Finishing up Apache Spark

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CIS 545 – Big Data Analytics

Penn Engineering

ODPi OpenDS4All

Portions of this lecture have been contributed to the OpenDS4All project, piloted by Penn, IBM, and the Linux Foundation

https://tinyurl.com/cis545-lecture-02-16-22

Recall: Sharding and Tables

Given a cluster with *n* workers, running remotely, Spark creates a table with *at least n* partitions (here, 200, where 100 are stored on each machine)

Spark will partition "automatically" but it's best to *repartition* on the key you want!

```
%%spark
# 10
link

my_l

link
  re
```

```
+------------------+--------------------+--------------------+--------------------+-
|               _id|                name|            locality|              skills|
+------------------+--------------------+--------------------+--------------------+-
|       in-00000001|[given_name -> Dr...|       United States|[Key Account Deve...|
|          in-00001|[given_name -> An...|Antwerp Area, Bel...|[Molecular Biolog...|
|          in-00006|[given_name -> Sh...|San Francisco, Ca...|[DNA, Nanotechnol...|
|   in-000montgomery|[given_name -> Ed...|San Francisco Bay...|                null|I
|in-000vijaychauhan|[given_name -> Vi...| Chennai Area, India|[Program Manageme...|A
+------------------+--------------------+--------------------+--------------------+-
only showing top 5 rows
```

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Computation in a Sharded System: Selection, Projection

```
+------------------+--------------------+--------------------+--------------------+-
|               _id|                name|            locality|              skills|
+------------------+--------------------+--------------------+--------------------+-
|       in-00000001|[given_name -> Dr...|       United States|[Key Account Deve...|
|          in-00001|[given_name -> An...|Antwerp Area, Bel...|[Molecular Biolog...|
|          in-00006|[given_name -> Sh...|San Francisco, Ca...|[DNA, Nanotechnol...|
|  in-000montgomery|[given_name -> Ed...|San Francisco Bay...|                null|T
|in-000vijaychauhan|[given_name -> Vi
+------------------+----------------
only showing top 5 rows
```

Selection + projection is “farme

```
linked_df.filter(linked_df.l
'name', 'locality']].show(5)
```

```
+--------------------+--------------------+-------------+
|                 _id|                name|     locality|
+--------------------+--------------------+-------------+
|         in-00000001|[given_name -> Dr...|United States|
|   in-100percenthair|[given_name -> Su...|United States|
|         in-1solone|[given_name -> Ha...|United States|
|     in-2raviagarwal|[given_name -> Ra...|United States|
|in-aarongatescarlton|[given_name -> Aa...|United States|
+--------------------+--------------------+-------------+
only showing top 5 rows
```

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Apply (with Python Functions) in Spark

https://docs.databricks.com/spark/latest/spark-sql/udf-python.html

```
%%spark
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType

acro = udf(lambda x: ''.join([n[0] for n ir

linked_df.select("id", acro("locality").ali
```

```
+------------------+-------+
|               _id|acronym|
+------------------+-------+
|       in-00000001|     US|
|          in-00001|    AAB|
|          in-00006|    SFC|
|   in-000montgomery|   SFBA|
|in-000vijaychauhan|    CAI|
+------------------+-------+
only showing top 5 rows
```

Note also that we used Spark's sele
arguments looks much like a list for

As with select / project, apply is run
parallel!

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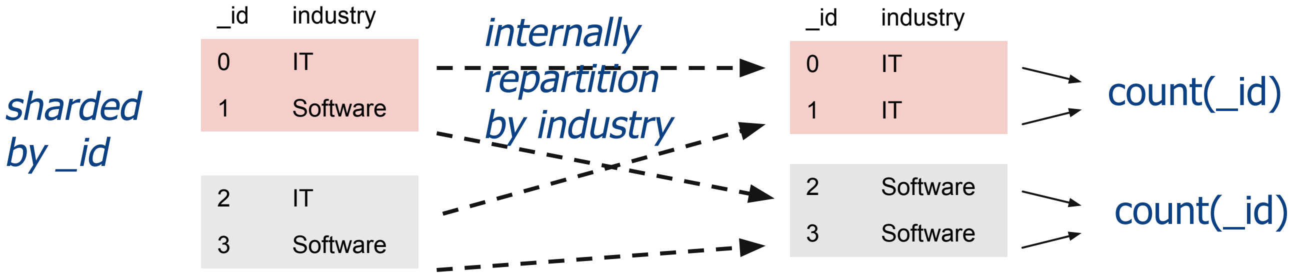
Grouping

Grouping needs *all* of the tuples in a group to be on the same machine, in order to do a computation over the group!

```
%%spark
# Which industries are most popular?
sqlContext.sql('select count(_id), industry '+\
'from linked_in group by industry '+\
'order by count(_id) desc').show(5)
```



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Failures

- In a large cluster running for a long time – machines may die or software may crash
- Spark actually handles such failures transparently
  - It periodically “checkpoints” or snapshots what has happened
  - And if a node dies, it can restart the computation elsewhere!

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Brief Review

https://canvas.upenn.edu/courses/1636888/quizzes/2771539 (08F)

Spark is not written in Python, which means;

a. Spark is slower than Pandas
b. schemas are strongly typed
c. we can't use Python strings
d. Spark must be written in C

How do we handle (a small number of) worker failures when Spark tasks are executed?

e. Spark handles this transparently
f. We need to buy new servers
g. We have to retry our jobs
h. We have to write try/except blocks in Python

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Recap

Summary of Big Data so far:

- We need to partition or *shard* data by keys, allowing machines to work in parallel across different shards
- Apache Spark is the most popular system for doing this right now
  - Supports Spark dataframes or Spark SQL
  - Some variations from Pandas: strong typing, syntax variations, special **udf** function
  - You can control sharding via **repartition**
  - Select, project, **apply** all work in parallel across shards
  - Grouping typically requires the machines to exchange or repartition data

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Big Data and Cloud Services

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CIS 545 – Big Data Analytics

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What Do People Mean by "Big Data"?

