Top Down Specialization for Apache Spark™

Why data privacy?

- A city’s voter list was used to identify voters’ medical records
- 97% of voters were identified by only using ZIP Codes and birth dates
- A New York Times reporter identified a women by using her web searches
- 96% of Netflix subscribers were uniquely identified in 2006

Important Definitions

Quasi-Identifiers

Attributes that when combined together can identify an individual

Sensitive Attributes

Attributes that we are trying to conceal when datasets are released

Taxonomy Trees

Hierarchy of distinct values in a dataset

k-anonymity

- A dataset is called k-anonymous when there are at least $k\mathbf{-1}$ records with the same quasi-identifier values

Education	Gender	City	Income
Grade 12	Female	Nepean	$65,000
Bachelor's	Male	Ottawa	$50,000
Master's	Male	Orleans	$50,000
PhD	Male	Gloucester	$100,000
Grade 12	Female	Nepean	$80,000
Associate	Female	Kanata	$90,000
Associate	Female	Kanata	$105,000
Bachelor's	Male	Ottawa	$50,000

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Education	Gender	City	Income
Grade 12	Female	Nepean	$65,000
Bachelor’s	Male	Ottawa	$50,000
~~Master’s~~ Graduate	Male	~~Orleans~~ Ottawa East	$50,000
~~PhD~~ Graduate	Male	~~Gloucester~~ Ottawa East	$100,000
Grade 12	Female	Nepean	$80,000
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Graduate	Male	Ottawa East	$50,000
Graduate	Male	Ottawa East	$100,000
Grade 12	Female	Nepean	$80,000
Associate	Female	Kanata	$90,000
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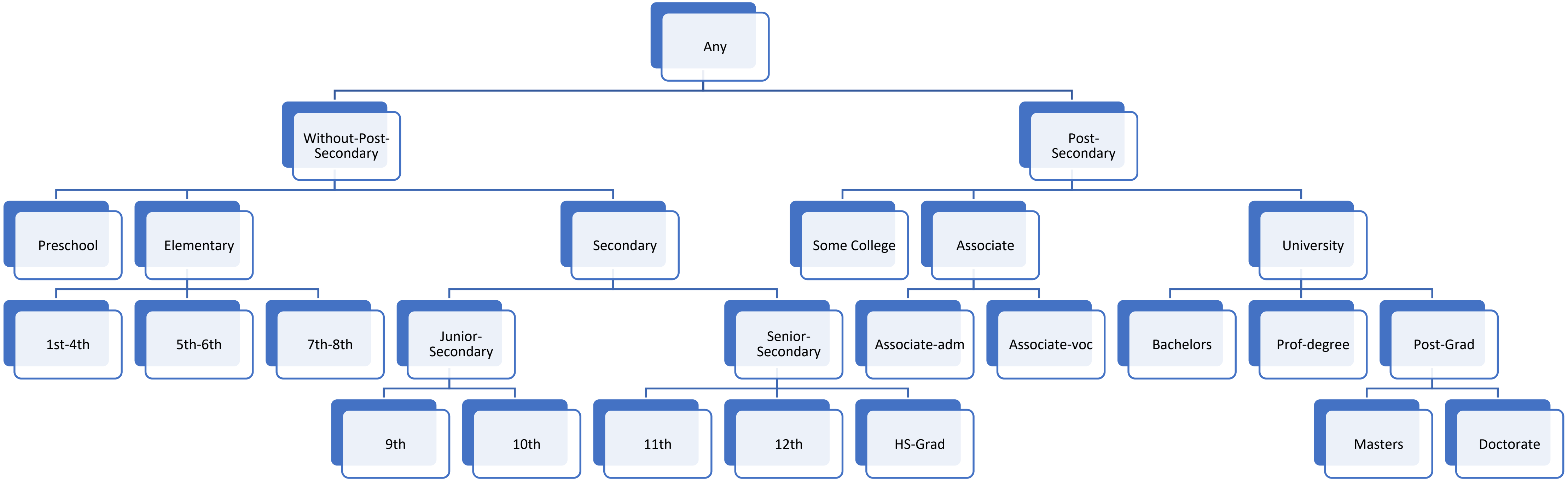
2-anonymous

