[544] BigQuery ML and Cost Management

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Learning Objectives

- create and use machine learning models with BigQuery
- describe the relationship between BigQueries two billing models (capacity and on-demand)
- manage and inspect BigQuery costs

Outline

BiqQuery ML Basics

Feature Transformation

Cost Management

Train/Test Split

BigQuery provides a DATA_SPLIT_METHOD config, but its a bit unusual.

Default behavior depends on dataset

- <500 rows: 100% training data
- <50K rows: 80% training data
- bigger: 10K rows for test, rest for training

Documentation: "When there is a data split, you can find the temporary split results (Training Data, Evaluation Data) on the Model Details page in the BigQuery Console and the model API data_split_result field. These split tables will be saved for 48 hours. If you will need them for longer than 48 hours, copy them out of the anonymous dataset for longer retention."

Recommendation:

- split manually using rand()<ratio in SQL (rand gives num between 0 and 1)
- disable BiqQuery splitting: **DATA_SPLIT_METHOD="NO_SPLIT"**

Training

Step 1: write a query to select both features and label

features

label
(to predict)

```
SELECT yesterday_temp, humidity, temp
FROM weather
```

Training

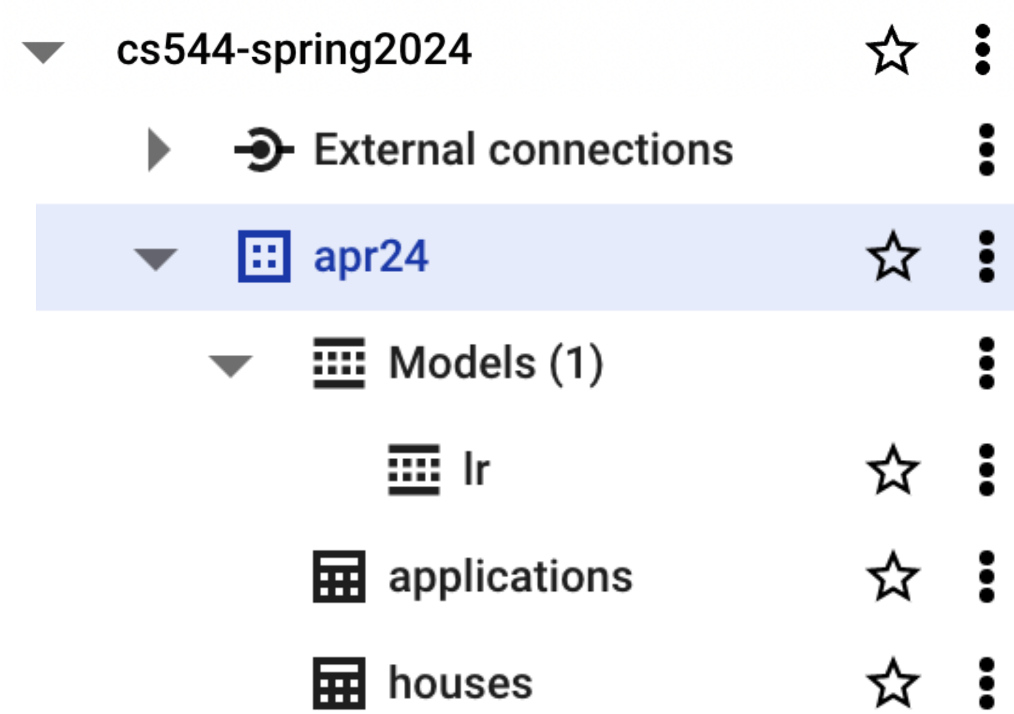
Step 2: choose a model name and create it

```
CREATE OR REPLACE MODEL myproj.mydataset.mymodel
OPTIONS(...)

AS

SELECT yesterday_temp, humidity, temp
FROM weather
```

name

hierarchy:

projects
- datasets
  - tables
  - models



Training

Step 3: choose type of model

```
CREATE OR REPLACE MODEL myproj.mydataset.mymodel
OPTIONS(MODEL_TYPE='LINEAR_REG')

AS

SELECT yesterday_temp, humidity, temp
FROM weather
```

Options: LINEAR_REG, LOGISTIC_REG, KMEANS, MATRIX_FACTORIZATION, PCA, AUTOENCODER, AUTOML_CLASSIFIER, AUTOML_REGRESSOR, BOOSTED_TREE_CLASSIFIER, BOOSTED_TREE_REGRESSOR, RANDOM_FOREST_CLASSIFIER, RANDOM_FOREST_REGRESSOR, DNN_CLASSIFIER, DNN_REGRESSOR, DNN_LINEAR_COMBINED_CLASSIFIER, DNN_LINEAR_COMBINED_REGRESSOR, ARIMA_PLUS, ARIMA_PLUS_XREG, TENSORFLOW, TENSORFLOW_LITE, ONNX, XGBOOST

Training

Step 4: indicate label column (others are assumed features)

```
CREATE OR REPLACE MODEL myproj.mydataset.mymodel
OPTIONS(MODEL_TYPE='LINEAR_REG',
        INPUT_LABEL_COLS=['temp'])
AS

SELECT yesterday_temp, humidity, temp
FROM weather
```

Using Trained Models

Each of these functions return a table related to a model.

what are the coefficients used to multiply features?
ML.WEIGHTS(MODEL ????)

what are the predictions given the features?
ML.PREDICT(MODEL ????, (????))

SQL query to get features

how well do we predict (various metrics) given the features+label?
ML.EVALUATE(MODEL ????, (????))

SQL query to get features and label

Using Trained Models

Each of these functions return a table related to a model.

what are the coefficients used to multiply features?

ML.WEIGHTS(MODEL ????)