"5 V's of Big Data", seeking *value*:

- Veracity: Data is of high *quality*
- Variety: Data is *heterogeneous*
- Volume:
  - Many rows
  - Large data objects
- Velocity: Data changes often

Data has many dimensions

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Part 1 – Data Wrangling and cleaning

You are here! 

Coming soon!

Roadmap for this Module

- Cloud-hosted compute clusters for big data
- Distributed Spark execution and joins
- Storing big data on the cloud
- View materialization

… Preparing us for looking at complex *graphs* of relationships!
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Elastic MapReduce and Clusters on the Cloud

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Clusters on the Cloud

How do we run Spark in clusters on the cloud?

- Cloud service “layers”
- Platform-as-a-service for big data

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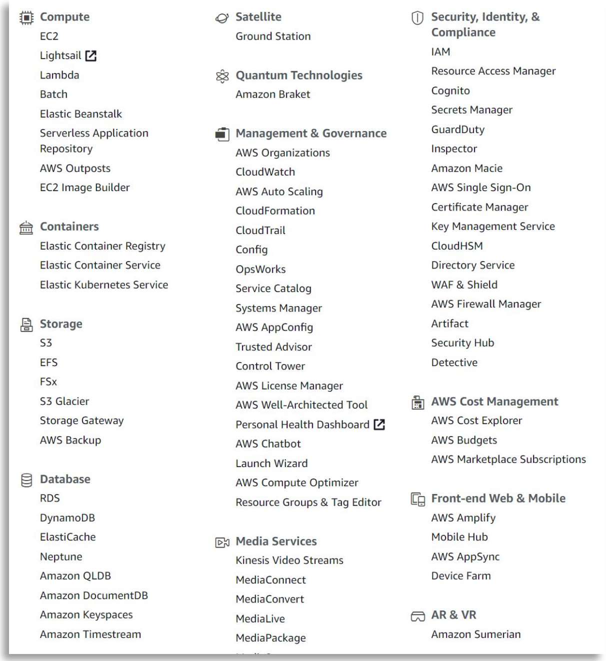
An Overwhelming Array of Services



Amazon has over 50 cloud services!

(Azure, Google, Oracle have fewer, but still a large number)

How do we decide what we need? Understand our options

No cloud standard exists, but we’ve converged on a rough taxonomy…

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A Taxonomy: Cloud *Service Layers*

Software as a Service (SaaS) – applications hosted on the cloud

- Netflix, GMail, Facebook, Salesforce

Platform as a Service (PaaS) – libraries, specialized platforms

- Colab, Google Compute Engine, Amazon Elastic MapReduce

Infrastructure as a Service (IaaS) – “raw” machines & storage

- Amazon Elastic Compute Cloud, Simple Storage Service

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Colab (and AWS SageMaker Notebook)

Cloud-hosted Platform-as-a-Service / Software-as-a-Service hybrid

- Google-customized Jupyter Notebook on Ubuntu 16.04 with Python 3.6
- (Possible to install single-node Spark)

But to get the most out of Spark, we need to connect Colab to a cluster!

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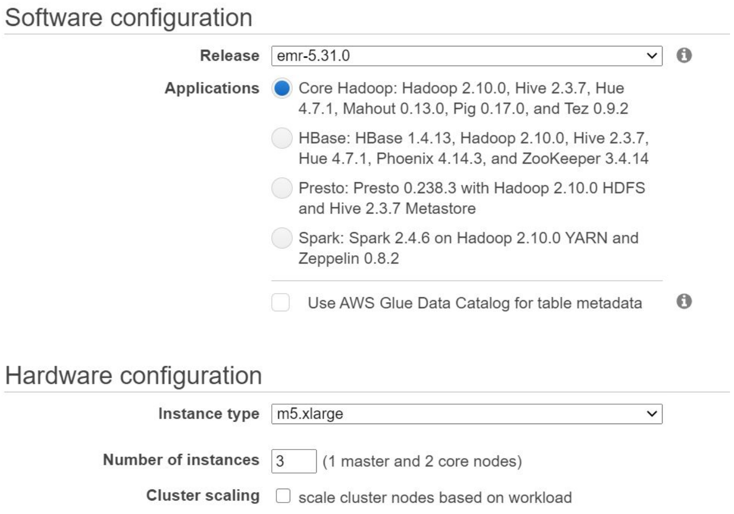
Our Main Focus:
AWS Elastic MapReduce

Preconfigured compute clusters!

- Built over EC2, and you can always go down to the EC2 level

Pick number of machines, configura details, launch and use!



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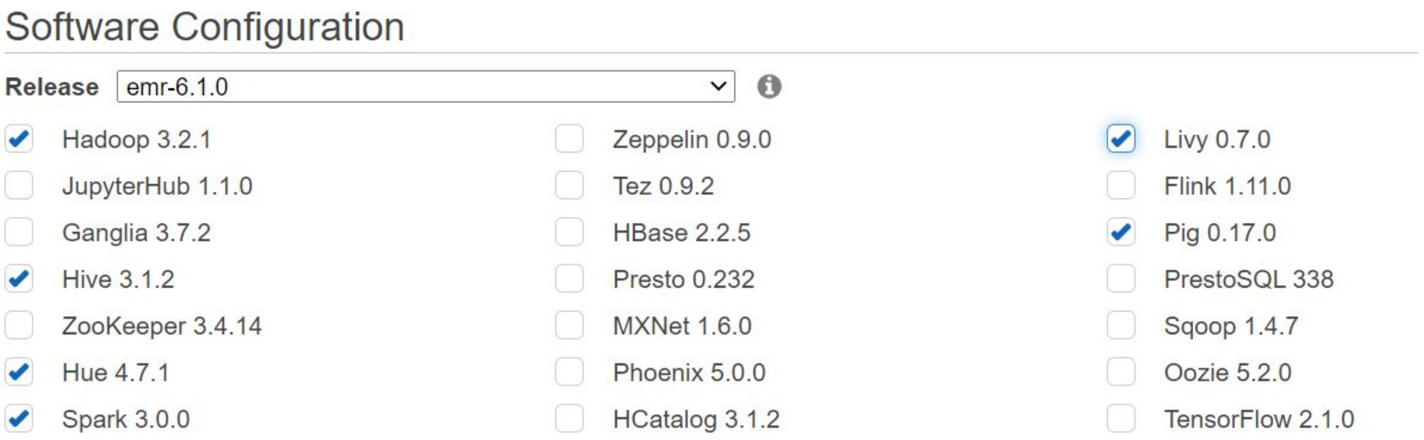
Software