Top Down Specialization - Overview

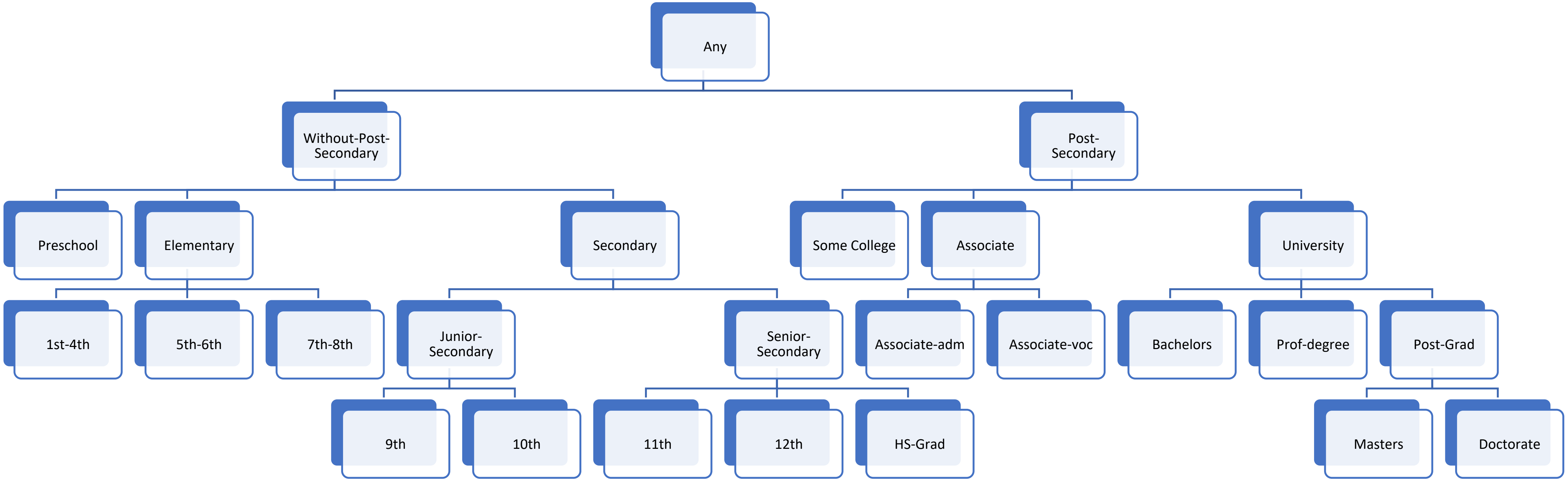


Pre-Processing

- Non QIDs are removed from the dataset
- QIDs and distinct values of SAs are grouped together and count calculated

Education	Gender	City	Income	Count
12^{th}	Female	Orleans	<=50k	3
Bachelors	Female	Gloucester	>50k	4
Doctorate	Female	Gloucester	>50k	1
Bachelors	Female	Nepean	>50k	4
Associate	Male	Kanata	<=50k	4
11^{th}	Male	Barrhaven	<=50k	2
Masters	Female	Perth	>50k	3

Pre-Processing – Building Path Maps



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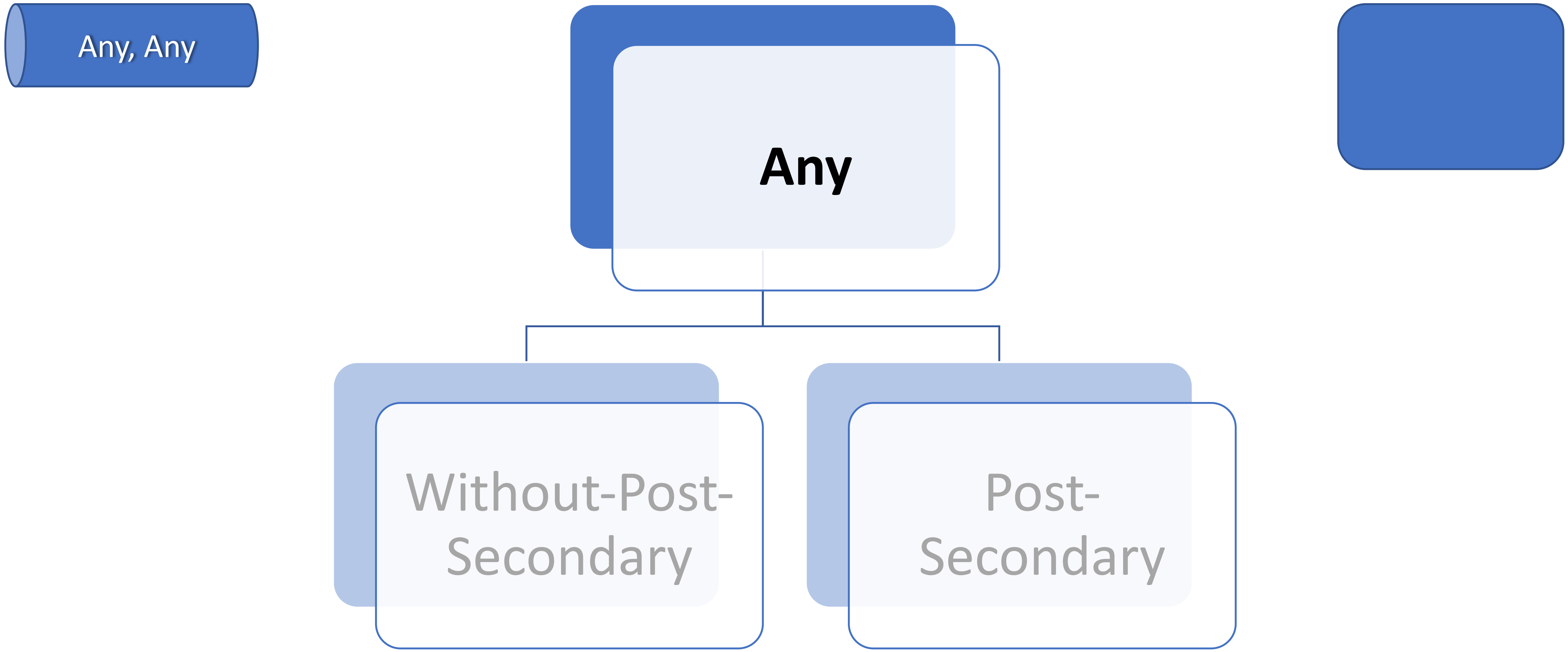

