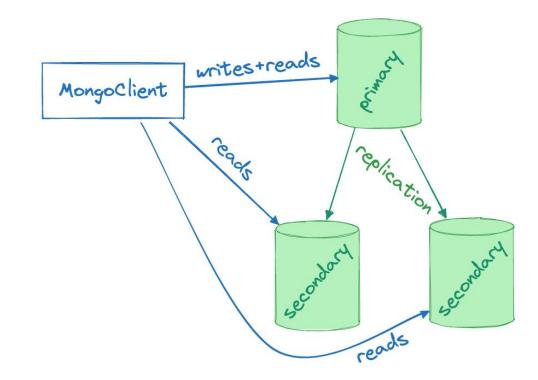
Predictive Scaling in MongoDB Atlas, an Experiment

Matthieu Humeau and A. Jesse Jiryu Davis Data Council 2024

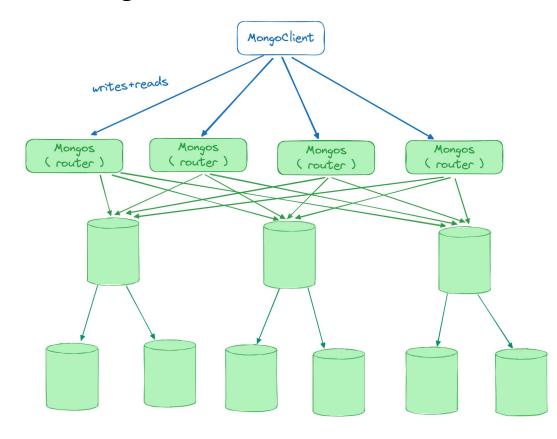


- NoSQL, document database
- MongoDB Query Language
- High consistency, high availability, ACID transactions

MongoDB replica set

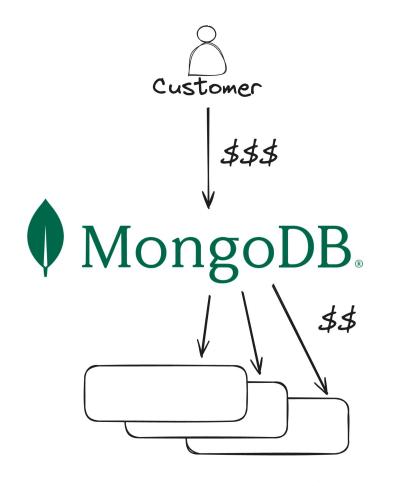


MongoDB sharded cluster



MongoDB Atlas

- "Developer Data Platform": DBaaS and much more
- Multi-region, multi-cloud
- MongoDB's cloud is actually the hyperscalers' clouds



Hyperscalers (Amazon Google Microsoft)

MongoDB Atlas tiers

Cluster Tier	Storage	RAM	vCPUs	Base Price
M10	10 GB	2 GB	2 vCPUs	\$0.08/hr
M20	20 GB	4 GB	2 vCPUs	\$0.20/hr
M30	40 GB	8 GB	2 vCPUs	\$0.54/hr
M40	80 GB	16 GB	4 vCPUs	\$1.04/hr
M50	160 GB	32 GB	8 vCPUs	\$2.00/hr
M60	320 GB	64 GB	16 vCPUs	\$3.95/hr

MongoDB Atlas vertical scaling

Take a secondary offline.

Detach its network storage.

Restart it with a different server size.

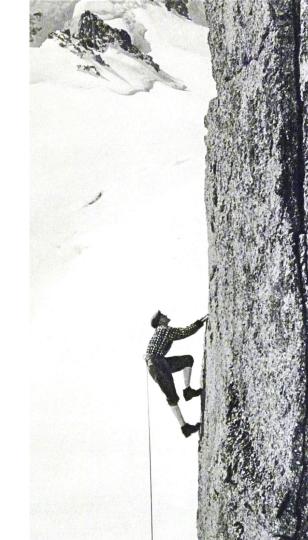
Reattach storage.