- For now: need at least Spark, Livy, Hive
  - We'll have a largely-preconfigured template for you
- Later for deep learning: MXNet, PyTorch

https://tinyurl.com/cis545-lecture-02-16-22

Creating a Cluster

Node type	Instance type
Master Master - 1	**m5.xlarge** 4 vCore, 16 GiB memory, EBS only storag EBS Storage: 64 GiB Add configuration settings
Core Core - 2	**m5.xlarge** 4 vCore, 16 GiB memory, EBS only storag EBS Storage: 64 GiB Add configuration settings
Task Task - 3	**m5.xlarge** 4 vCore, 16 GiB memory, EBS only storag EBS Storage: 64 GiB Add configuration settings

m5.8xlarge	32	128	EBS only
m5.12xlarge	48	192	EBS only
m5.16xlarge	64	256	EBS only
m5.24xlarge	96	384	EBS only
m5a.xlarge	4	16	EBS only
m5a.2xlarge	8	32	EBS only
m5a.4xlarge	16	64	EBS only
m5a.8xlarge	32	128	EBS only
m5a.12xlarge	48	192	EBS only
m5a.16xlarge	64	256	EBS only
m5a.24xlarge	96	384	EBS only

Spot

Use on-demand as max price

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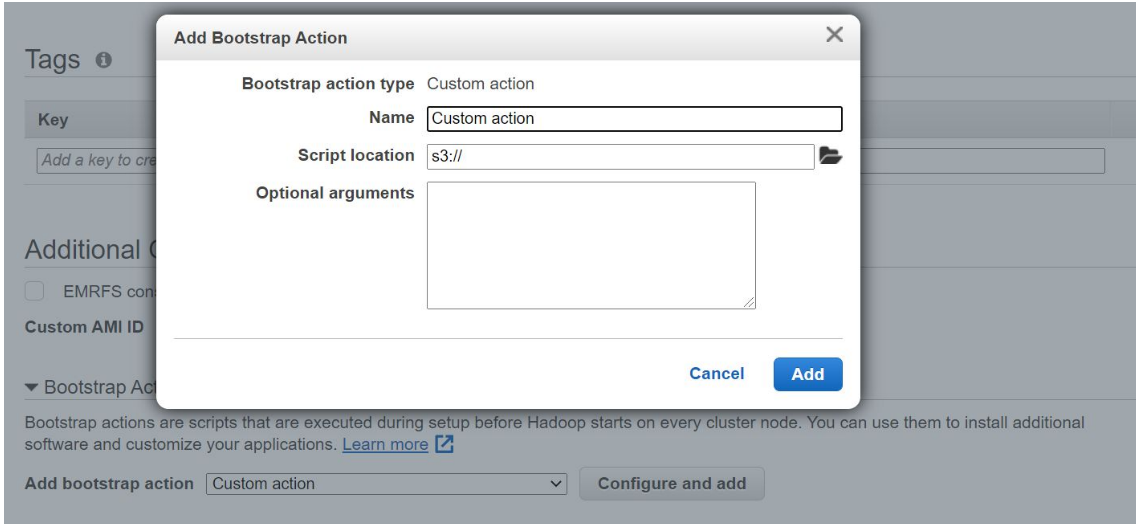
Bootstrap Actions

To install Python (or Java/Scala) packages across the cluster, set up a shell script as a *bootstrap action* and place on AWS S3



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A Spark Cluster

Summary

ID:	j-1TI9TBPVGD6YY
Creation date:	2020-10-03 10:28 (UTC-4)
Elapsed time:	9 minutes
After last step completes:	Cluster waits
Termination protection:	Off Change
Tags:	-- View All / Edit
Master public DNS:	ec2-54-159-35-214.compute-1.amazonaws.com Connect to the Master Node Using SSH

Configuration details

Release label:	emr-6.1.0
Hadoop distribution:	Amazon 3.2.1
Applications:	Hive 3.1.2, Pig 0.17.0, Hue 4.7.1, Spark 3.0.0, Livy 0.7.0, MXNet 1.6.0
Log URI:	s3://aws-logs-884743372678-us-east-1/elasticmapreduce/
EMRFS consistent view:	Disabled
Custom AMI ID:	--

Not secure | ec2-54-159-35-214.compute-1.amazonaws.com:8998/ui

LIVY Sessions

Interactive Sessions

Show 10 entries Search:

Session Id	Application Id	Name	Owner	Proxy User	Session Kind	State	Logs
0					pyspark	starting	session