example:

```
SELECT *
FROM ML.WEIGHTS(MODEL mymodel)
```

TopHat, Demos

FINAL EXAM CUT OFF POINT

Outline

BiqQuery ML Basics

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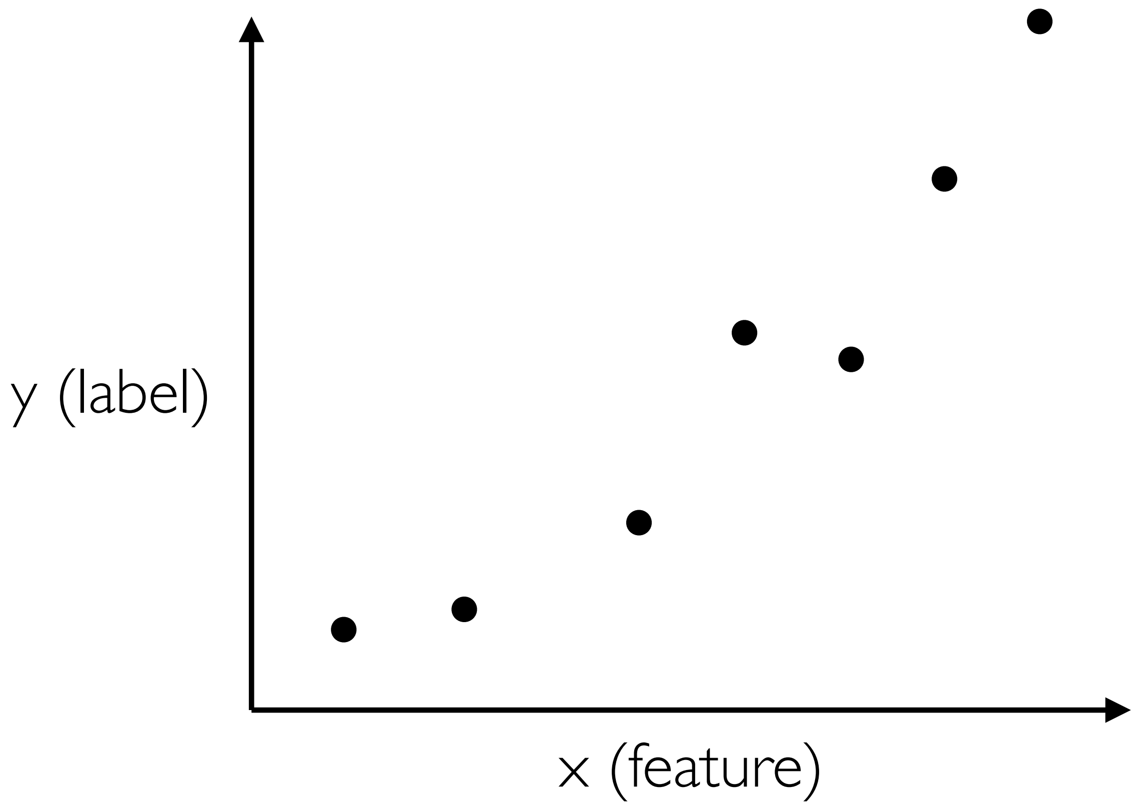
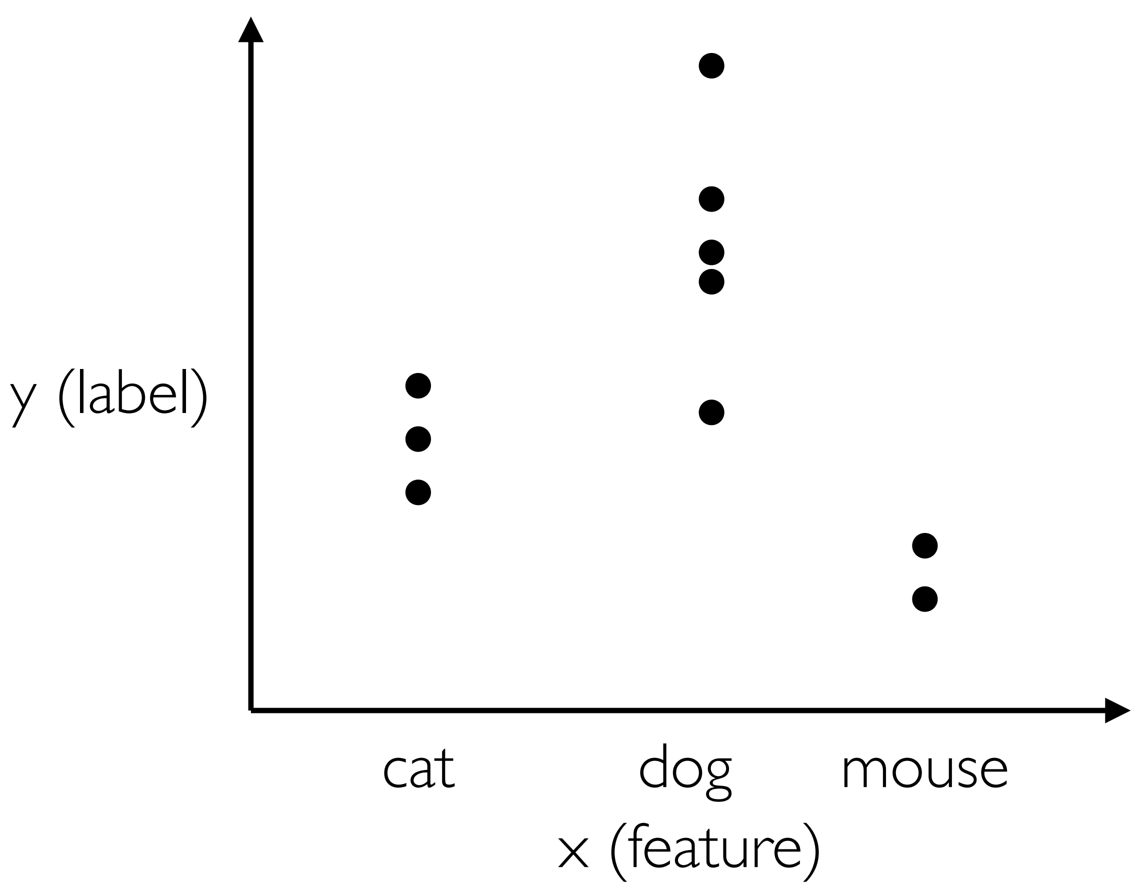
Cost Management