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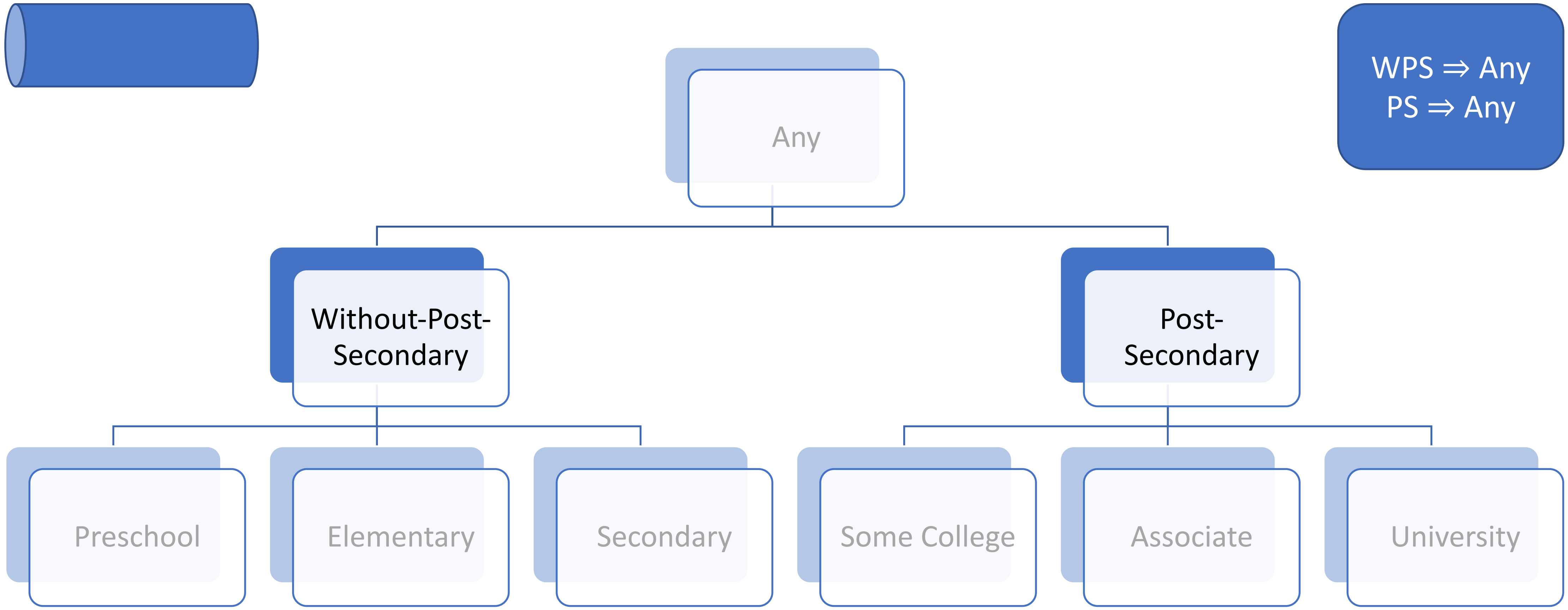