Showing 1 to 1 of 1 entries Previous 1 Next

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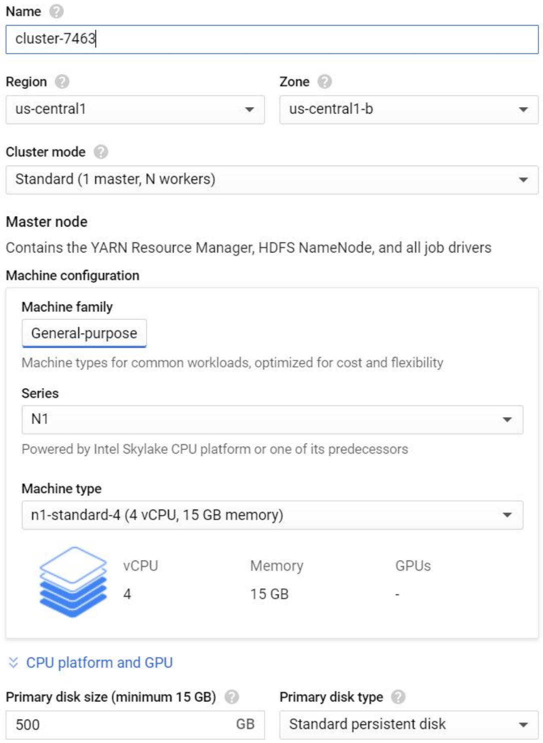
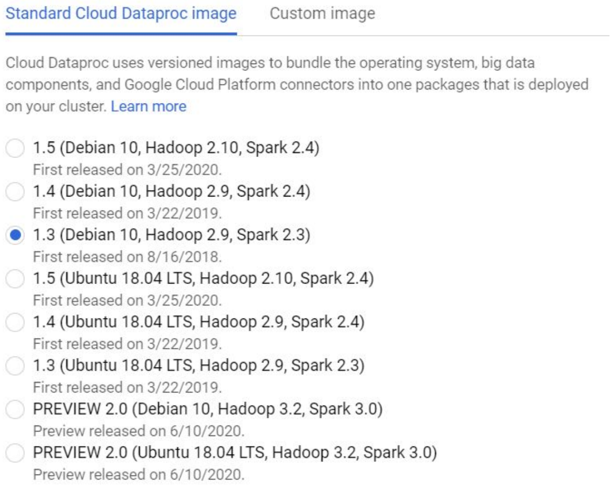
Google DataProc





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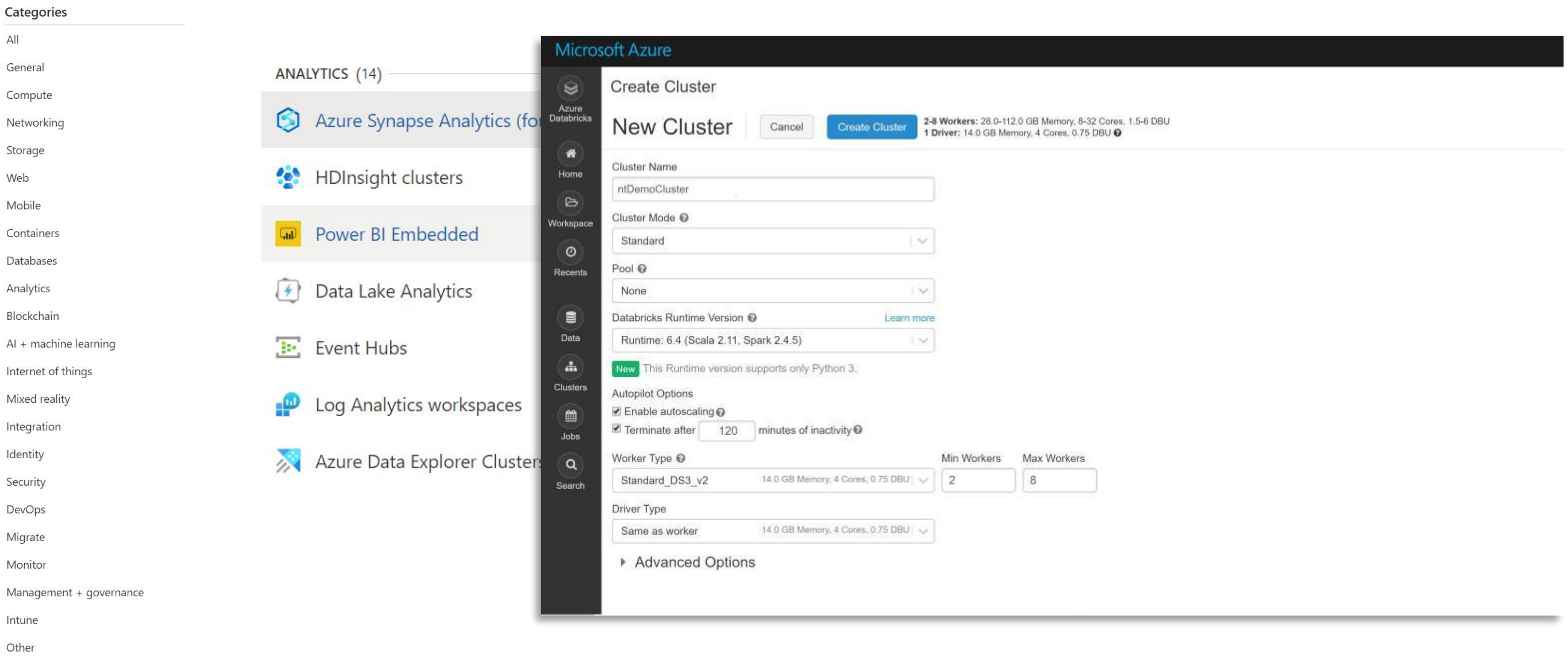
Microsoft Azure Databricks



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Brief Review

https://canvas.upenn.edu/courses/1636888/quizzes/2771536 (09B)

Apache Spark is an instance of:

a. Software-as-a-Service (SaaS)
b. Cloud-as-a-Service (CaaS)
c. Platform-as-a-Service (PaaS)
d. Infrastructure-as-a-Service (IaaS)