Patterns and Features





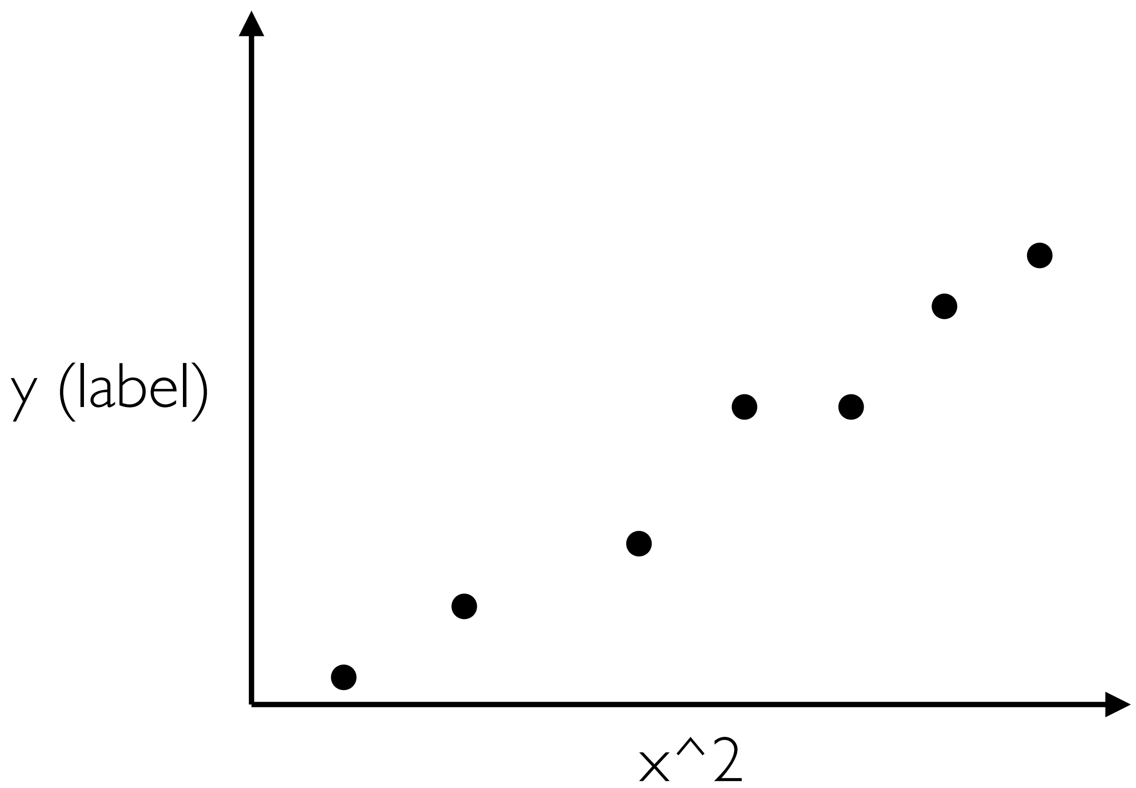
non-linear patterns

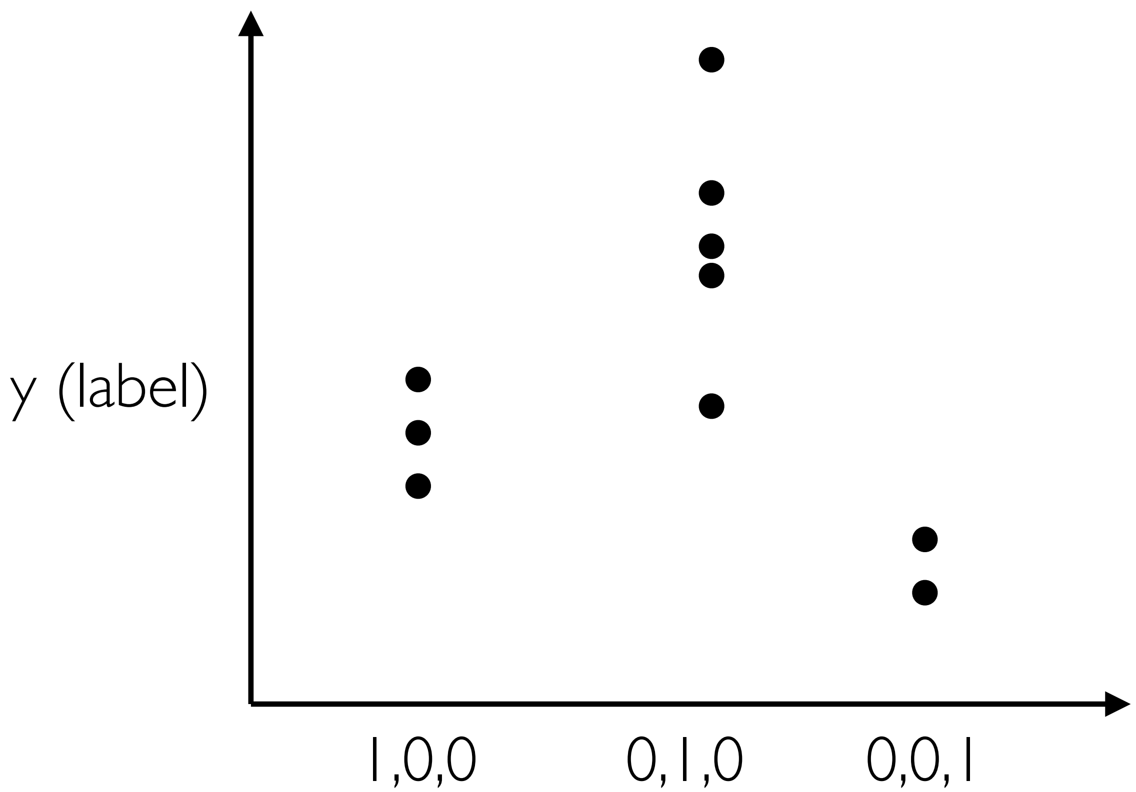
- some models (e.g., DNNs) naturally handle this
- others (e.g., LinearRegression) do not

categorical features

- some models (e.g., DTs) naturally handle this
- others (e.g., LinearRegression) do not

Feature Transformation





non-linear patterns

- can introduce new features than are computed as functions of originals (e.g., x2=x^2)
- a linear model over the new features corresponds to a non-linear model over the originals

categorical features

- encode categorical features as numbers (e.g., as matrix of zeros and ones for OneHot encoding