Wait for it to catch up to the primary.

Scale the other secondary likewise.

Step down the primary and scale it.

Scaling takes ~15 minutes



Auto-scaling Today

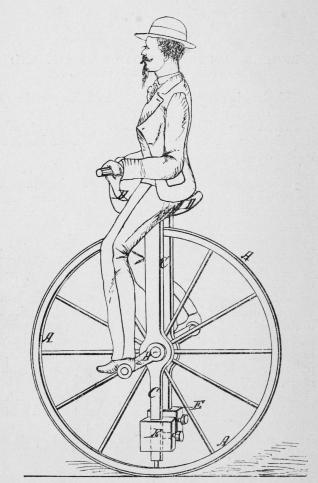
We scale infrequently and reactively:

- scale up by one tier after 1 hour of overload,

- scale down by one tier after 24 hours of underload.

Clusters can be over/underloaded for long periods!

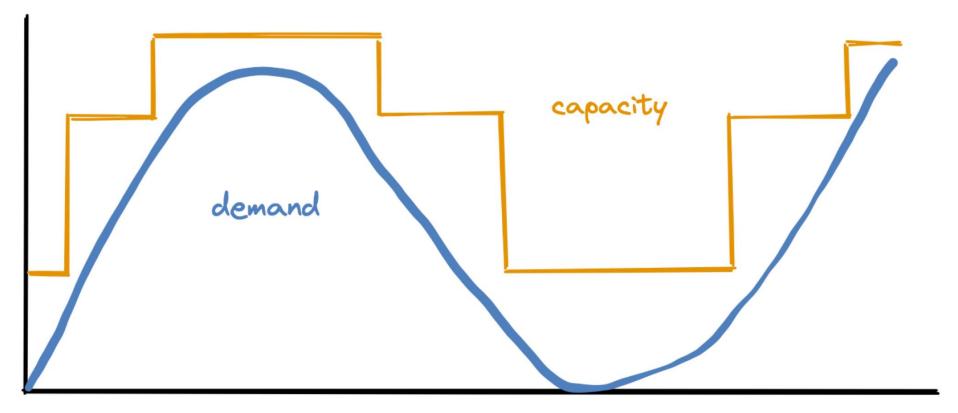
Clusters are **already** overloaded when they start scaling up.



T. W. Ward, of New York. Velocipede. No. 88,683. Patented April 6, 1869.

FUTURE

Ideal Future



Ideal Future

Forecast each cluster's resource needs.

Scale a cluster up **before** it's overloaded.

Scale it down **as soon as** it's underloaded.

Scale directly to the right size, skipping intermediate tiers.

Predictive Scaling Experiment

We keep servers' performance metrics in a data warehouse, 1-minute intervals.

We chose 10,000 clusters, analyzed their 2023 history.

Split the history into a training period and a testing period.

Trained models to forecast the clusters' demand and CPU utilization.

Guessed how a predictive scaler would've performed during testing period, compared to the reactive scaler that was running at that time.