To `pip install` Python packages so they are usable in Spark jobs, you need to

e. Run `!pip install` from Colab
f. Add an EMR bootstrap action
g. Run `!pip install` from your `%%spark` cell
h. Run anaconda from Colab

https://tinyurl.com/cis545-lecture-02-16-22

Recap of Cloud Cluster Management

One type of *platform-as-a-service* – pay-as-you-go clusters with preconfigured software

You'll generally:

- Install Apache Spark + Livy (and Hive for its SQL libraries)
  - *Bootstrap* script lets you install libraries on all nodes
- Configure at least 16GB RAM, 3 nodes – beware you are billed by how long the cluster is running!
- **We'll have a preconfigured CloudFront template for you**

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How Spark Works on a Cluster

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CIS 545 – Big Data Analytics

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From SQL to a Spark Query Plan

https://tinyurl.com/cis545-007

```
yelp_business_sdf = spark.read.format("csv").option("header",
"true").load("yelp_business.csv")

avg_reviews_by_city_sdf = spark.sql(\
  'select city, avg(stars) as avg_rating '\
  'from yelp_
  'group by c
avg_reviews_b
```

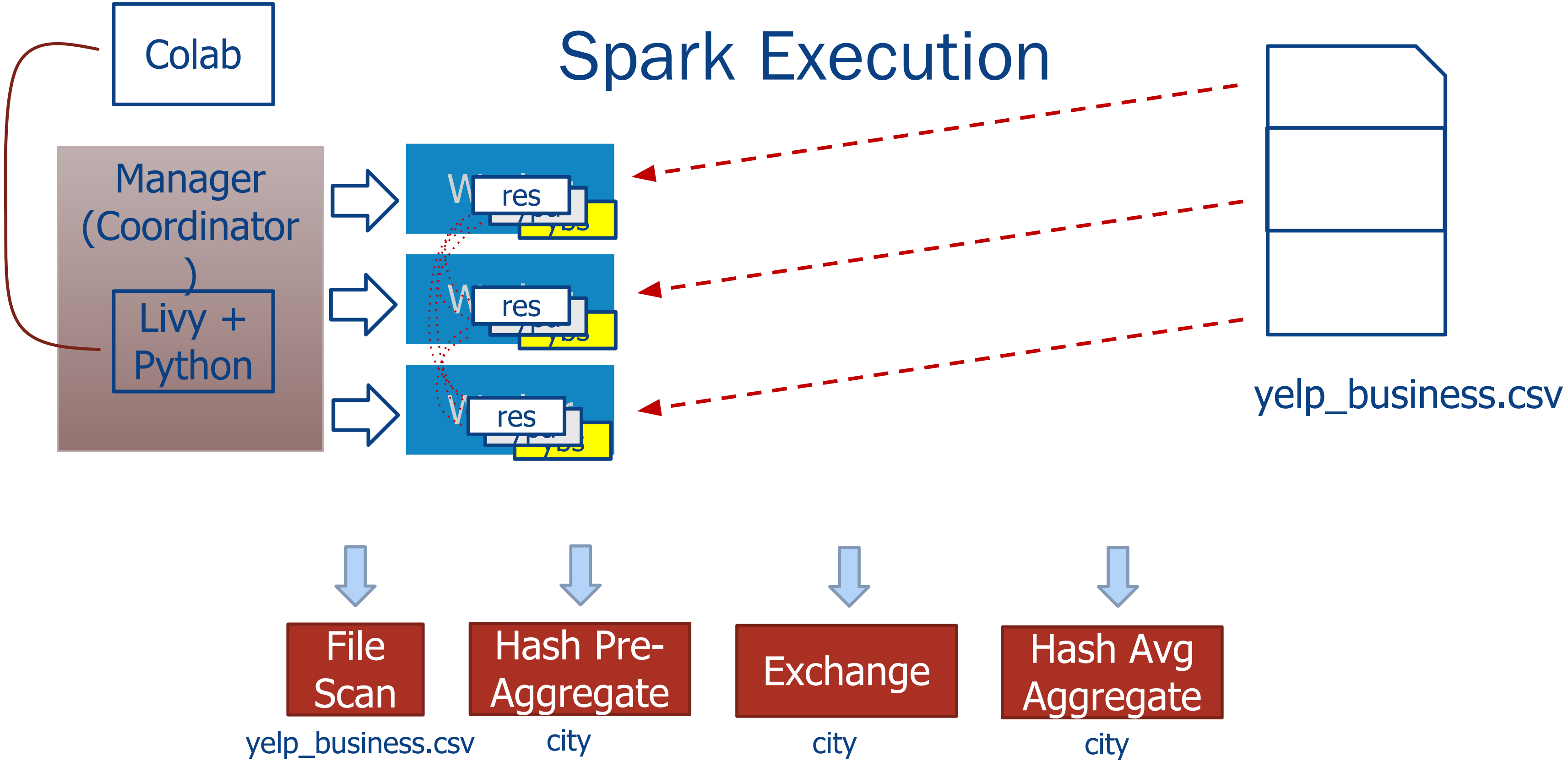
```
+------------------+------------+--------------------+--------------+-----+
|              name|neighborhood|             address|          city|state|
+------------------+------------+--------------------+--------------+-----+
|   Dental by Design|        null|4855 E Warner Rd,...|     Ahwatukee|   AZ|
| Stephen Szabo Salon|       null|   3101 Washington Rd|      McMurray|   PA|
|Western Motor Veh...|        null|6025 N 27th Ave, ...|       Phoenix|   AZ|
|   Sports Authority|        null|5000 Arizona Mill...|         Tempe|   AZ|
                                                 Ave|Cuyahoga Falls|   OH|
                                                 ---+--------------+-----+
```

