CS 327E Class 9

November 19, 2018

Announcements

- What to expect from the next 3 milestones (Milestones 8 - 10)
- How to get feedback on your cross-dataset queries and pipeline designs today. Sign-up sheet: https://tinyurl.com/y9fdogqk

1) How is a `ParDo` massively parallelized?

A. The `ParDo`’s `DoFn` is run on multiple workers and each worker processes a different split of the input elements.

B. The instructions inside the `ParDo`’s `DoFn` are split up among multiple workers and each worker runs a single instruction over all the input elements.

2) If a `ParDo` is processing a `PCollection` of 100 elements, what is the **maximum** parallelism that could be obtained for this pipeline?

A. 50
B. 100
C. 200
D. None of the above

3) If a `PCollection` of 100 elements is divided into 10 bundles by the runner and each bundle is run on a different worker, what is the actual parallelism of this pipeline?

A. 50
B. 100
C. 200
D. None of the above

4) In a pipeline that consists of a sequence of `ParDos` `1-` *`n`*, how can the runner execute the transforms on multiple workers while minimizing the communication costs between the workers?

A. Alter the bundling of elements between each `ParDo` such that an element produced by `ParDo1` on worker A gets consumed by `ParDo2` on worker B.

B. Maintain the bundling of elements between the `ParDos` such that an element that is produced by `ParDo1` on worker A gets consumed by `ParDo2` on worker A.

C. Split up the workers into *n* groups and run each `ParDo` on a different group of workers.

D. Split up the `ParDos` into their own pipelines as it is not possible to reduce the communication costs when multiple transforms exist in the same pipeline.

5) What happens when a `ParDo` fails to process an element?

A. The processing of the failed element is restarted on the same worker.
B. The processing of the failed element is restarted on a different worker.
C. The processing of all the bundle is restarted on either the same worker or a different worker.
D. The processing of the entire `PCollection` is restarted on either the same worker or a different worker.

Case Study

Analysis Questions:

- Are young technology companies as likely to sponsor H1B workers as more established companies?
- How does the compensation of H1B workers compare to the average earnings of domestic workers who are performing the same role and living in same geo region?

Datasets:

- H1B applications for years 2015 - 2018 (source: US Dept of Labor)
- Corporate registrations for various states (source: Secretary of States)
- Occupational Employment Survey for years 2015 - 2018 (source: Bureau of Labor Statistics)

Code Repo: https://github.com/shirleycohen/h1b_analytics

Objectives

Cross-Dataset Query 1:

- Join H1B’s Employer table with the Sec. of State’s Corp. Registry table on the company’s name and location. Get the age of the company from the incorporation date of the company’s registry record. Group the employers by age (0 - 5 years old, 6 - 10 years old, 11 - 20 years old, etc.) and see how many younger tech companies sponsor H1B workers.

- Technical challenges: 1) matching employers within the H1B dataset due to inconsistent spellings of the company’s name and 2) matching employers across H1B and Corporate Registry datasets due to inconsistent spellings of the company’s name and address.

Objectives

Cross-Dataset Query 2:

- Join H1B’s Job table with the Bureau of Labor Statistics’ Wages and Geography tables on the soc_code and job location. Calculate the annual salary from the hourly wages reported in the Wages table and compare this number to the H1B workers’ pay.

- Technical challenges: joining the job location to the BLS geography area requires looking up the job location’s county and mapping the country name to the corresponding area code in the Geography table.