Demos

Outline

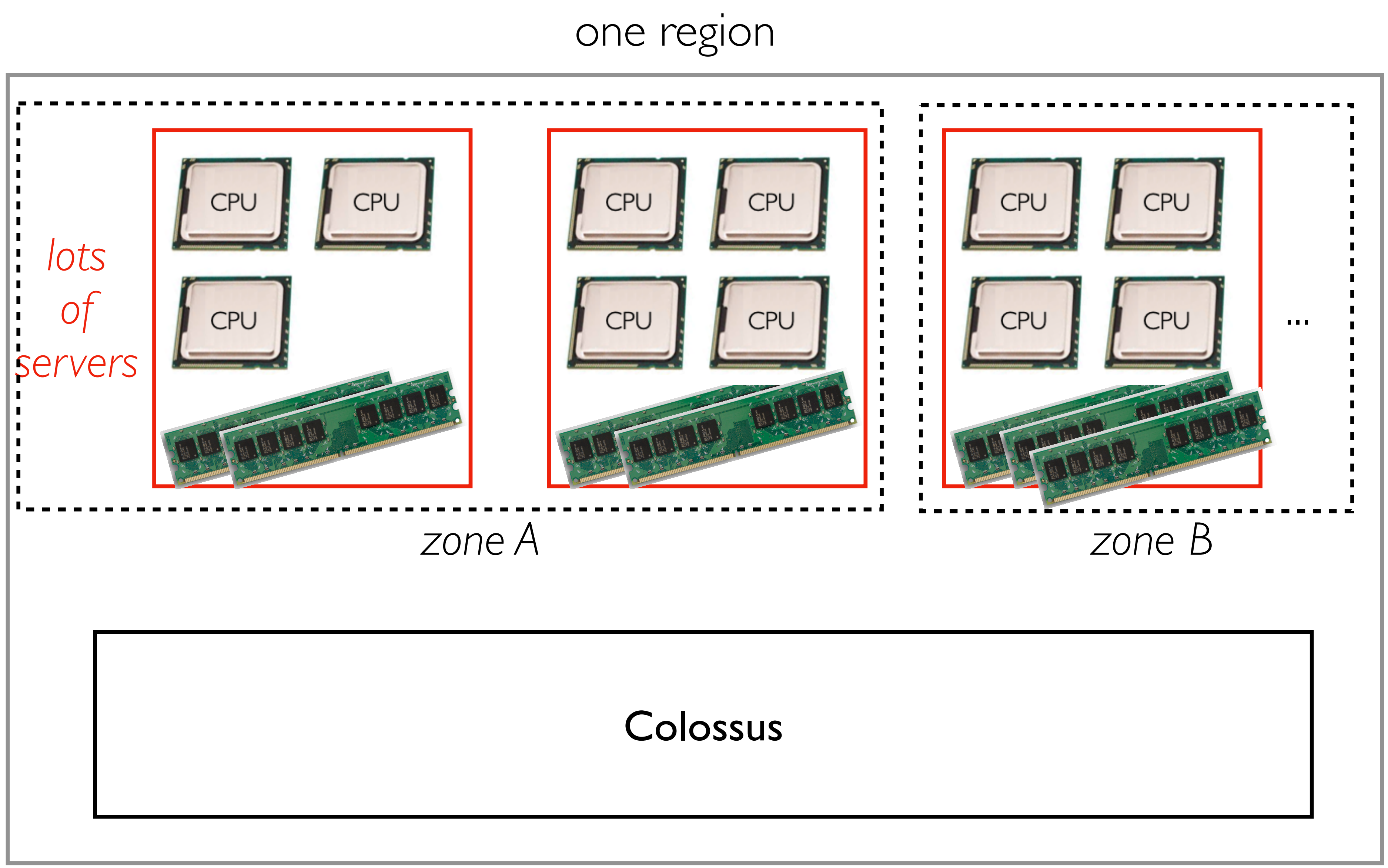
BiqQuery ML Basics

Feature Transformation

Cost Management

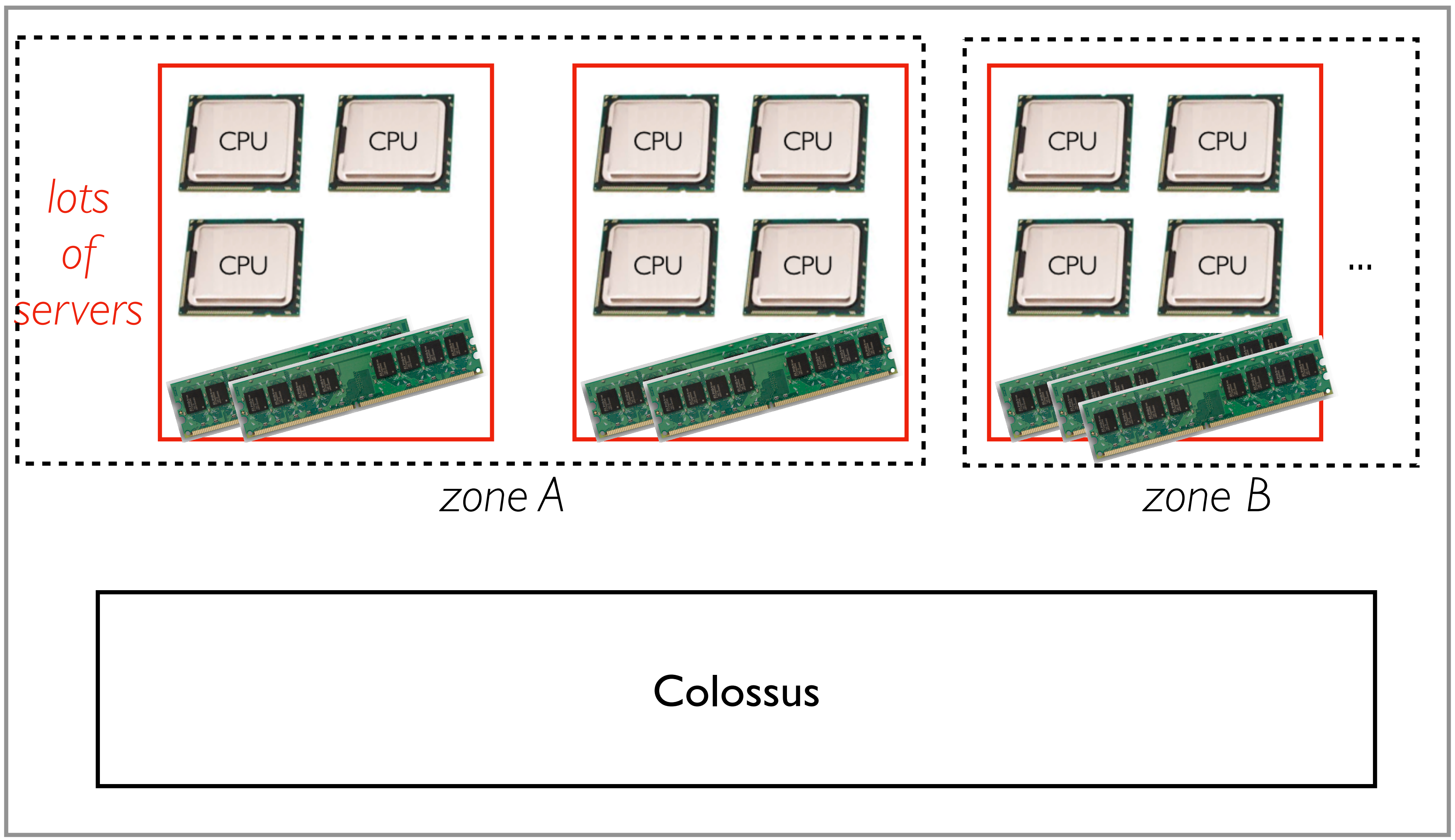
Resources

other regions...