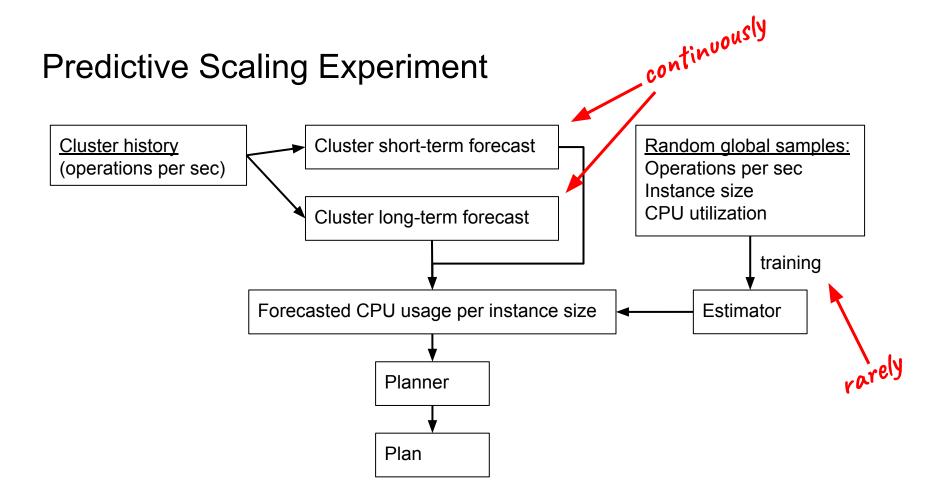
Predictive Scaling Experiment

Three components:

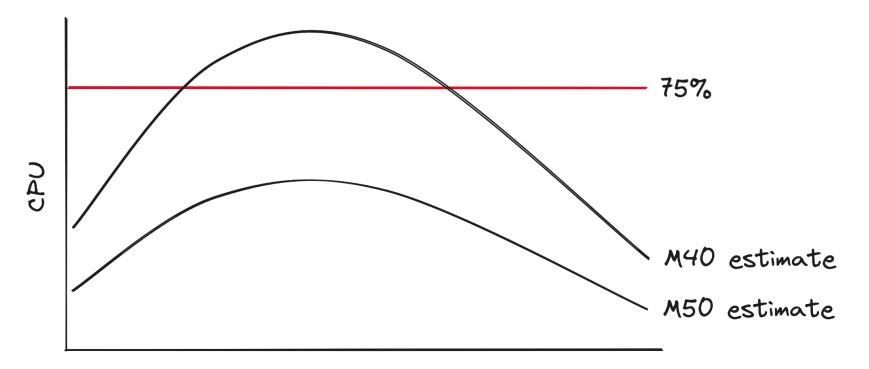
Forecaster: forecasts each cluster's future workload.

Estimator: estimates CPU% for any workload, any instance size.

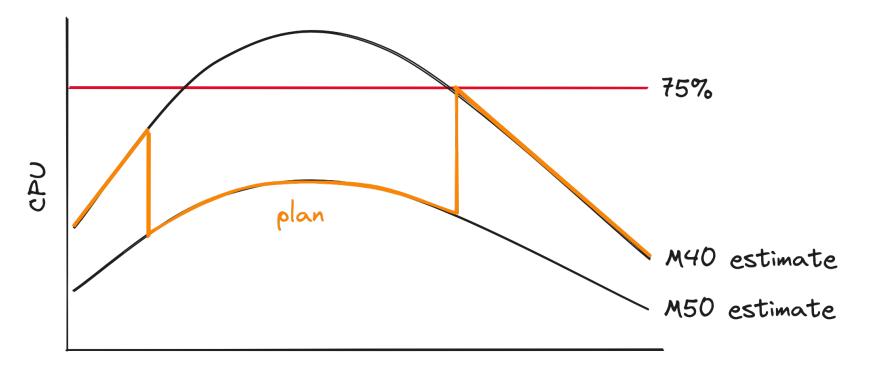
Planner: chooses cheapest instance that satisfies forecasted demand.



Predictive Scaling Experiment: Planner



Predictive Scaling Experiment: Planner



Time ->

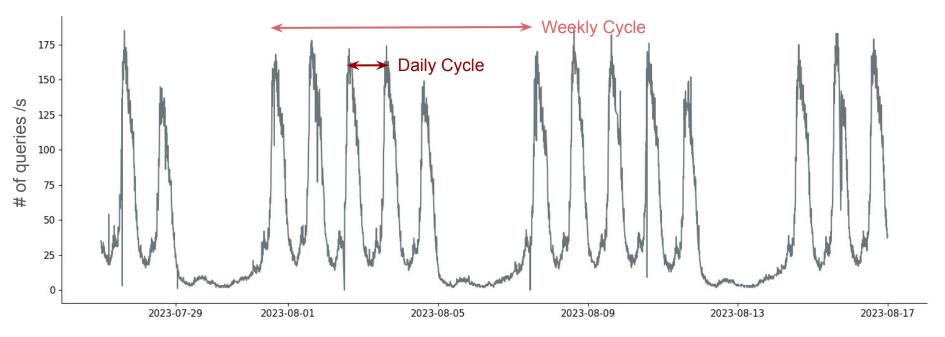
Forecast customer-driven metrics, such as:

- Queries/s
- Connections
- Query complexity represented by number of items scanned by the solver
- DB size

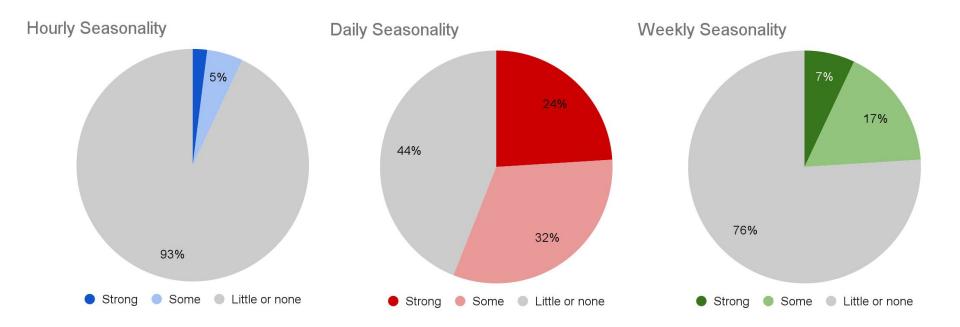
These metrics are **independent*** from the instance size and the state of the cluster



Predicting seasonal variations in demand

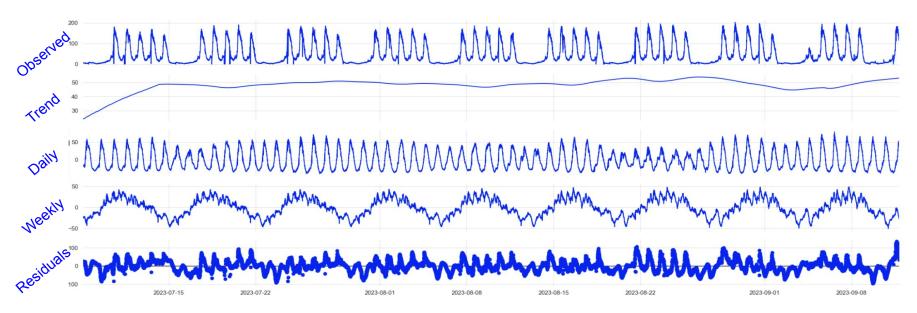


How often is demand seasonal?

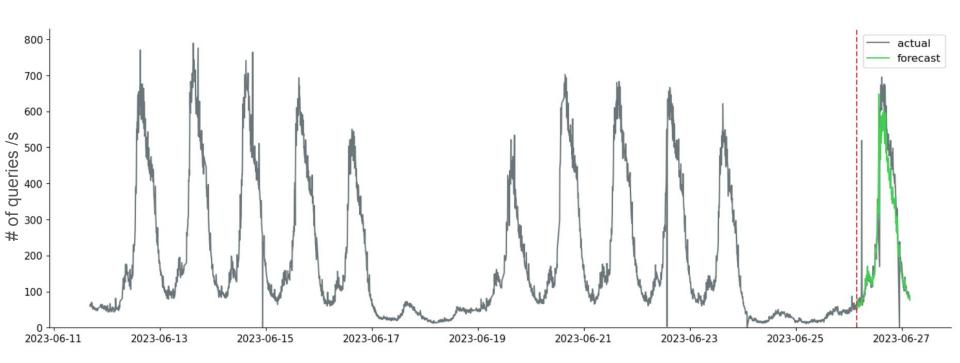


Best Forecasting Model:

- Multi-Season Trend decomposition using LOESS (MSTL)
- + ARIMA forecast of residuals



Forecast example



How accurate is it?