First Dataset

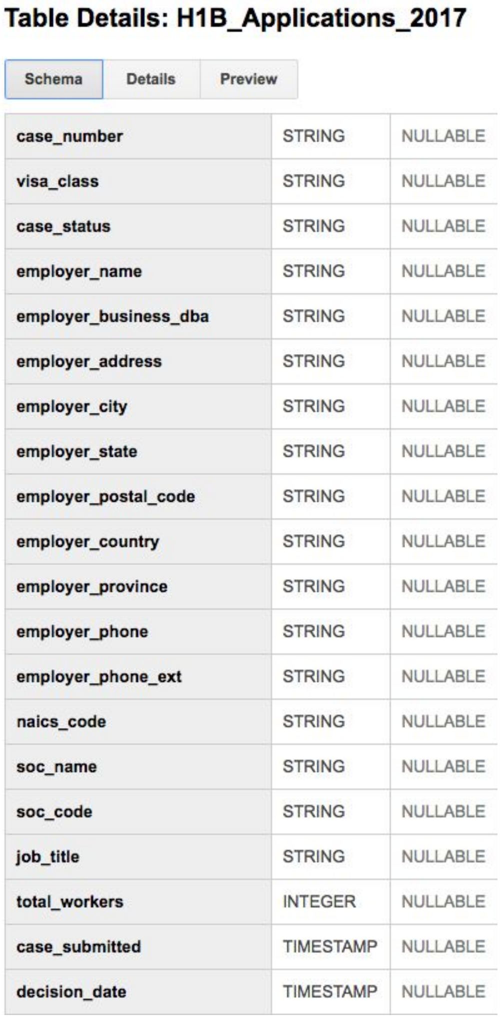
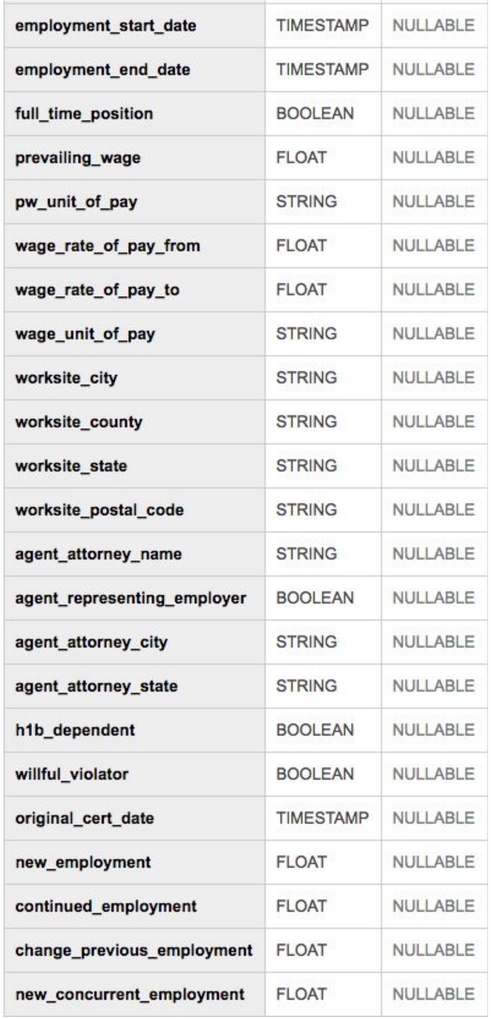
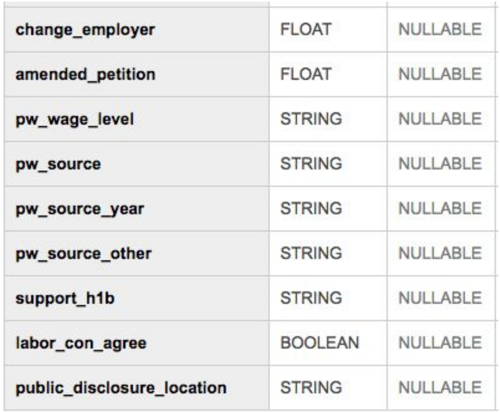


Table Details: H1B_Applications_2017

Schema | Details | Preview





case_number	STRING	NULLABLE
visa_class	STRING	NULLABLE
case_status	STRING	NULLABLE
employer_name	STRING	NULLABLE
employer_business_dba	STRING	NULLABLE
employer_address	STRING	NULLABLE
employer_city	STRING	NULLABLE
employer_state	STRING	NULLABLE
employer_postal_code	STRING	NULLABLE
employer_country	STRING	NULLABLE
employer_province	STRING	NULLABLE
employer_phone	STRING	NULLABLE
employer_phone_ext	STRING	NULLABLE
naics_code	STRING	NULLABLE
soc_name	STRING	NULLABLE
soc_code	STRING	NULLABLE
job_title	STRING	NULLABLE
total_workers	INTEGER	NULLABLE
case_submitted	TIMESTAMP	NULLABLE
decision_date	TIMESTAMP	NULLABLE
employment_start_date	TIMESTAMP	NULLABLE
employment_end_date	TIMESTAMP	NULLABLE
full_time_position	BOOLEAN	NULLABLE
prevailing_wage	FLOAT	NULLABLE
pw_unit_of_pay	STRING	NULLABLE
wage_rate_of_pay_from	FLOAT	NULLABLE
wage_rate_of_pay_to	FLOAT	NULLABLE
wage_unit_of_pay	STRING	NULLABLE
worksite_city	STRING	NULLABLE
worksite_county	STRING	NULLABLE
worksite_state	STRING	NULLABLE
worksite_postal_code	STRING	NULLABLE
agent_attorney_name	STRING	NULLABLE
agent_representing_employer	BOOLEAN	NULLABLE
agent_attorney_city	STRING	NULLABLE
agent_attorney_state	STRING	NULLABLE
h1b_dependent	BOOLEAN	NULLABLE
willful_violator	BOOLEAN	NULLABLE
original_cert_date	TIMESTAMP	NULLABLE
new_employment	FLOAT	NULLABLE
continued_employment	FLOAT	NULLABLE
change_previous_employment	FLOAT	NULLABLE
new_concurrent_employment	FLOAT	NULLABLE
change_employer	FLOAT	NULLABLE
amended_petition	FLOAT	NULLABLE
pw_wage_level	STRING	NULLABLE
pw_source	STRING	NULLABLE
pw_source_year	STRING	NULLABLE
pw_source_other	STRING	NULLABLE
support_h1b	STRING	NULLABLE
labor_con_agree	BOOLEAN	NULLABLE
public_disclosure_location	STRING	NULLABLE