- Query engine: Dremel running on many servers with lots of CPU+RAM
- Storage engine: Capacitor files in Colossus file system
  (not clear if Dremel+Colossus servers are co-located on same machines)

Resources



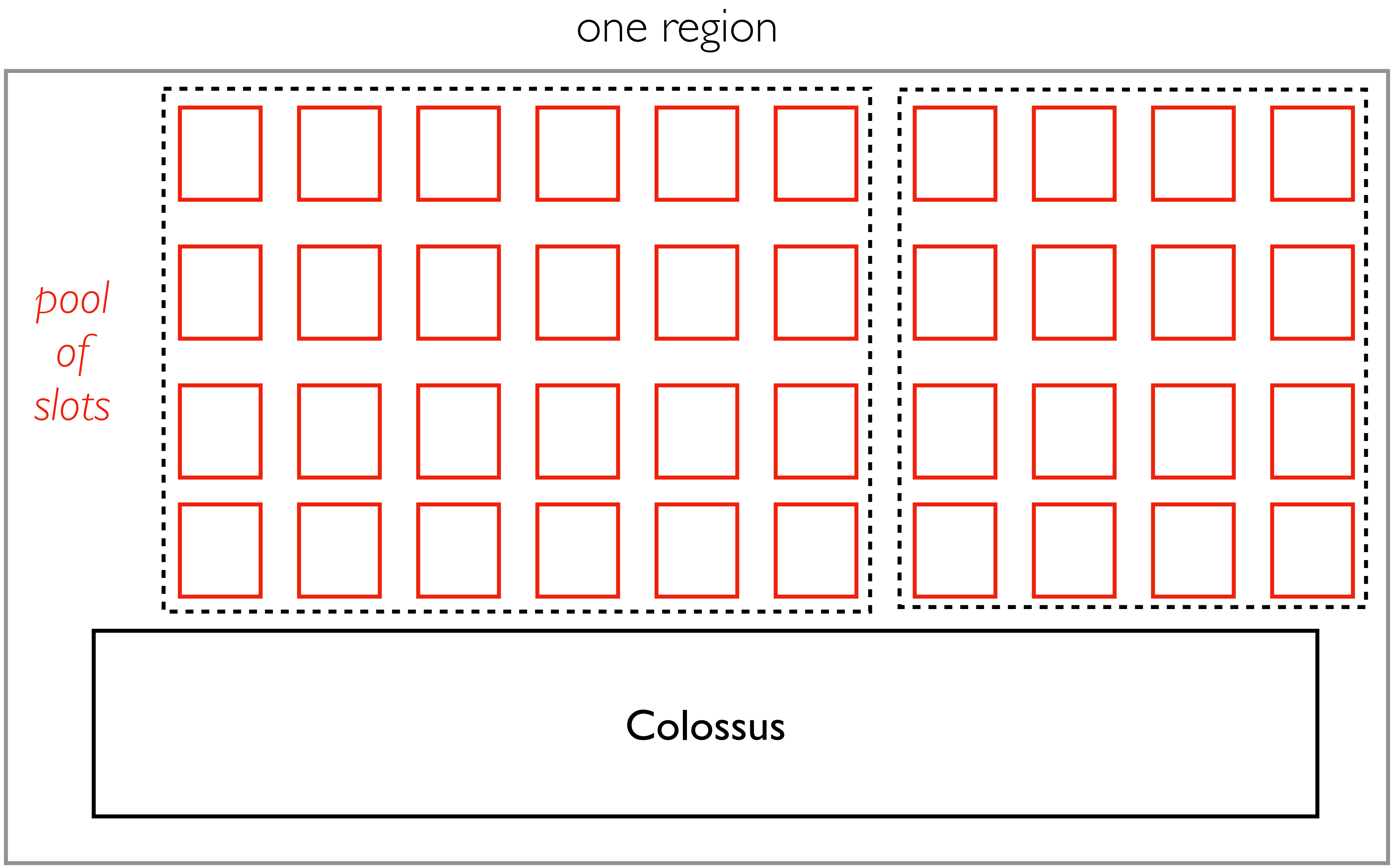
Resources

capacity billing [
- compute/memory
- Colossus storage
- Colossus I/O

] on-demand billing

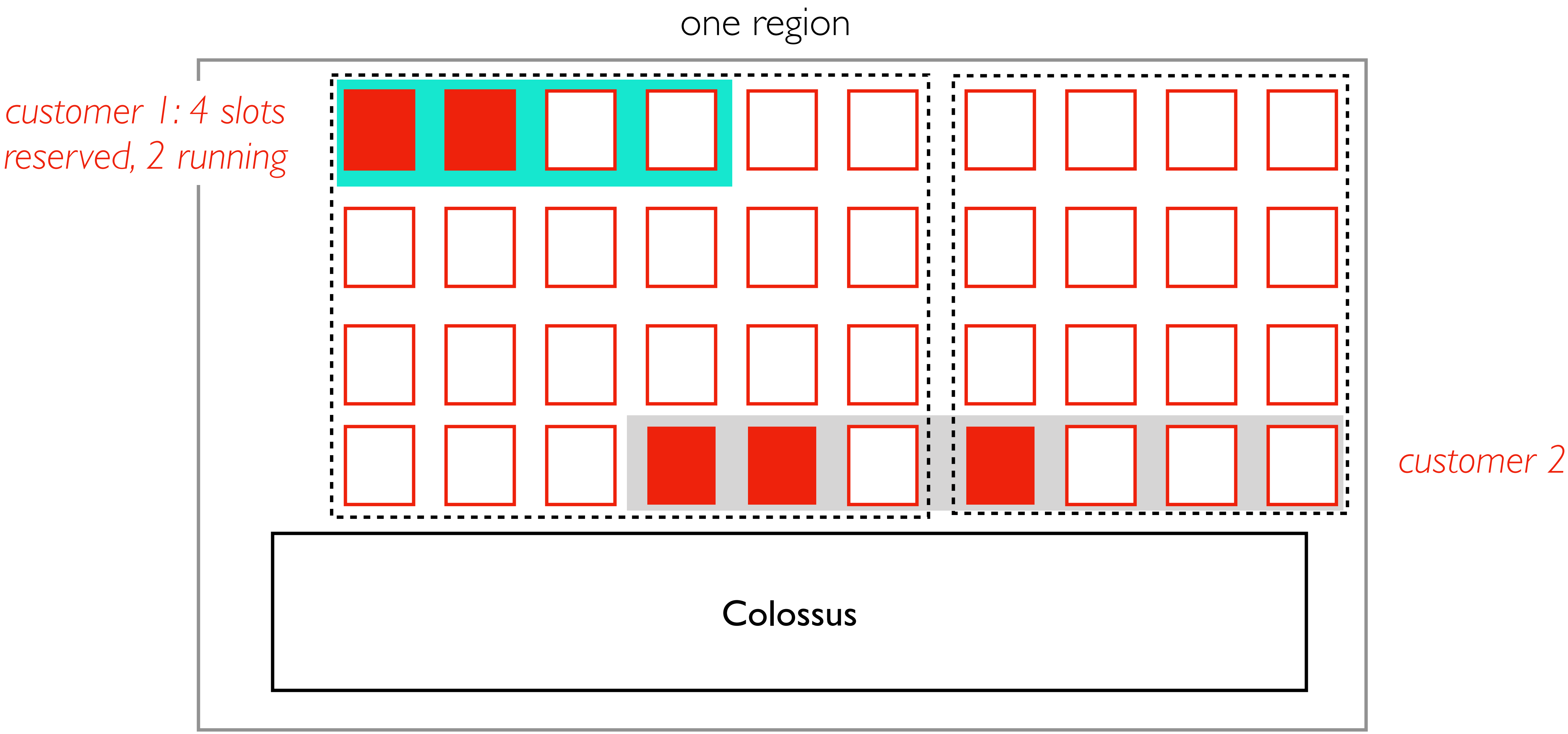
BigQuery Slots

other regions...