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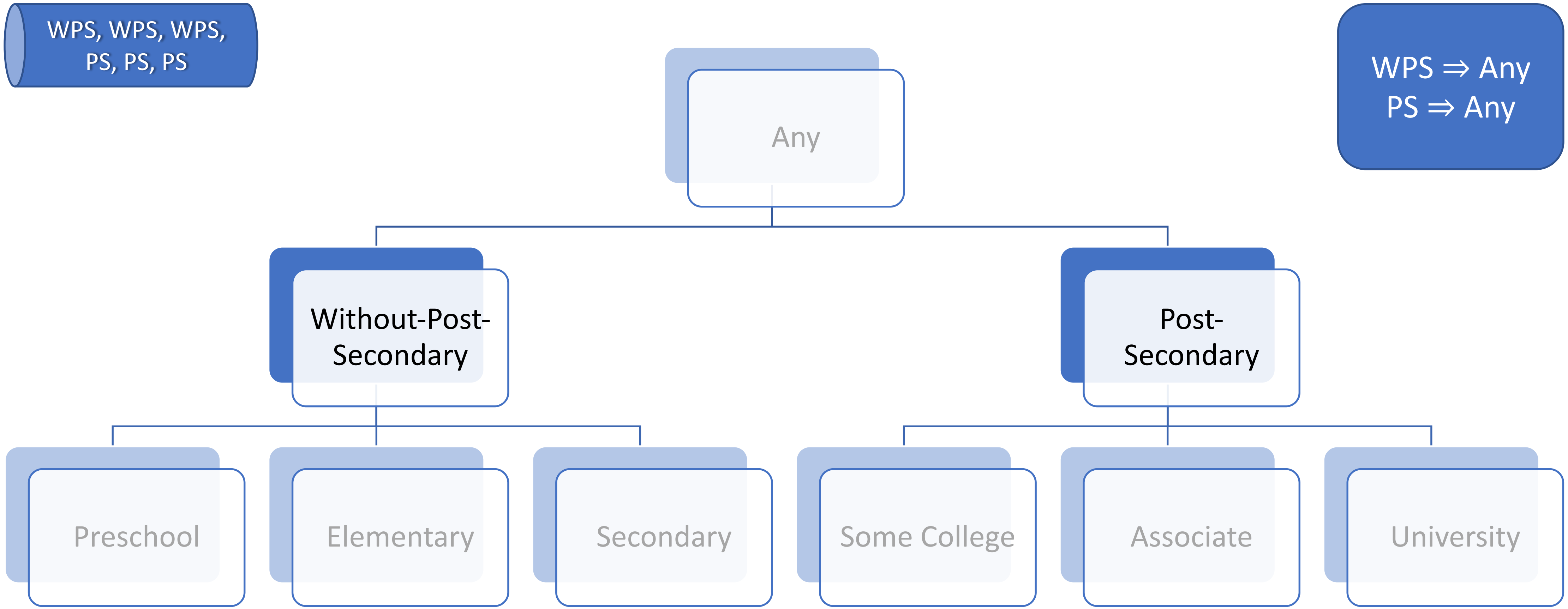
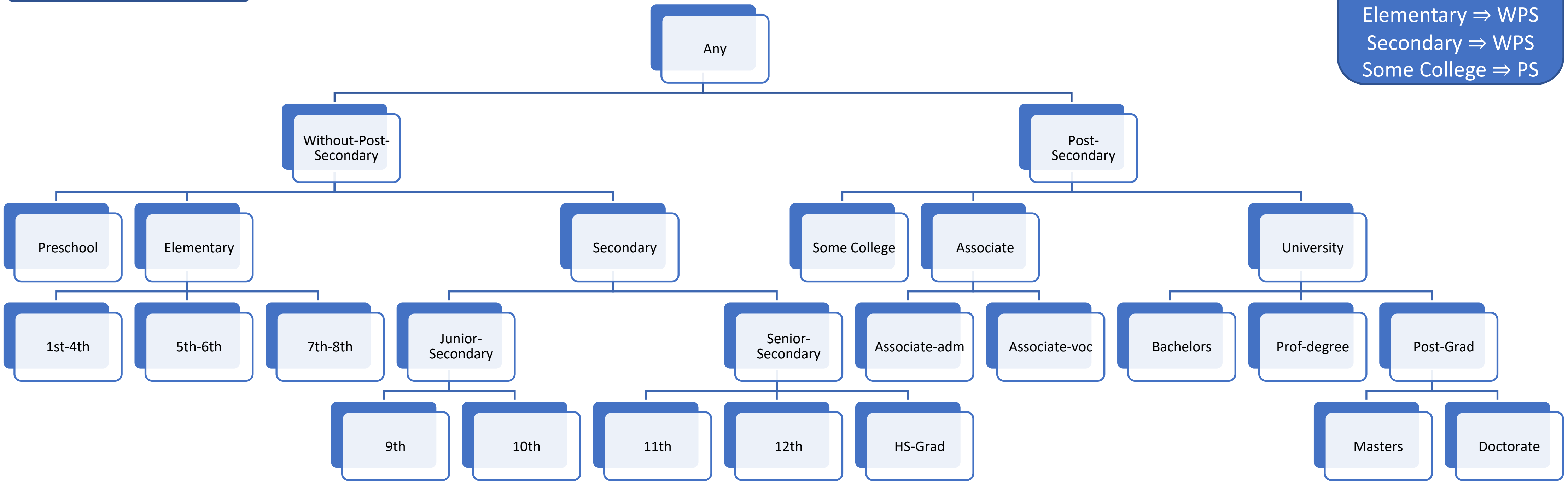