Table Details:

2015 table: 241 MB size, 618,804 rows

2016 table: 233 MB size, 647,852 rows

2017 table: 253 MB size, 624,650 rows

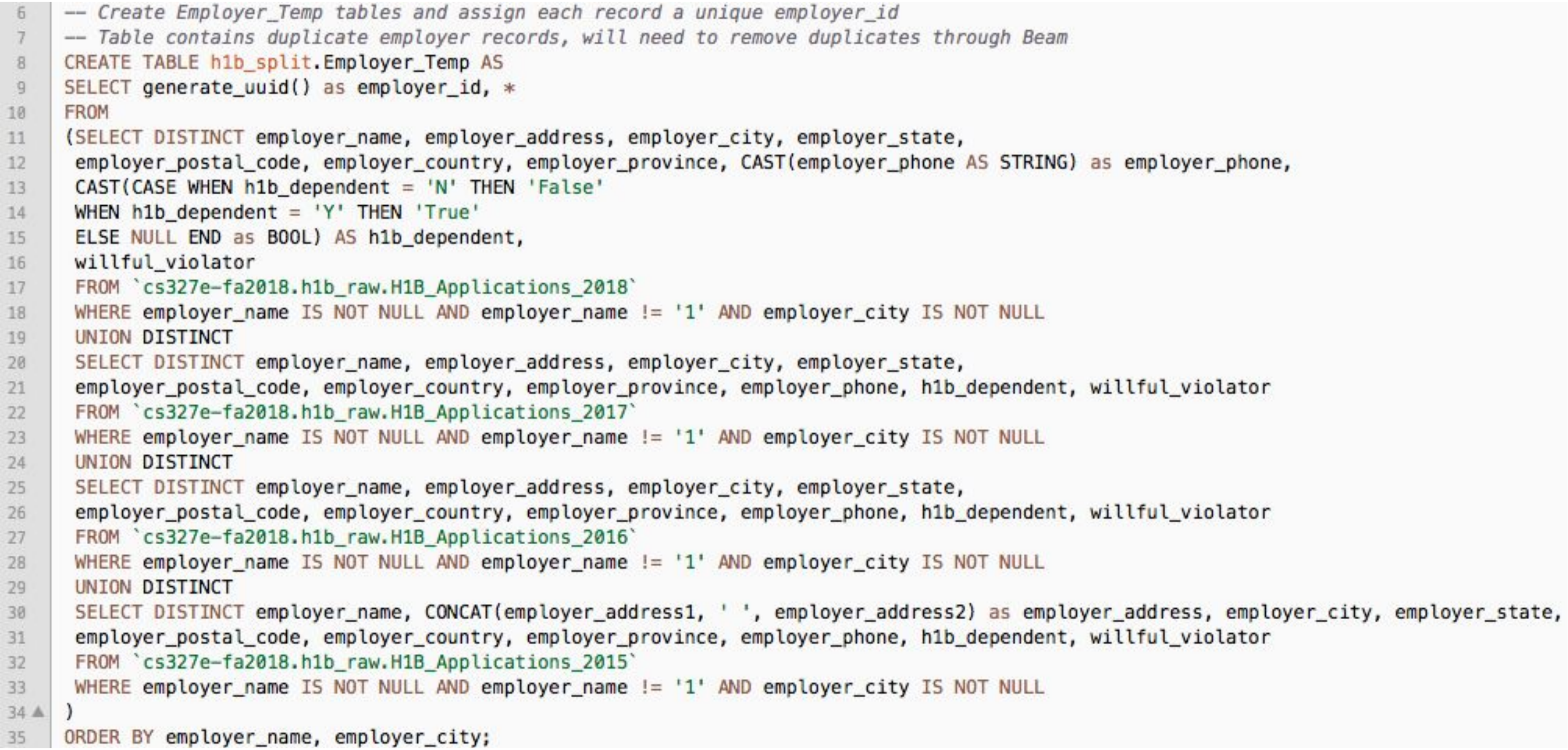
2018 table: 283 MB size, 654,162 rows

Table Schemas:

-A few schema variations between the tables (column names, data types).

