jobs
  - Focus on compute instances
  - Available options:
    - On-demand
    - Spot
    - Reserved (not in this work)

The basic tradeoff

- On demand: guaranteed, but expensive
- Spot: usually cheaper, but interruptions/delays



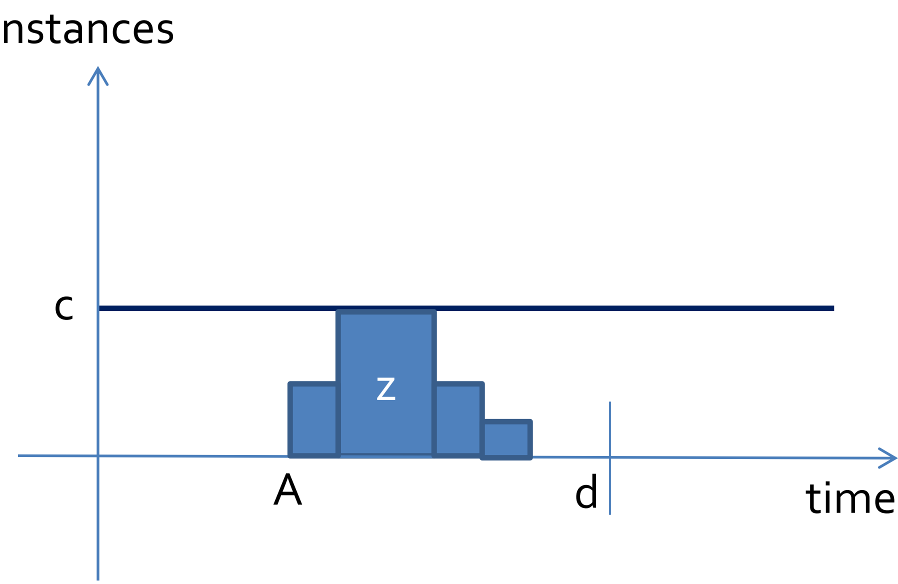
- EC2 case studies
  - Spot instances are often used
  - However no principled mechanisms to choose between on-demand and spot instances.

Outline

- The model (jobs, allocations)
- The online-learning algorithm
- Experiments
- Conclusion

The job model

- Arrival (A)
- Job size (z) [instance hr]
- Parallelism constraint (c)
- Value function $V(\tau)$
  - E.g., strict deadline (d)

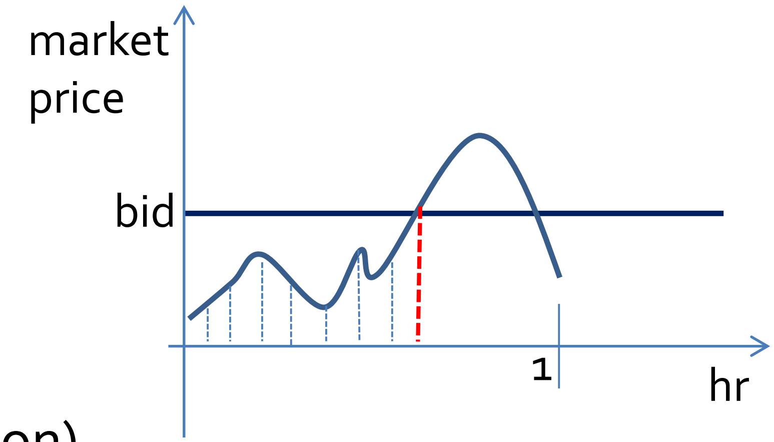


- Utility: $V(\tau)$-Cost(resources)

Objective: Maximize job utilities

Job resource allocation

- For simplicity, we restrict attention to single size
- Decisions per job: # on-demand, [# spot, bid]
  - Can modify decisions every hour
- Allocation/payment
  - On-demand:
    - Fixed price per-instance-hr
  - Spot:
    - Varying price (e.g., 5 min resolution)
    - Get instances (and pay) only if bid above market price
      - Pay the market price



Algorithm in a nutshell

- A set of parameterized policies
- "Attach" a policy to each arriving job
- Policy picked at random
  - Successful policies have higher probability of being chosen
  - Probabilities updated after each job departure
- Online-learning algorithm is essentially about how to update the probabilities.
  - Ensures good performance even though we don't know in advance which policies will work well

Parameterized policies

1. Choosing between on-demand and spot
   a. Deadline-centric: start with spot, switch to on-demand when M hours from deadline
   b. Rate-centric: Fixed rate $\sigma \in [0,1]$ of on-demand instances
2. Bidding on spot instances
   a. Fixed bid b
   b. Variable bid $\int_y p_s(y)\gamma^{\tau-y}dy + \epsilon$
3. Abandon job? (Value vs. cost, deadline vs. remaining compute, etc.)