Pre-Processing – Building Path Maps

WPS ⇒ Any
PS ⇒ Any
Preschool ⇒ WPS
Elementary ⇒ WPS
Secondary ⇒ WPS
Some College ⇒ PS



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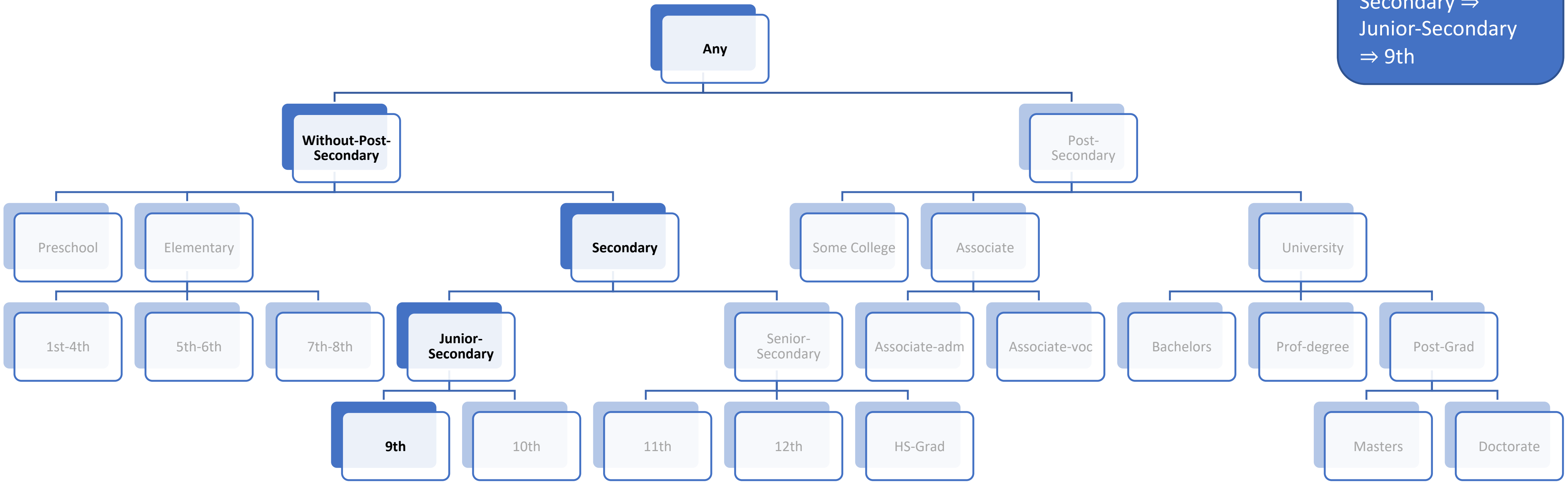


9th:
Any ⇒ WPS ⇒ Secondary ⇒ Junior-Secondary ⇒ 9th

Step 1 - Generalization

- Generalize all QIDs to the root of the anonymization level.