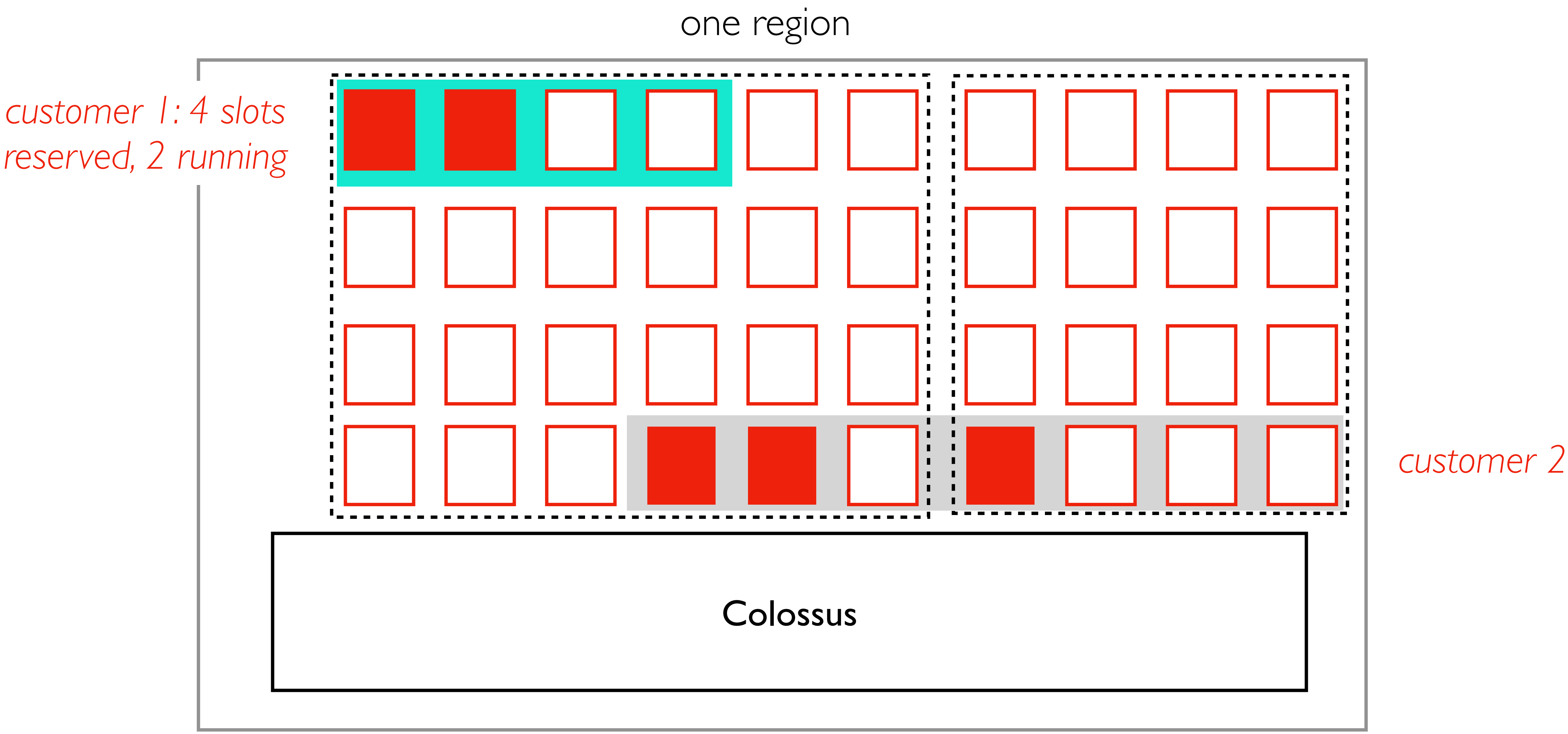
- the compute and memory resources of the servers are broken down into a pool of "slots"
- a slot has approximately ½ cores and 1 GB of RAM
- if newer servers get added with faster CPUs or different core/memory ratios, the exact resources can change a bit

Billing Model 1: Capacity Pricing (compute based)



- customers can pay a fixed rate for slot capacity (about $0.96 for 1 slot day)
- whether or not they use the slot does not affect the cost
- reservations aren't fixed to one location (execution will ideally happen near the data).
- *slightly more expensive than the e2-medium instances we used this semester, which have 2x compute and 4x memory resources (but not free Colossus I/O). But VMs are IaaS and BigQuery is PaaS.*

Billing Model 1: Capacity Pricing (compute based)