- Policy: deadline/rate centric + Fixed/variable bid

Online-learning algorithm

- Main loop: for each job j
  - For each policy π
    - Calculate $U_j(\pi)$
    - Set $w_\pi := w_\pi e^{\eta_j U_j(\pi)}$
- Note: $U_j(\pi)$ cannot be evaluated immediately – "delayed feedback"
- Delayed feedback not standard in online-learning
  - required developing a tailored algorithm

Algorithm guarantees

- Criterion: Regret
  - $\max_{\pi} \frac{1}{J} \sum_j U_j(\pi) - \frac{1}{J} \sum_j U_j(\pi_j)$

Policy chosen by alg for job j

- Theorem: Regret vanishes to zero as total number of jobs (J) increases
  - Regret proportional to 1/sqrt(J)

Evaluation

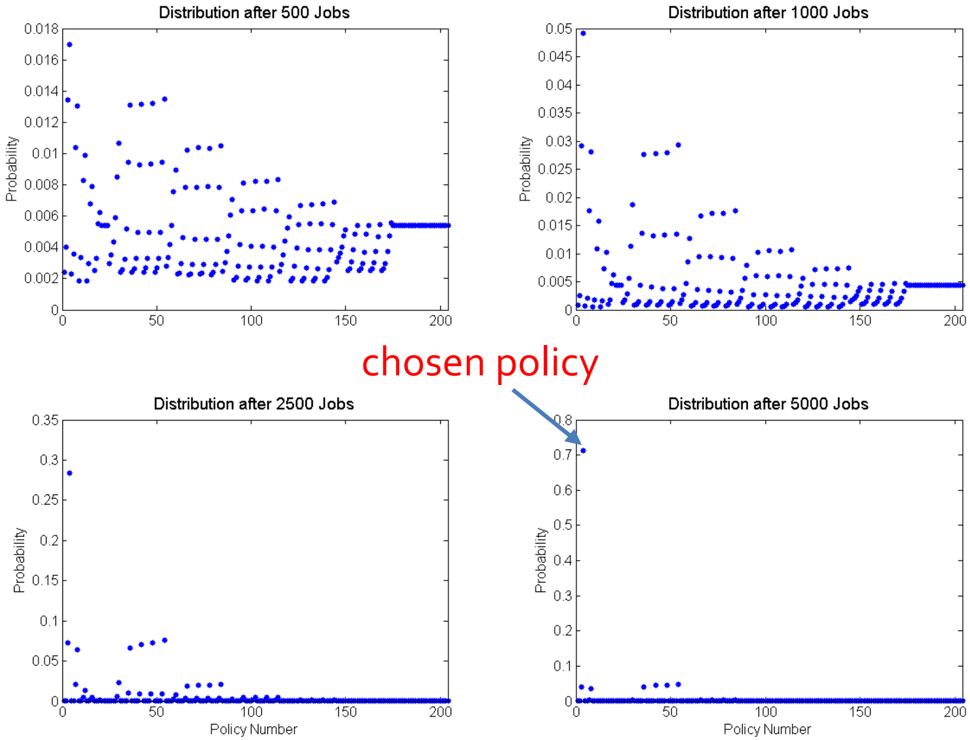
- Simplified assumptions:
  - No checkpointing overhead
  - No delays in obtaining requested instances
- Synthetic data
  - Facilitates "debugging" the algorithm
- Real data
  - EC2 spot-price history
  - Map-reduce job traces

Simulations - synthetic data

- Setup:
  - A pool of hundreds of policies
  - Job size drawn uniformly at random
  - Deadline/value also drawn at random, proportionally to size
  - Spot price is a stochastic process; in each experiment, we change its characteristics