Education	Gender	City	Income	Count	Aggregate
Any	Any	Any	<=50k	3	
Any	Any	Any	>50k	4	
Any	Any	Any	>50k	1	
Any	Any	Any	>50k	4	
Any	Any	Any	<=50k	4	
Any	Any	Any	<=50k	2	
Any	Any	Any	>50k	3	

Step 1 – Pick Anonymization Level

- Generalize all QIDs to the root of the anonymization level
- For every anonymization level, calculate information gain and privacy loss

Education	Gender	City	Income	Count	Aggregate
WPS	Any	Any	<=50k	3	7
WPS	Any	Any	>50k	4	
PS	Any	Any	>50k	**1**	**14**
PS	Any	Any	>50k	**4**	
PS	Any	Any	<=50k	**4**	
PS	Any	Any	<=50k	**2**	
PS	Any	Any	>50k	**3**	

Step 2 – Pick Anonymization Level

- Generalize all QIDs to the root of the anonymization level
- For every anonymization level, calculate information gain and privacy loss

Education	Gender	City	Income	Count	Aggregate
Any	Any	East	<=50k	3	8
Any	Any	East	>50k	4	
Any	Any	East	>50k	1	
Any	Any	**West**	>50k	**4**	**13**
Any	Any	**West**	<=50k	**4**	
Any	Any	**West**	<=50k	**2**	
Any	Any	**West**	>50k	**3**	

Step 3 – Score Best Option

- Anonymization level values are aggregated for every partition
- Aggregations are merged into one-row table with the totals

Education	Gender	City	Income	Count	Edu_Agg	City_Agg
WPS	Any	East	<=50k	3	7	8
WPS	Any	East	>50k	4		
PS	Any	East	>50k	1	14	
PS	Any	West	>50k	4		13
PS	Any	West	<=50k	4		
PS	Any	West	<=50k	2		
PS	Any	West	>50k	3		

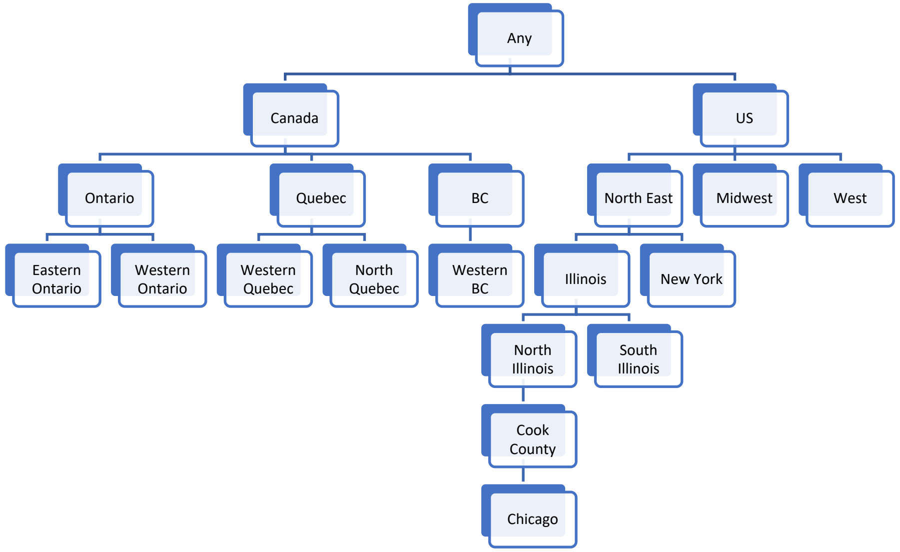
<u>Best Score: City</u>

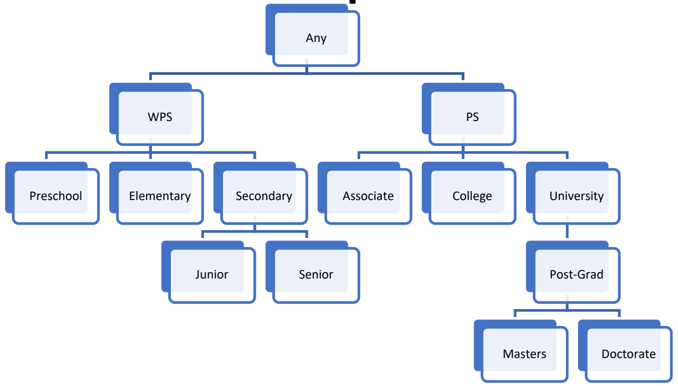
Orleans: Any ⇒ Canada ⇒ Ontario ⇒ Eastern Ontario ⇒ Greater Ottawa Area ⇒ Ottawa East ⇒ Orleans

Chicago: Any ⇒ United States ⇒ North East ⇒ Illinois ⇒ North Illinois ⇒ Cook County ⇒ Chicago

Step 3 – Score Best Option

- Anonymization level values are aggregated for every partition
- Aggregations are merged into one-row table with the totals
- Final individual scores stored in a map, best option chosen, anonymization levels updated, k calculated, reiterate if required.