- Median MAPE (Mean Abs. Perc. Error)

	Seasonal Clusters	Non-seasonal Clusters
Connections	3%	50%
Query Rate	19%	71%
Scanned objects Rate	27%	186%

Not usable

=> Self-censoring mechanism based on forecast confidence

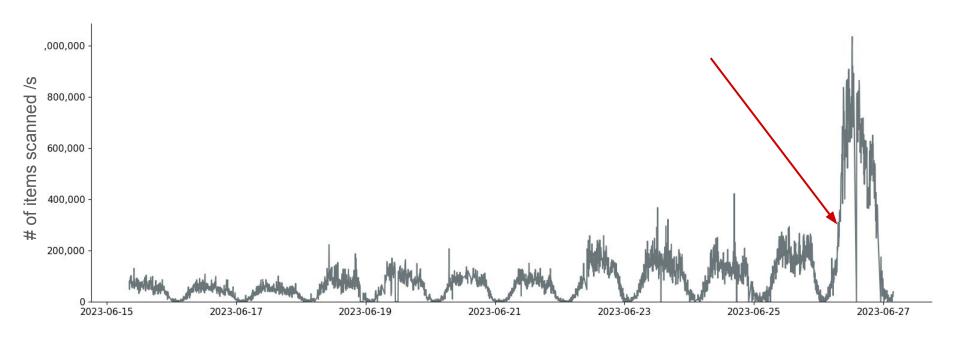
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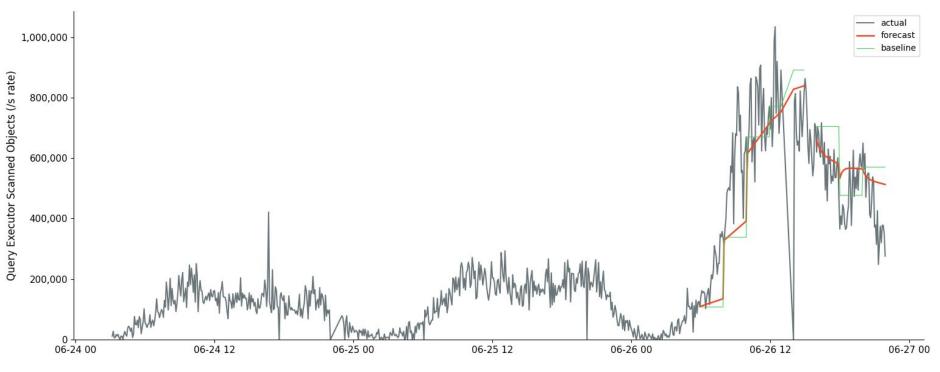
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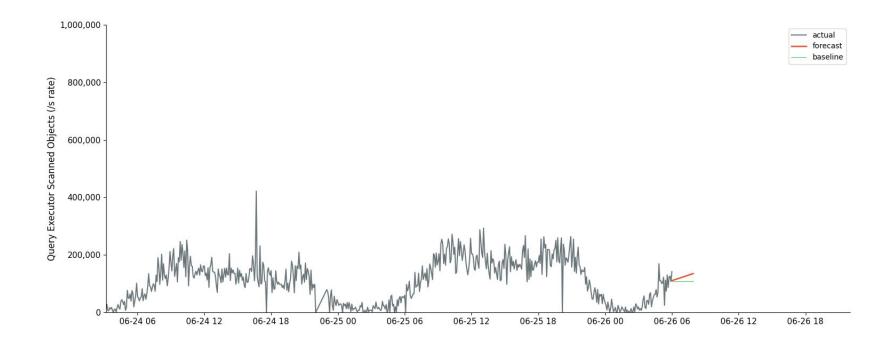
Not usable