File Scan	Hash Pre-Aggregate	Exchange	Hash Avg Aggregate
yelp_business.csv	city	city	city

```
*(2) HashAggrega
+- Exchange hash
   +- *(1) Hash
           [part
      +- FileSca                                                      V,
         Location: InMemoryFileIndex[file:/content/yelp_business.csv],
         PartitionFilters: [], PushedFilters: [], ReadSchema:  struct<city:string,stars:string>
```

https://tinyurl.com/cis545-lecture-02-16-22

Spark Execution



https://tinyurl.com/cis545-lecture-02-16-22

Distributed Joins

```
same_city_sdf = spark.sql(
  'select b1.name, b2.name from yelp_business b1 join yelp_business b2 '\
  ' on b1.city = b2.city and b1.name <> b2.name')
```

yelp_business

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 1
KQPW8	Western Motor Vehicles	Phoenix	Server 0
8DShNS	Sports Authority	Tempe	Server 1

Sharded by ID

https://tinyurl.com/cis545-lecture-02-16-22

Distributed Joins

```
same_city_sdf = spark.sql(
  'select b1.name, b2.name from yelp_business b1 join yelp_business b2 '\
  ' on b1.city = b2.city and b1.name <> b2.name')
```

yelp_business

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 1
KQPW8	Western Motor Vehicles	Phoenix	Server 0
8DShNS	Sports Authority	Tempe	Server 1

Sharded by ID

Create two copies, sharded by city

https://tinyurl.com/cis545-lecture-02-16-22

Distributed Joins

```
same_city_sdf = spark.sql(
  'select b1.name, b2.name from yelp_business b1 join yelp_business b2 '\
  ' on b1.city = b2.city and b1.name <> b2.name')
```

yelp_business

id	name	city	
FYNWN1	Dental by Design	**Ahwatukee**	Server 0
BADF	My Wine Cellar	**Ahwatukee**	Server 1
KQPW8	Western Motor Vehicles	**Phoenix**	Server 0
8DShNS	Sports Authority	**Tempe**	Server 1

Sharded by ID

Exchange / repartition / shuffle

yelp_business

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 0
KQPW8	Western Motor Vehicles	Phoenix	Server 1
8DShNS	Sports Authority	Tempe	Server 1

Sharded by city

https://tinyurl.com/cis545-lecture-02-16-22

Distributed Joins

```
same_city_sdf = spark.sql(
  'select b1.name, b2.name from yelp_business b1 join yelp_business b2 '\
  ' on b1.city = b2.city and b1.name <> b2.name')
```

yelp_business (b1)

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 0
KQPW8	Western Motor Vehicles	Phoenix	Server 1
8DShNS	Sports Authority	Tempe	Server 1

yelp_business (b2)

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 0
KQPW8	Western Motor Vehicles	Phoenix	Server 1
8DShNS	Sports Authority	Tempe	Server 1

name	name
My Wine Cellar	Dental by Design
Dental by Design	My Wine Cellar

https://tinyurl.com/cis545-lecture-02-16-22

Variation: (Left) Outerjoin

```
same_city_sdf = spark.sql(
  'select b1.name, b2.name from yelp_business b1 left join yelp_business b2 '\
  ' on b1.city = b2.city and b1.name <> b2.name')
```

yelp_business (b1)

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 0
KQPW8	Western Motor Vehicles	Phoenix	Server 1
8DShNS	Sports Authority	Tempe	

yelp_business (b2)

id	name	city	
FYNWN1	Dental by Design	Ahwatukee	Server 0
BADF	My Wine Cellar	Ahwatukee	Server 0
KQPW8	Western Motor Vehicles	Phoenix	Server 1
	...thority	Tempe	Server 1

name	name
My Wine Cellar	Dental by Design
Dental By Design	My Wine Cellar
Western Motor...	NULL
Sports Authority	NULL

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Minimizing *Shuffle/Exchange* Steps

- Every time we do a join or a group-by, we need the data to be sharded on the key
  - If it isn't, we need to do an *exchange* or *repartition*!
- A good strategy: *amortize* the repartitions across multiple operations if possible!

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Catalyst: Spark's Query Optimizer Generates the Plans

- Spark's query optimizer seeks to:
  - Estimate how big the input sources are
- Estimate how many results will be produced in each filter, join, groupby – compare different orderings of operations
- Find the strategy that minimizes the overall cost, including repartitions and join costs

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Spark Handles Failures!

What happens if one of our worker nodes dies?

Spark re-reads its input data using the other nodes, and re-executes the missing part of the query!

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Brief Review

https://canvas.upenn.edu/courses/1636888/quizzes/2771512 (09C)

When Spark runs on a cluster, it creates and executes a Spark query plan when

a. we execute a cell with a Pandas operation
b. we execute a cell that invokes an action like show() or save()
c. we execute a cell with a dataframe operation like a join
d. we execute a cell with an SQL query

Given two dataframes **students(id,name)** and **enrolled(course_id,student_id)**, if we execute a query to join on the student IDs, Spark must:

e. ensure **students** is sharded by **ID** and **enrolled** is sharded by **student_id**, or add exchange operators as needed
f. perform a hash join within each of the worker nodes, without adding any exchange operators
g. ensure **students** is sharded by ID and **enrolled** is sharded by **course_id**, or add exchange operators as needed
h. sort the **enrolled** dataframe by **course_id**

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Recap

Apache Spark queries are *lazy* to maximize what can be optimized

Upon an *action* like show(), the queries are combined and a *plan* is generated – which minimizes cost

Group-by and join require *the data to be sharded on the key* – may need to *exchange* or *reshuffle* or *repartition* data

If a worker fails in execution, its work is re-executed

Spark's Catalyst query optimizer seeks to find the minimum-cost plan, but occasionally you may need to manually override it

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Storing Data on the Cloud

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CIS 545 – Big Data Analytics

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Where Do We *Put* Our Big Data?

- A cloud file system?
- A cloud NoSQL system?
- A cloud relational DBMS?

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Key questions

How complex and large is the data and its content?

- videos, images; JSON; large CSVs

How will I query my data?

- e.g., by pathname, by properties, by features

Do I need transactions?