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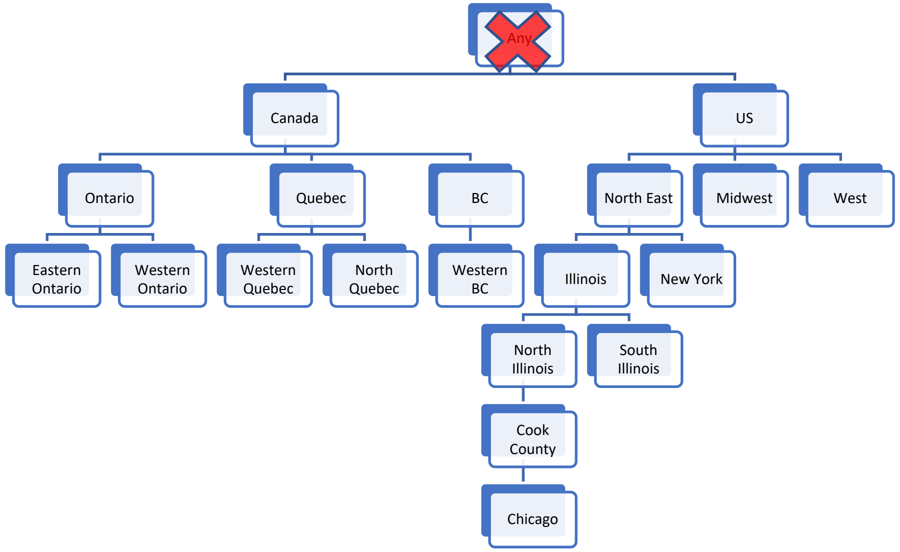

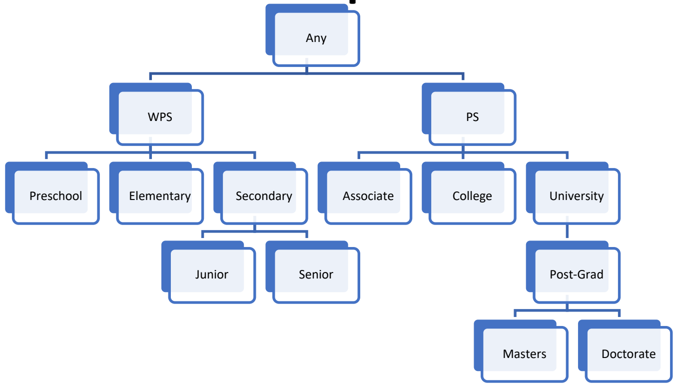

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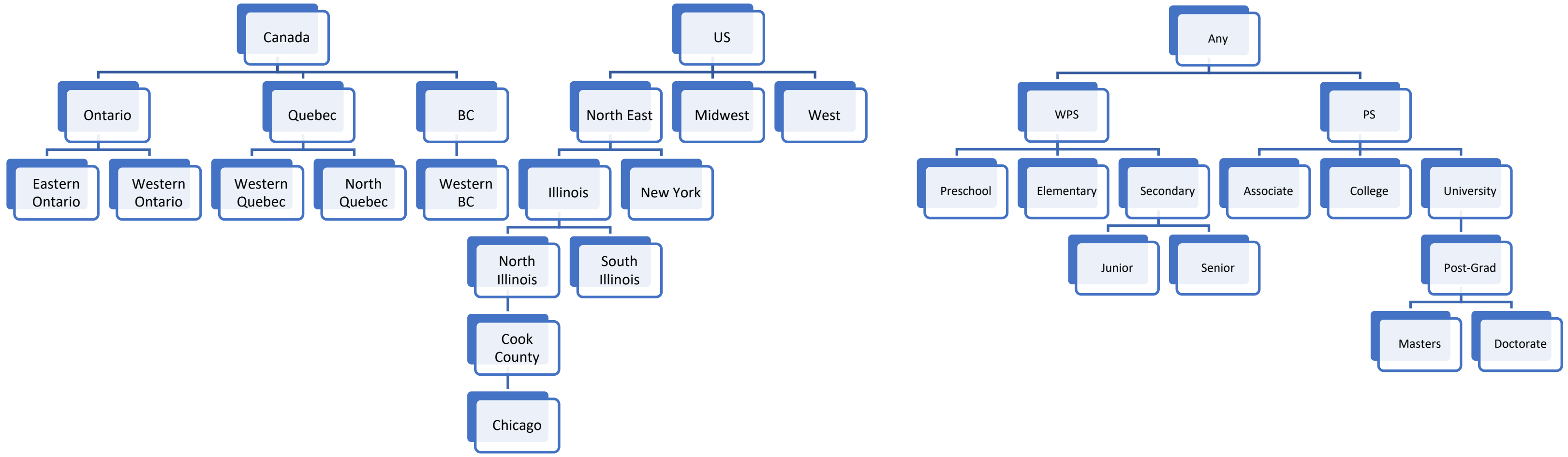