-All schema variations resolved through CTAS statements.

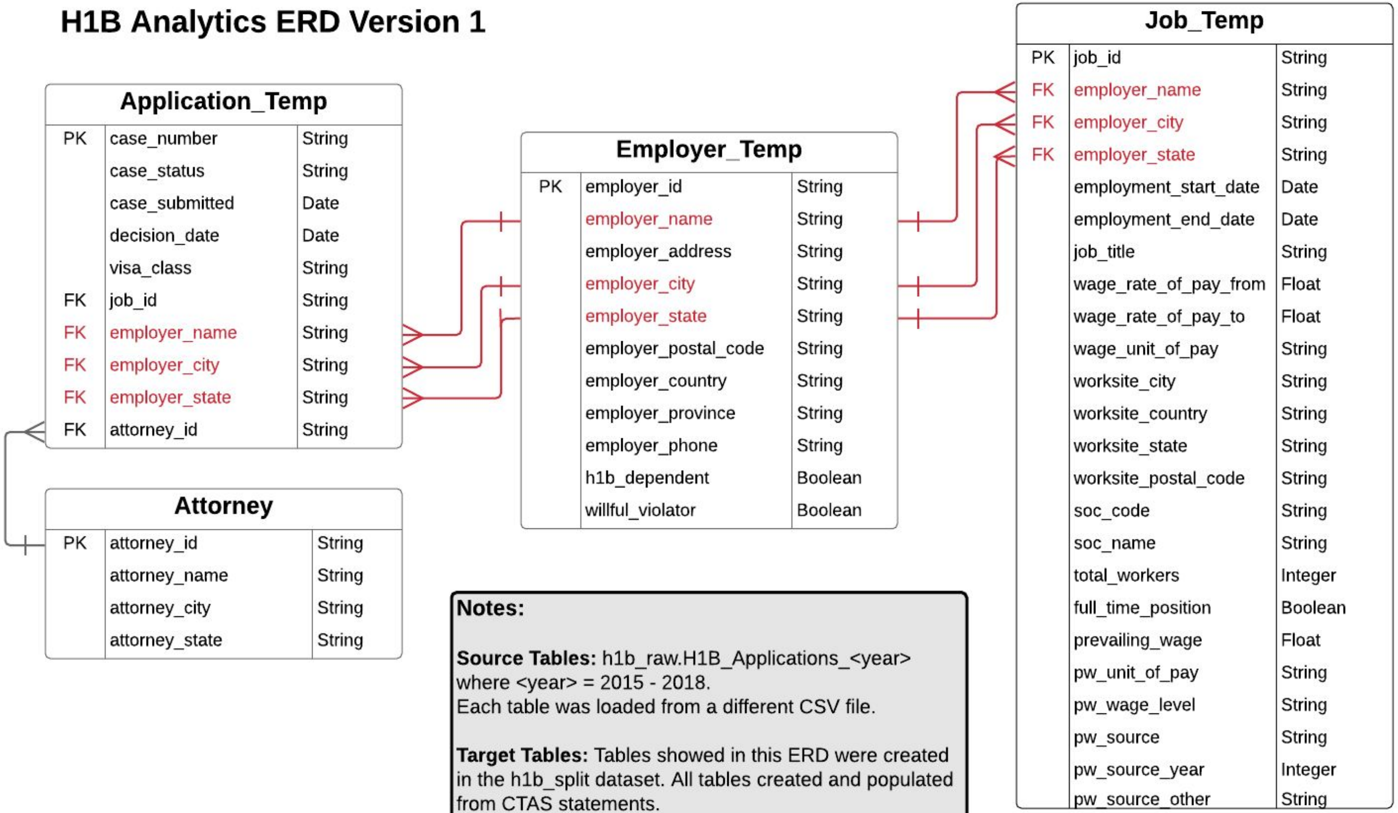
SQL Transforms



```sql
-- Create Employer_Temp tables and assign each record a unique employer_id
-- Table contains duplicate employer records, will need to remove duplicates through Beam
CREATE TABLE h1b_split.Employer_Temp AS
SELECT generate_uuid() as employer_id, *
FROM
(SELECT DISTINCT employer_name, employer_address, employer_city, employer_state,
 employer_postal_code, employer_country, employer_province, CAST(employer_phone AS STRING) as employer_phone,
 CAST(CASE WHEN h1b_dependent = 'N' THEN 'False'
 WHEN h1b_dependent = 'Y' THEN 'True'
 ELSE NULL END as BOOL) AS h1b_dependent,
 willful_violator
 FROM `cs327e-fa2018.h1b_raw.H1B_Applications_2018`
 WHERE employer_name IS NOT NULL AND employer_name != '1' AND employer_city IS NOT NULL
 UNION DISTINCT
 SELECT DISTINCT employer_name, employer_address, employer_city, employer_state,
 employer_postal_code, employer_country, employer_province, employer_phone, h1b_dependent, willful_violator
 FROM `cs327e-fa2018.h1b_raw.H1B_Applications_2017`
 WHERE employer_name IS NOT NULL AND employer_name != '1' AND employer_city IS NOT NULL
 UNION DISTINCT
 SELECT DISTINCT employer_name, employer_address, employer_city, employer_state,
 employer_postal_code, employer_country, employer_province, employer_phone, h1b_dependent, willful_violator
 FROM `cs327e-fa2018.h1b_raw.H1B_Applications_2016`
 WHERE employer_name IS NOT NULL AND employer_name != '1' AND employer_city IS NOT NULL
 UNION DISTINCT
 SELECT DISTINCT employer_name, CONCAT(employer_address1, ' ', employer_address2) as employer_address, employer_city, employer_state,
 employer_postal_code, employer_country, employer_province, employer_phone, h1b_dependent, willful_violator
 FROM `cs327e-fa2018.h1b_raw.H1B_Applications_2015`
 WHERE employer_name IS NOT NULL AND employer_name != '1' AND employer_city IS NOT NULL
)
ORDER BY employer_name, employer_city;
```