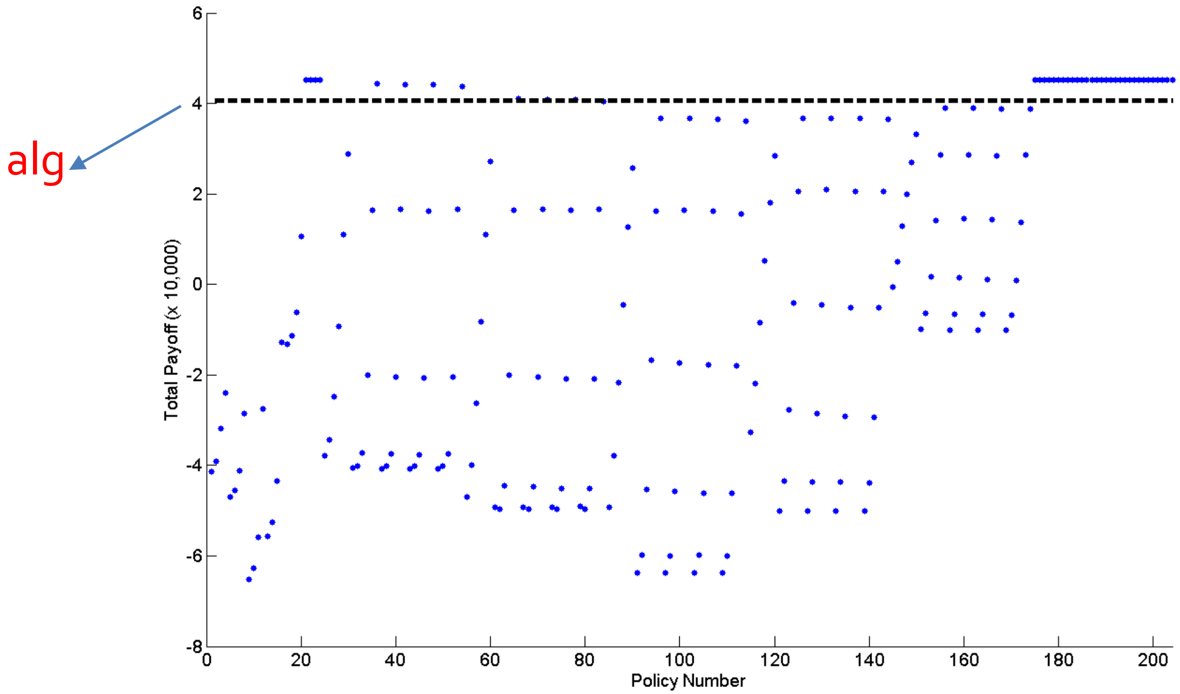
Simulations - synthetic data

- on-demand price is 0.25
- Experiment 1: Relatively low spot price (0.1+0.05x, where x is a Gaussian RV)
  - Outcome: Algorithm converges to using only spot instances with fixed bid=0.25.



Simulations - synthetic data

- Experiment 2: spot-price as before for first 10% of jobs, then becomes 0.2+0.05x
  - Outcome: algorithm converges to using only on-demand instances



Simulations - synthetic data

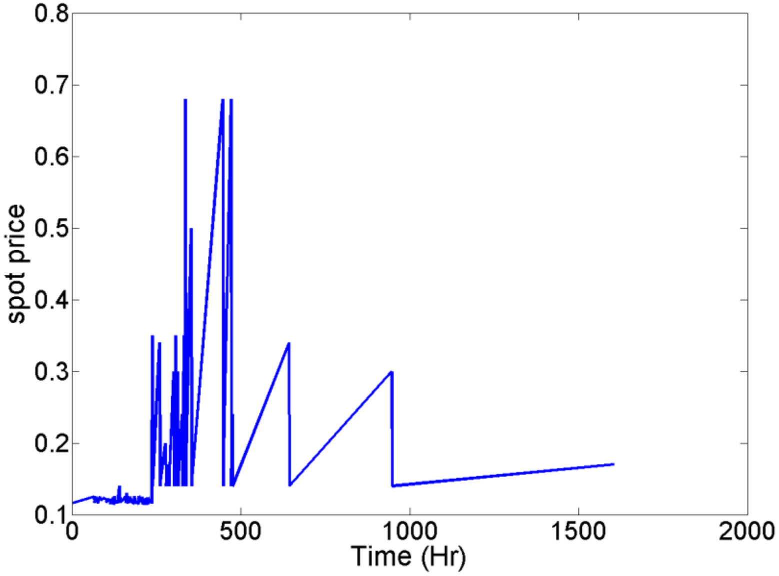
- Experiment 3:
  - We let the spot price alternate between 0 for an hour and 0.3 for the next hour
  - Best policies are variable-bid policies with $\gamma = 0$ (price prediction based only on the last price)

Simulations – real data

- Setup:
  - “Translate” map-reduce jobs to our job model
  - Deadline taken as the job actual termination time from traces
  - Value added synthetically

Simulations – real data

- Spot-price as shown below
- Policy evolvement – first, alg uses both fixed and variable bid policies; however, when price becomes more stable, alg prefers fixed bid strategies
- Avg regret of our alg is 34 times better than the average regret



Related work

- Building statistical models for spot-prices [BBST13, JTB11]
- On-demand/spot assignment for bag of tasks [VOK13]
- Reserved instances [SDIE13]

Conclusion

- Online learning algorithm for choosing between on-demand and spot instances
  - \+ No probabilistic assumptions
  - \+ Incorporates a variety of policies
  - \+ Incorporates job deadlines
  - \+ Can be extended to many other resource allocation scenarios in cloud computing
- Future directions:
  - – More scenarios
  - – Including reserved instances