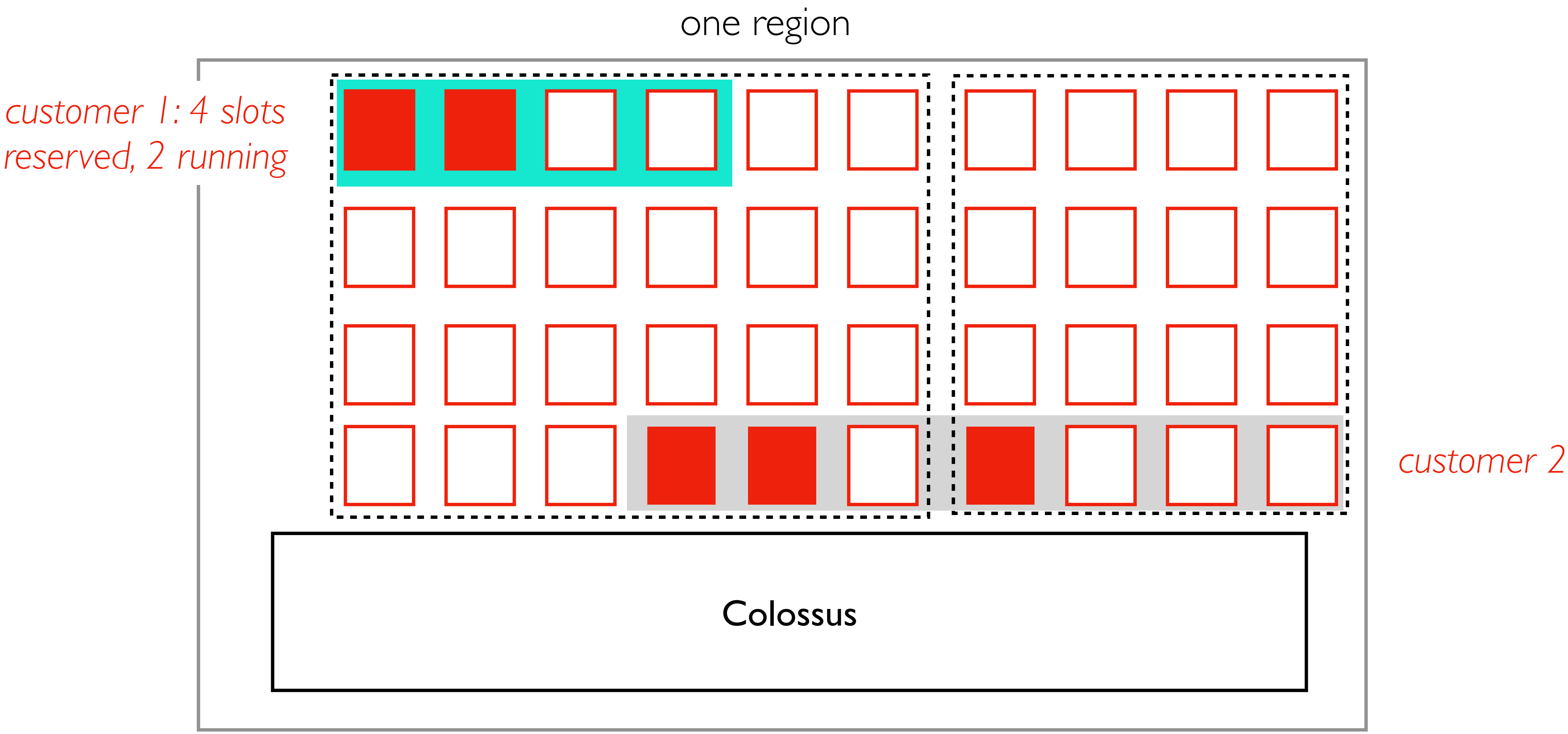


Excess capacity cases:

- not reserved
- reserved, but not currently used

Billing Model 2 (On-Demand) draws from this excess...

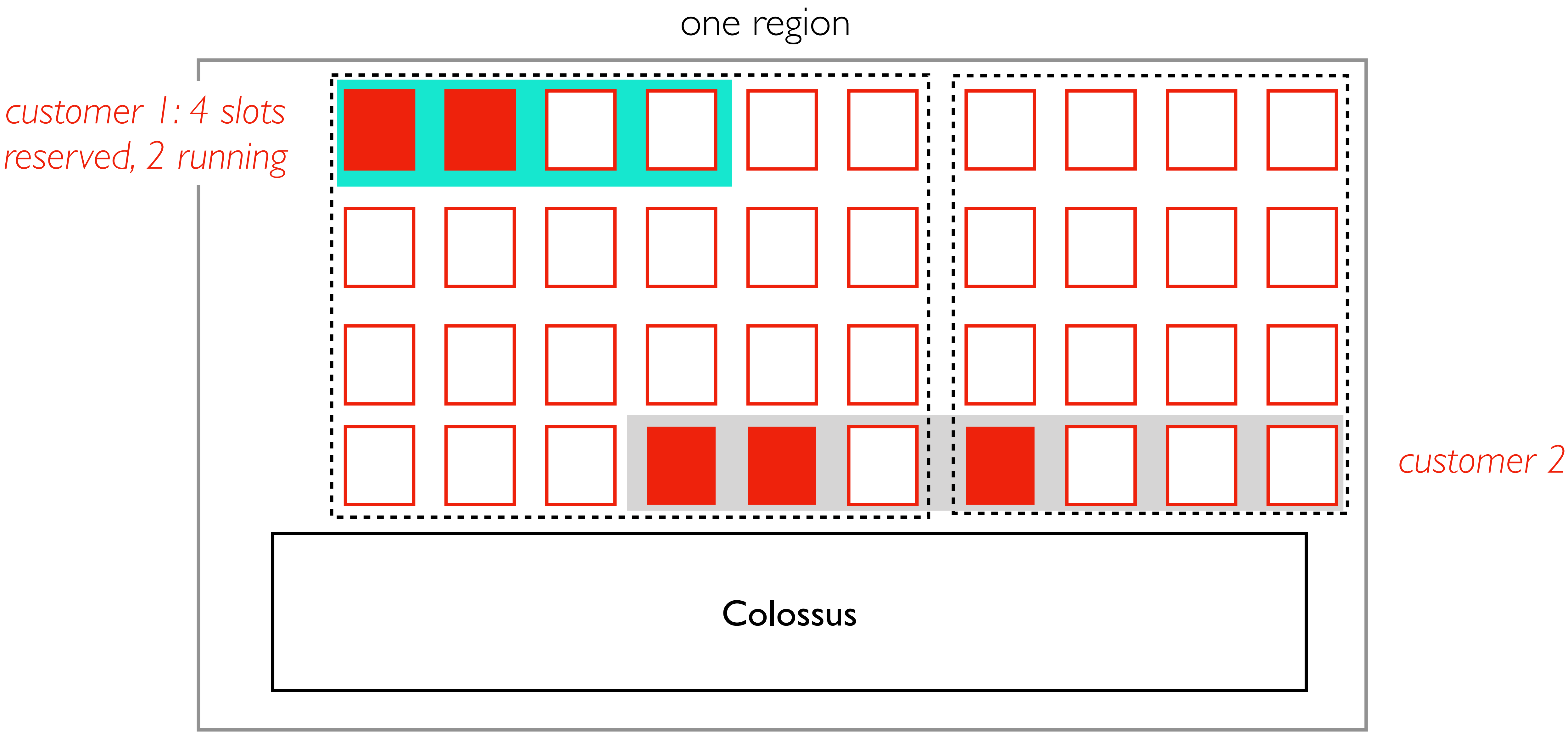
Billing Model 2: On-Demand Pricing (I/O based)



Pricing:

- pay for Colossus I/O after free tier (about $6.25/TB)
- slots (compute/memory) are free
- use whatever is left over from capacity-based usage (up to 2000 slots!)
- preemptible: a task running in a slot can be interrupted (if a reservation is suddenly needed or new on-demand jobs start -- want to share capacity between these fairly)

Billing Model 2: On-Demand Pricing (I/O based)



Pricing:

- pay
- slots
- use 2000 slots!)
- preemptible: a task running in a slot can be interrupted (if a reservation is suddenly needed or new on-demand jobs start -- want to share capacity between these fairly)

BigQuery tasks are atomic and idempotent so we have exactly-once semantics. Don't want interrupted and restarted tasks to cause duplicate results.