Source File: https://github.com/shirleycohen/h1b_analytics/blob/master/h1b_ctas.sql

H1B Analytics ERD Version 1



Application_Temp

PK	case_number	String
	case_status	String
	case_submitted	Date
	decision_date	Date
	visa_class	String
FK	job_id	String
FK	employer_name	String
FK	employer_city	String
FK	employer_state	String
FK	attorney_id	String

Attorney

PK	attorney_id	String
	attorney_name	String
	attorney_city	String
	attorney_state	String

Employer_Temp

PK	employer_id	String
	employer_name	String
	employer_address	String
	employer_city	String
	employer_state	String
	employer_postal_code	String
	employer_country	String
	employer_province	String
	employer_phone	String
	h1b_dependent	Boolean
	willful_violator	Boolean

Job_Temp

PK	job_id	String
FK	employer_name	String
FK	employer_city	String
FK	employer_state	String
	employment_start_date	Date
	employment_end_date	Date
	job_title	String
	wage_rate_of_pay_from	Float
	wage_rate_of_pay_to	Float
	wage_unit_of_pay	String
	worksite_city	String
	worksite_country	String
	worksite_state	String
	worksite_postal_code	String
	soc_code	String
	soc_name	String
	total_workers	Integer
	full_time_position	Boolean
	prevailing_wage	Float
	pw_unit_of_pay	String
	pw_wage_level	String
	pw_source	String
	pw_source_year	Integer
	pw_source_other	String

Notes:

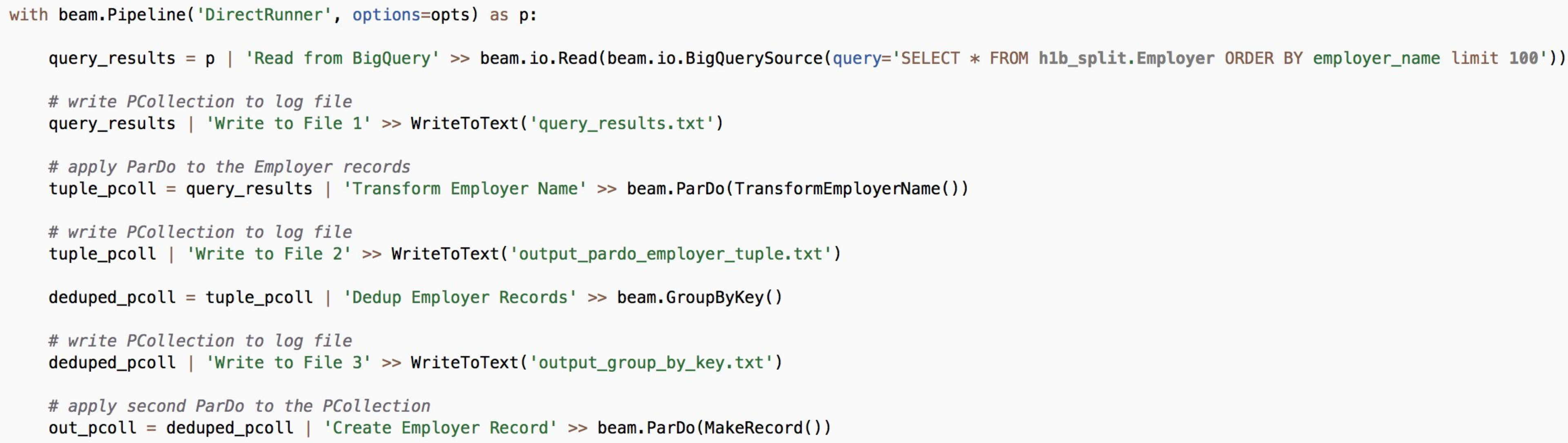
Source Tables: h1b_raw.H1B_Applications_<year> where <year> = 2015 - 2018.
Each table was loaded from a different CSV file.

Target Tables: Tables showed in this ERD were created in the h1b_split dataset. All tables created and populated from CTAS statements.

Issues with Target Tables:
- Employer_Temp contains duplicate records due to mispellings of the employer name and city.
- Job_Temp and Application_Temp are missing references to Employer table via employer_id.

Beam Transform for Employer Table

- Removes duplicate records from Employer Table
- Version 1 of pipeline uses the Direct Runner for testing and debugging

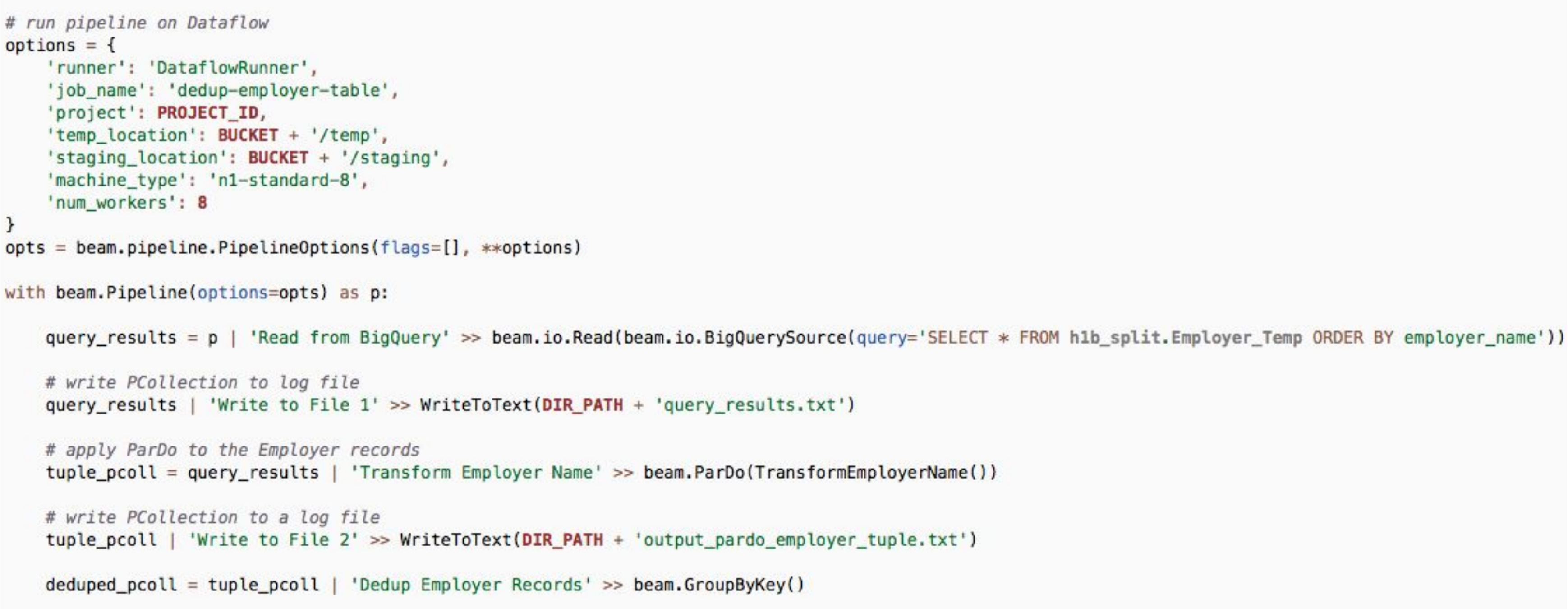


```
with beam.Pipeline('DirectRunner', options=opts) as p:

    query_results = p | 'Read from BigQuery' >> beam.io.Read(beam.io.BigQuerySource(query='SELECT * FROM h1b_split.Employer ORDER BY employer_name limit 100'))

    # write PCollection to log file
    query_results | 'Write to File 1' >> WriteToText('query_results.txt')

    # apply ParDo to the Employer records
    tuple_pcoll = query_results | 'Transform Employer Name' >> beam.ParDo(TransformEmployerName())

    # write PCollection to log file
    tuple_pcoll | 'Write to File 2' >> WriteToText('output_pardo_employer_tuple.txt')

    deduped_pcoll = tuple_pcoll | 'Dedup Employer Records' >> beam.GroupByKey()

    # write PCollection to log file
    deduped_pcoll | 'Write to File 3' >> WriteToText('output_group_by_key.txt')

    # apply second ParDo to the PCollection
    out_pcoll = deduped_pcoll | 'Create Employer Record' >> beam.ParDo(MakeRecord())
```