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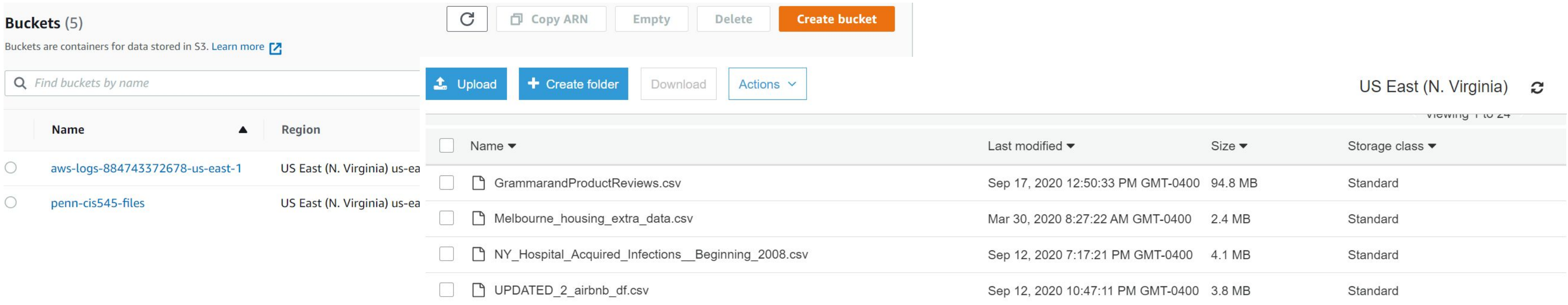
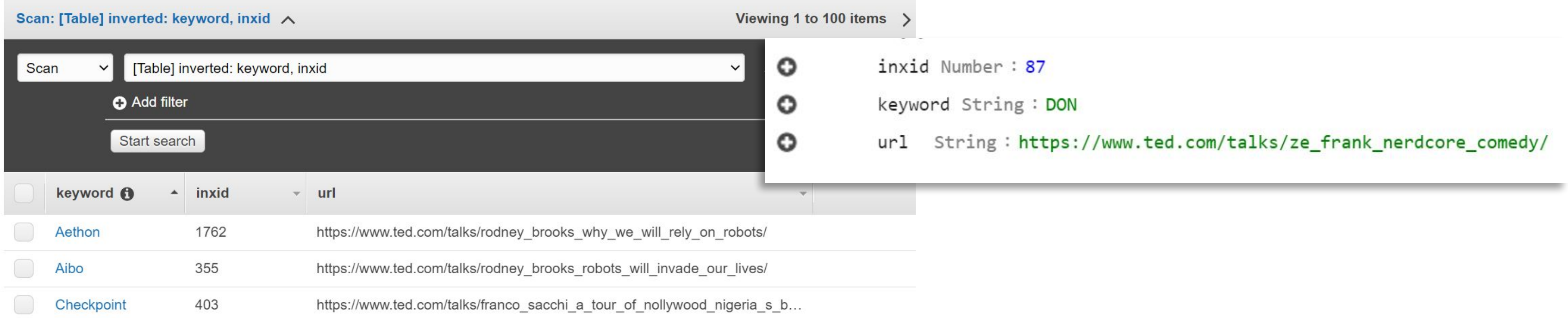
S3 (or GCS) for Storing Large Objects



- Amazon S3 supports “buckets” – virtual disk volumes
- Can use “`s3a://bucketname/filename`” to specify an S3 file
  - For dataframes: df.write.parquet(), sqlContext.read.parquet()

https://tinyurl.com/cis545-lecture-02-16-22

DynamoDB (or BigTable) for Small Object Lookup



- Given objects in a *map* from keys to hierarchical values – DynamoDB is a good choice
  - Values may be JSON data, dictionaries (max 4KB / field)
- Queries largely limited to lookups by key

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RDBMSs for Queriable Objects

- Relational DBMSs are best if we want:
  - Complex queries that return *subsets* of data to Spark
  - Atomic updates across tables, in transactions
- Interoperability with the most tools

- Amazon RDS lets us launch PostgreSQL, Oracle, MariaDB, …

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Brief Review

https://canvas.upenn.edu/courses/1636888/quizzes/2771525 (09D)

If we have tabular data that we are retrieving solely by an ID, our best choice(s) for storage are likely to be:

a. DynamoDB or RDS
b. neither DynamoDB nor RDS
c. DynamoDB only
d. RDS only

If we have satellite photos, we are likely to want to store these on:

e. RDS
f. our laptop
g. DynamoDB
h. S3

https://tinyurl.com/cis545-lecture-02-16-22

Recap

- Our focus in this class: processing big data
- But there are multiple places we can save it:
  - "Large object stores" like S3 – videos, images, large CSVs, large parquet files
  - NoSQL stores like DynamoDB – JSON, simple objects
  - RDBMSs like RDS – tabular data that we'll query

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Materialization of Query Results

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University of Pennsylvania

CIS 545 – Big Data Analytics

Portions of this lecture have been contributed to the OpenDS4All project, piloted by Penn, IBM, and the Linux Foundation

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When We Have Big Data, We May Need to Make Storage Decisions

We've seen data with embedded *hierarchy*

- LinkedIn people included lists of education or job experiences
- Key idea: *split these into subtables, explode the lists*
- There's a goal of storing data without redundancy

But: Sometimes portions of data *overlap*, e.g., both parent and subclasses have some common instances