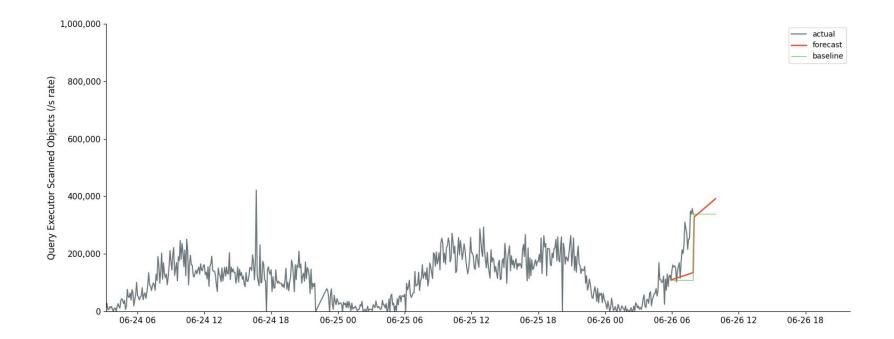
What about unexpected (= non-seasonal) changes in demand?

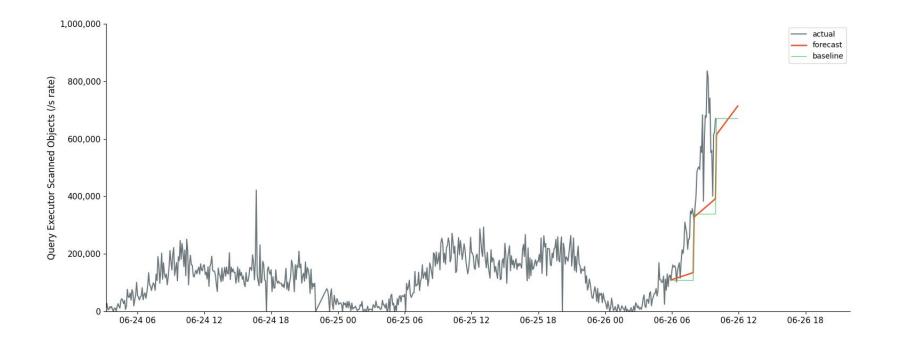


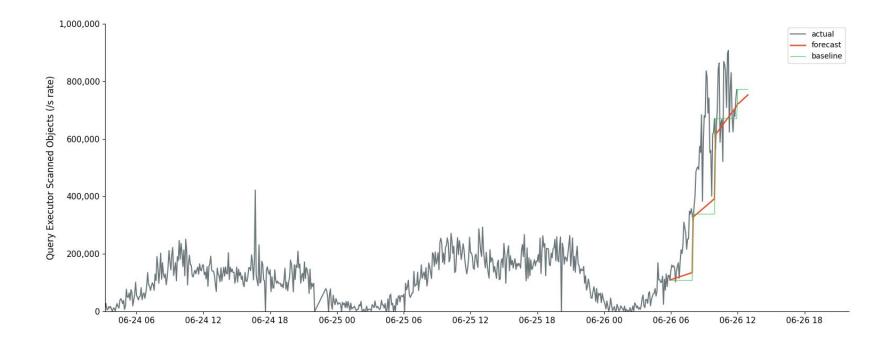
Approximation of local trends for near future