Comparison

Capacity Billing

- very predictable costs
- very predictable performance (other customers don't affect you)
- discounts if commit to buying lots of cores for long time (e.g., a year)
- pay when using nothing
- can't use lots of resources for a short while

On-Demand Billing

- pay-as-you-go: use nothing, pay nothing
- if resources are available, you can use 1000 cores at once -- very fast!
- how to make sure you don't accidentally spend more than intended?

Estimating/Capping On-Demand Costs

Filter   Metric : bigquery.googleapis.com/quota/query/usage   Enter property name or value

Quota	Dimensions (e.g. location)	Limit	Current usage percentage	Current usage
Query usage per day		1,048,576 MiB (1 TiB)	0%	0 MiB
Query usage per day per user		Unlimited	–	

Options:

- Limit per day:
  https://console.cloud.google.com/iam-admin/quotas

- Estimate before run:
  `job_config=bigquery.QueryJobConfig(dry_run=True)`

- Set max per query:
  `bigquery.QueryJobConfig(maximum_bytes_billed=200*1024**2)`

- See most expensive queries:
  `cs320-f21.region-us.INFORMATION_SCHEMA.JOBS_BY_PROJECT`

Demos

Partitioning

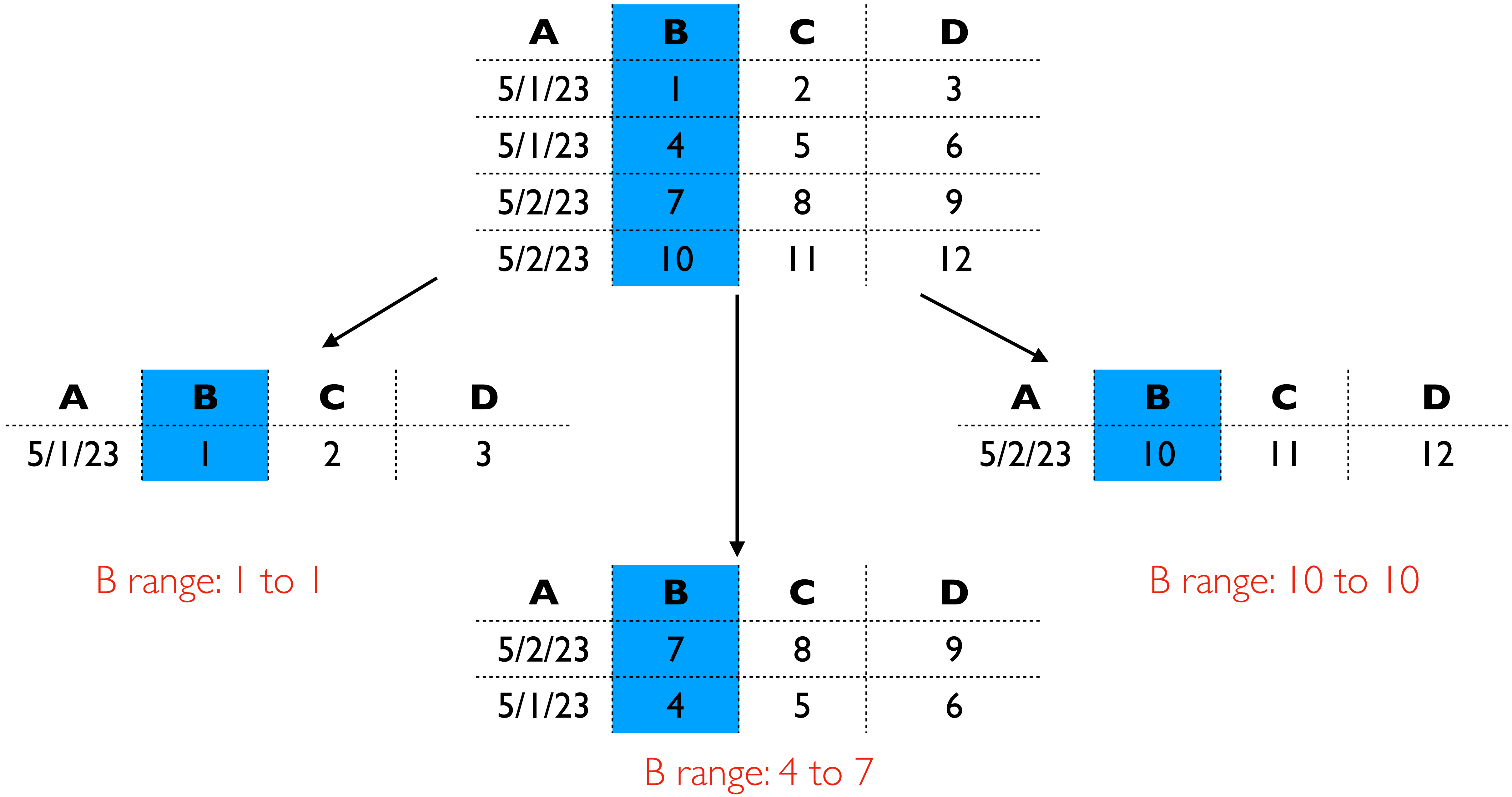
A	B	C	D
5/1/23	1	2	3
5/1/23	4	5	6
5/2/23	7	8	9
5/2/23	10	11	12

A	B	C	D
5/1/23	1	2	3
5/1/23	4	5	6

A	B	C	D
5/2/23	7	8	9
5/2/23	10	11	12

- each unique value in a partition column corresponds to a partition (basically a mini table)
- WHERE filters can limit which mini tables need to be read (saving I/O cost)
- limited options for types (e.g., ints, dates)
- only works well when substantial data per partition

Clustering



- semi sorted: sub files are non overlapping on cluster key, but no order within file
- all types, combinations of columns possible
- some queries will be cheaper because they can look at subset of files

Clustering

A	B	C	D
5/1/23	1	2	3
5/1/23	4	5	6
5/2/23	7	8	9
5/2/23	10	11	12

clustered

A	B	C	D
5/1/23	1	2	3

B range: 1 to 1

A	B	C	D
5/2/23	7	8	9
5/1/23	4	5	6

B range: 4 to 7

A	B	C	D
5/2/23	10	11	12

B range: 10 to 10

- some min ratio of data is clustered
- don't want few new rows to force total reorg

A	B	C	D
5/2/23	5	1	2
5/1/23	12	3	4

unclustered

Demos