Source File: https://github.com/shirleycohen/h1b_analytics/blob/master/transform_employer_table_single.py

Beam Transform for Employer Table

- Removes duplicate records from Employer Table
- Version 2 of pipeline uses the Dataflow Runner for parallel processing



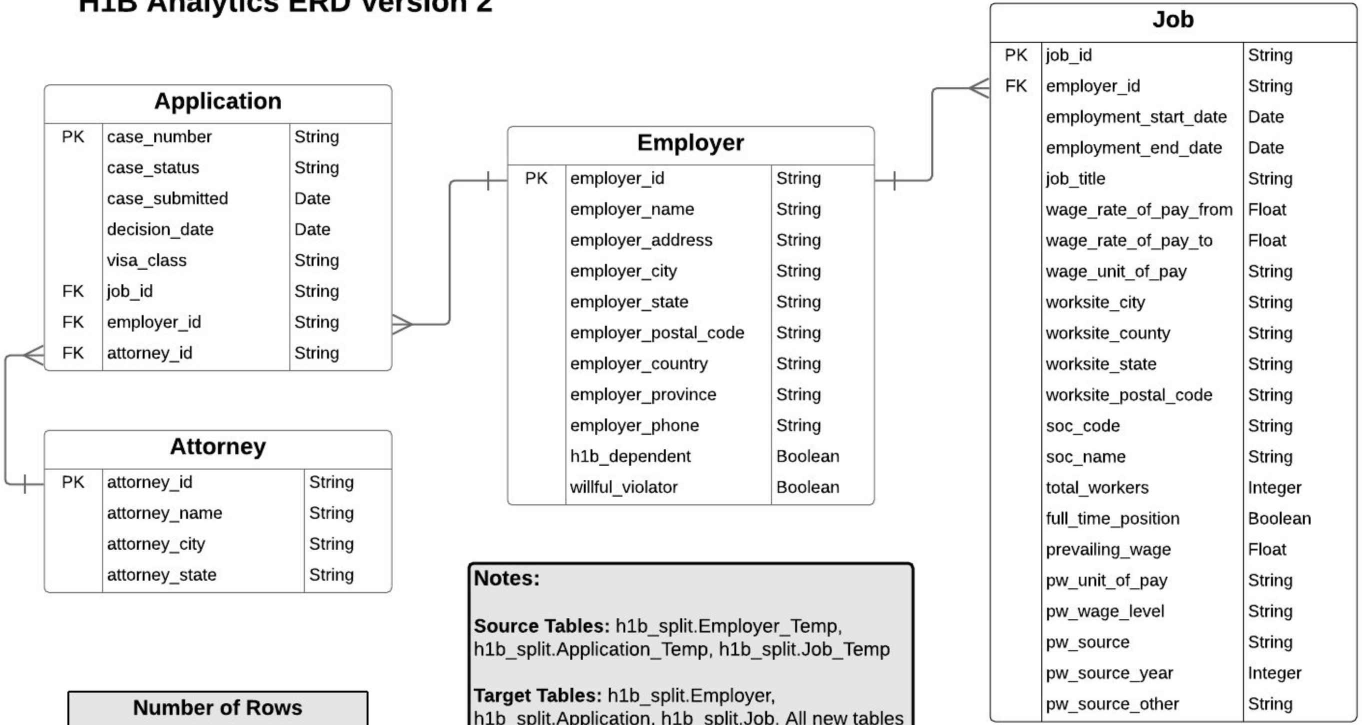
```
# run pipeline on Dataflow
options = {
    'runner': 'DataflowRunner',
    'job_name': 'dedup-employer-table',
    'project': PROJECT_ID,
    'temp_location': BUCKET + '/temp',
    'staging_location': BUCKET + '/staging',
    'machine_type': 'n1-standard-8',
    'num_workers': 8
}
opts = beam.pipeline.PipelineOptions(flags=[], **options)

with beam.Pipeline(options=opts) as p:

    query_results = p | 'Read from BigQuery' >> beam.io.Read(beam.io.BigQuerySource(query='SELECT * FROM h1b_split.Employer_Temp ORDER BY employer_name'))

    # write PCollection to log file
    query_results | 'Write to File 1' >> WriteToText(DIR_PATH + 'query_results.txt')

    # apply ParDo to the Employer records
    tuple_pcoll = query_results | 'Transform Employer Name' >> beam.ParDo(TransformEmployerName())

    # write PCollection to a log file
    tuple_pcoll | 'Write to File 2' >> WriteToText(DIR_PATH + 'output_pardo_employer_tuple.txt')

    deduped_pcoll = tuple_pcoll | 'Dedup Employer Records' >> beam.GroupByKey()
```