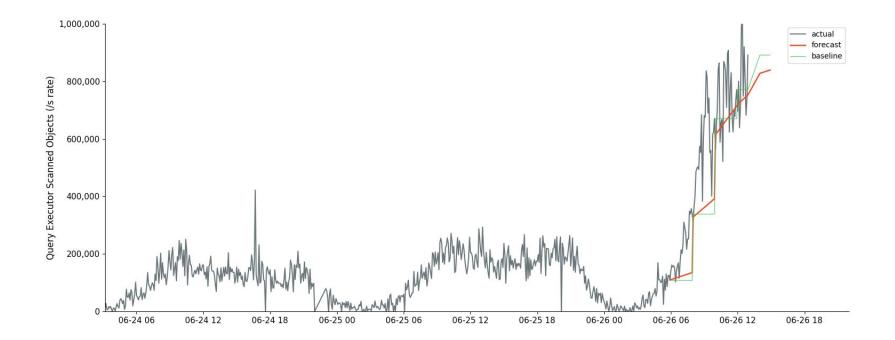


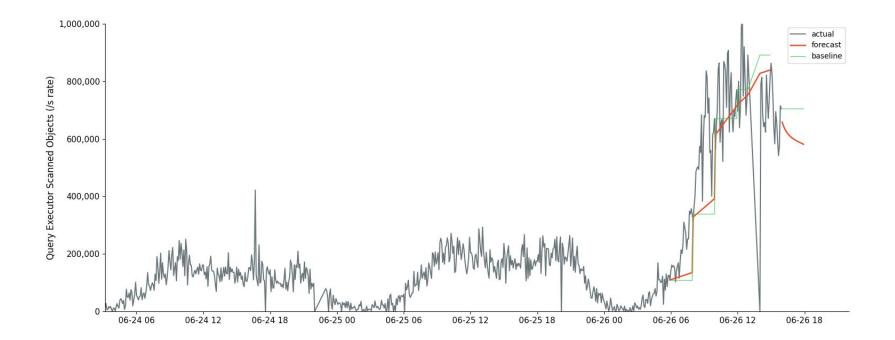


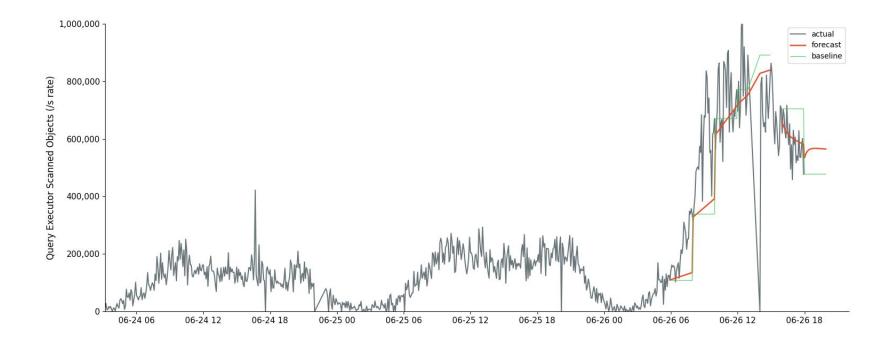


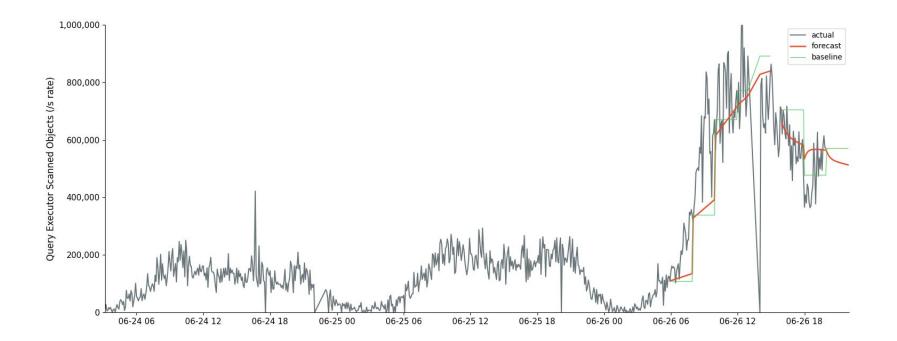












We compared to naive approach: future will look like the last observation

Local trend approach beats it 68% of the time (29% reduction in error)