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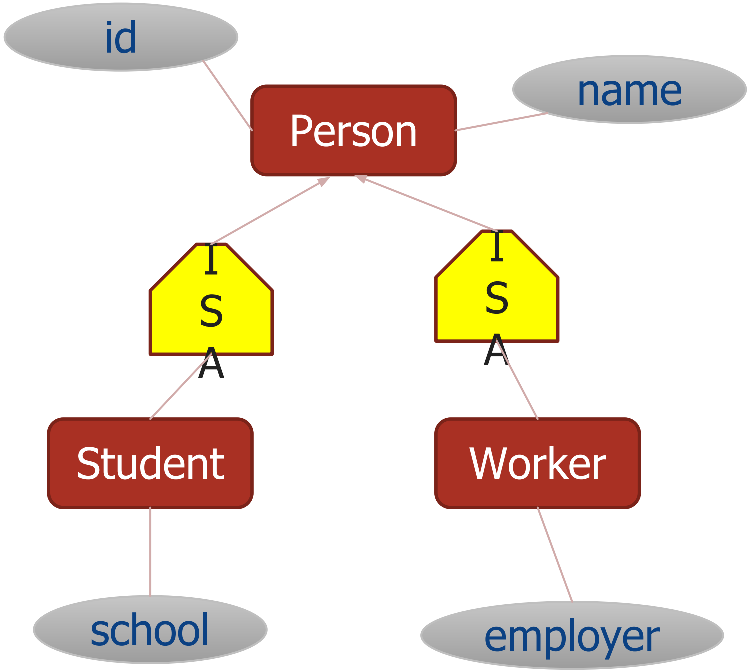
An Example of Instances and Subclasses



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Person

id	name
123	Ai
456	Jay
789	Kaye

Student

id	school
456	Penn
789	MIT

Worker

id	employer
789	Lutron

Materialization

Ideally, our original data is stored without redundancy – this makes it easier to maintain

But as we generate analysis results, we may want to strategically store redundant info! "View materialization"!

Let's apply to people, students, and workers…

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Student and Worker are Naturally *Views*

```
CREATE VIEW WorkerPerson(id, name, employer) AS
  SELECT *
  FROM Person NATURAL JOIN Worker
```

WorkerPerson

id	name	employer
789	Kaye	Lutron

```
CREATE VIEW StudentPerson(id, name, employer) AS
  SELECT *
  FROM Person NATURAL JOIN Student
```

StudentPerson

id	name	school
456	Jay	Penn
789	Kaye	MIT

but views are simply named queries treated as tables…

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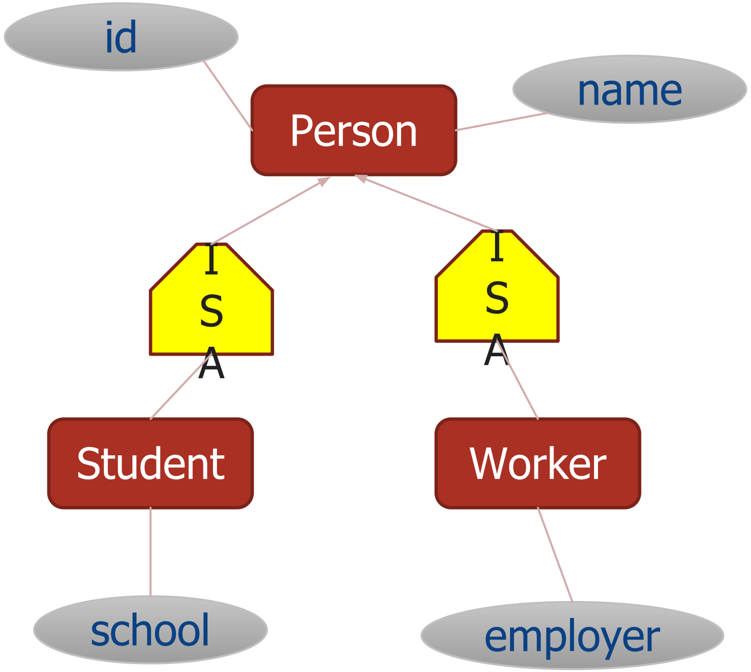
An Example of Instances and Subclasses with Redundancy!



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Person

id	name
123	Ai
456	Jay
789	Kaye

Worker

id	employer
789	Lutron

Student

id	school
456	Penn
789	MIT

StudentPerson

id	name	school
456	Jay	Penn
789	Kaye	MIT

WorkerPerson

id	name	employer
789	Kaye	Lutron

More Generally…

- In Spark, we can take any Dataframe and **persist** it…

```
same_city_sdf = spark.sql('select b1.name, b2.name as name2  '\
    'from yelp_business b1 join yelp_business b2 '\
    ' on b1.city = b2.city and b1.name <> b2.name')
same_city_sdf.persist()
```

- Now any time we reference same_city_sdf it will use the stored version!

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Other Uses for Materialization

- Commonly used subqueries
- Generated reports or hierarchical data
- Recursive computations (we'll see these over graphs)

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Brief Review

https://canvas.upenn.edu/courses/1636888/quizzes/2771500 (09E)

If we use inheritance in an E-R diagram, the tables are naturally partitioned such that

a. we only store instances in the child tables
b. instances show up in parent and child tables, but columns other than ID are split
c. the same columns show up in parent and child tables, but instances are split
d. we repeat both instances and all columns in parent and child tables

View materialization is accomplished by

e. calling `materialize()` on a dataframe
f. creating a view in SparkSQL
g. saving the input CSV
h. calling `persist()` on a dataframe

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Recap

- View materialization sacrifices storage (and cost of updating) for query performance
- Very commonly used in big data scenarios
- Can be done by saving a result directly, or by DataFrame.persist()

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Module Wrap-up

- As we scale to bigger and more complex data, need to harness compute clusters
- Spark runs across multiple workers, shuffles data as necessary for joins and grouping
  - Query optimizer seeks to minimize these costs
- We have a series of options for storing our data
- Sometimes it's useful to trade off space for query performance

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More Complex Relationships

- Most of our discussion has been about “direct” relationships
  - Student TAKES a class
  - a student ISA person
- In the real world, lots of transitive relationships!
  - Real and digital social networks, the Internet, road networks, supplier networks, …
  - Leads to Part 3: graphs!

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