Source File: https://github.com/shirleycohen/h1b_analytics/blob/master/transform_employer_table_cluster.py

Beam Transforms for Job and Application Tables

- Clean the employer name and city and find the matching employer_id from Employer table to use as reference in the Job and Application tables
- Pipeline Sketch for Job Table:
    1. Read in all the records from the Employer and Job tables in BigQuery and create a `PCollection` from each source
    2. Clean up the employer’s name and city from the Job `PCollection` (using `ParDo`)
    3. Join the Job and Employer `PCollections` on employer’s name and city (using `CoGroupByKey`).
    4. Extract the matching employer_id from the results of the join and add it to the Job element (using `ParDo`)
    5. Remove employer’s name and city from the Job element (using `ParDo`)
    6. Write out new Job table to BigQuery
- Repeat procedure for Application table

H1B Analytics ERD Version 2



Application

PK	case_number	String
	case_status	String
	case_submitted	Date
	decision_date	Date
	visa_class	String
FK	job_id	String
FK	employer_id	String
FK	attorney_id	String

Attorney

PK	attorney_id	String
	attorney_name	String
	attorney_city	String
	attorney_state	String

Employer

PK	employer_id	String
	employer_name	String
	employer_address	String
	employer_city	String
	employer_state	String
	employer_postal_code	String
	employer_country	String
	employer_province	String
	employer_phone	String
	h1b_dependent	Boolean
	willful_violator	Boolean

Job

PK	job_id	String
FK	employer_id	String
	employment_start_date	Date
	employment_end_date	Date
	job_title	String
	wage_rate_of_pay_from	Float
	wage_rate_of_pay_to	Float
	wage_unit_of_pay	String
	worksite_city	String
	worksite_county	String
	worksite_state	String
	worksite_postal_code	String
	soc_code	String
	soc_name	String
	total_workers	Integer
	full_time_position	Boolean
	prevailing_wage	Float
	pw_unit_of_pay	String
	pw_wage_level	String
	pw_source	String
	pw_source_year	Integer
	pw_source_other	String

Notes:

Source Tables: h1b_split.Employer_Temp, h1b_split.Application_Temp, h1b_split.Job_Temp

Target Tables: h1b_split.Employer, h1b_split.Application, h1b_split.Job. All new tables created and populated from Beam pipelines.

Changes since previous version:
- Removed **187,117** duplicate records from Employer table based on uniqueness criteria of (employer name, city) pairs.
- Added reference to employer_id from Job and Application tables.

Number of Rows

	v1	v2
Employer	348,876	161,759
Job	2,230,779	2,230,625
Application	2,633,426	2,633,156
Attorney	19,861	N/A

Milestone 8

http://www.cs.utexas.edu/~scohen/milestones/Milestone8.pdf