- Query rate - Connections





connections created rate 2 100 Historical CPU 0 Estimator prediction 3,000 Query rate 2,000 80 1,000 CPU Utilization (%) 0 60 6 Documents updated rate 4 40 2 n 10,000 20 8,000 scamed objects rate 6,000 4,000 0 2,000 08:1800 08.2000 \$1,81° 19:00 NO 08-19.06 80.10 10° 18,1806 0 8-19-12 8-19-12 8-18-14 08-1800 1900 3:19.12 19,10 8-1800 1812 1010 1900 08:2000

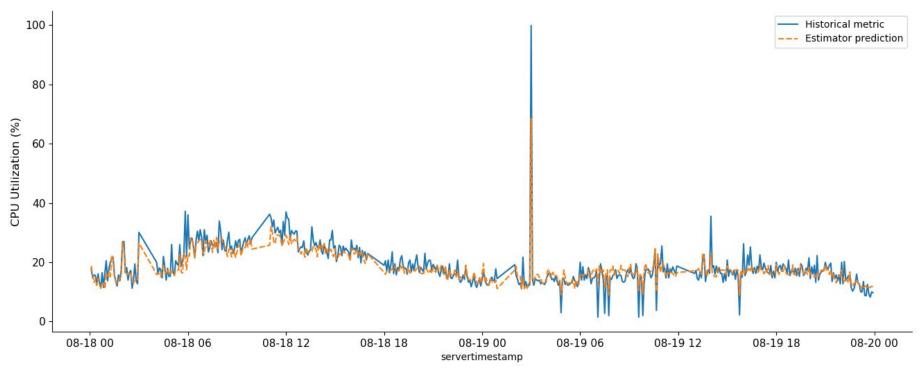
Predictive Scaling Experiment: Estimator

In ML terms: regression problem to predict CPU utilization

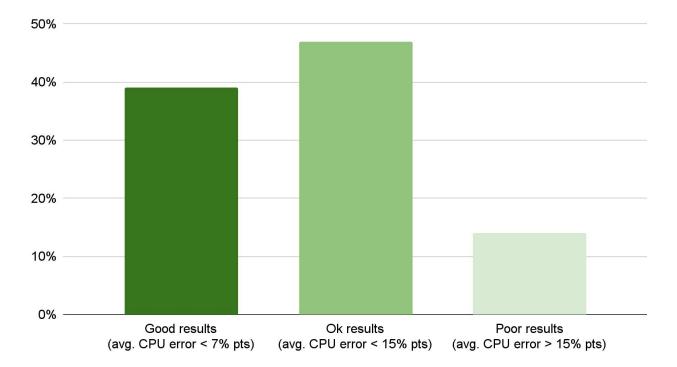
Model:

- Gradient Boosted Trees
- Trained on 25M records with 20 features

Example of Estimator result:



Distribution of Estimator accuracy on test population



Predictive Scaling Experiment: Conclusion

Putting it all together

	Predictive auto-scaler	Reactive auto-scaler
Avg. distance from 75% util. target	18.6%	32.1%
Avg. under-utilization	18.3%	28.3%
Avg. over-utilization	0.4%	3.8%

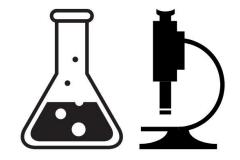
Avg. Estimated \$ cost savings: \$0.09 per cluster/h

Future work

On addressing the Estimator's shortcomings:

- Additional data about hardware spec
- Model memory with CPU
- Add query pattern data

Run live simulations to validate accuracy results



Product Release

Goal is to integrate with current reactive scaler



Unknown release date for now. Beta release to come...

Further Info

- This work inspired by Rebecca Taft's PhD thesis: <u>emptysqua.re/blog/e-store-and-p-store</u>
- Also interesting:
 - "Is Machine Learning Necessary for Cloud Resource Usage Forecasting?" ACM Symposium on Cloud Computing 2023
- MongoDB Atlas: <u>mongodb.com/atlas</u>
- Jesse's Twitter: @jessejiryudavis (Matthieu abstains from Twitter)

Join us for Q & A in Room 115