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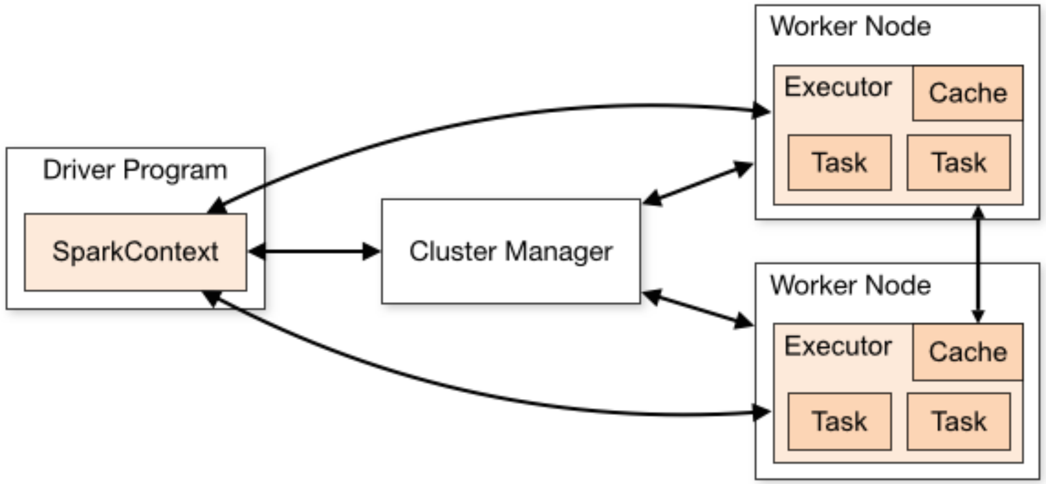
Enhancing performance

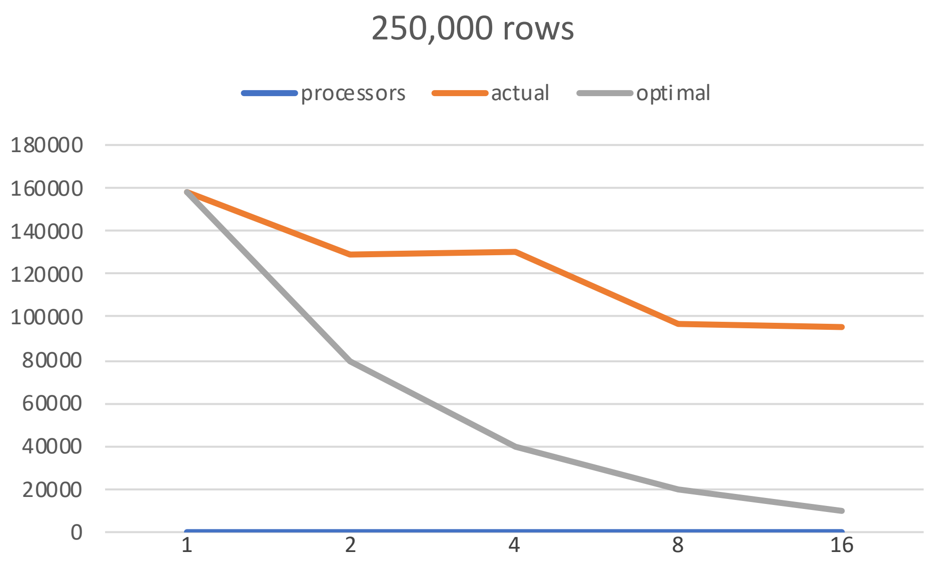
- Apache Spark is a fast and general-purpose cluster computing system
- Minimize aggregations to maximum 1 per iteration
- Maximum partitions set to p where p is number of processors
- Prefer tail iteration over looping for code that runs on Spark

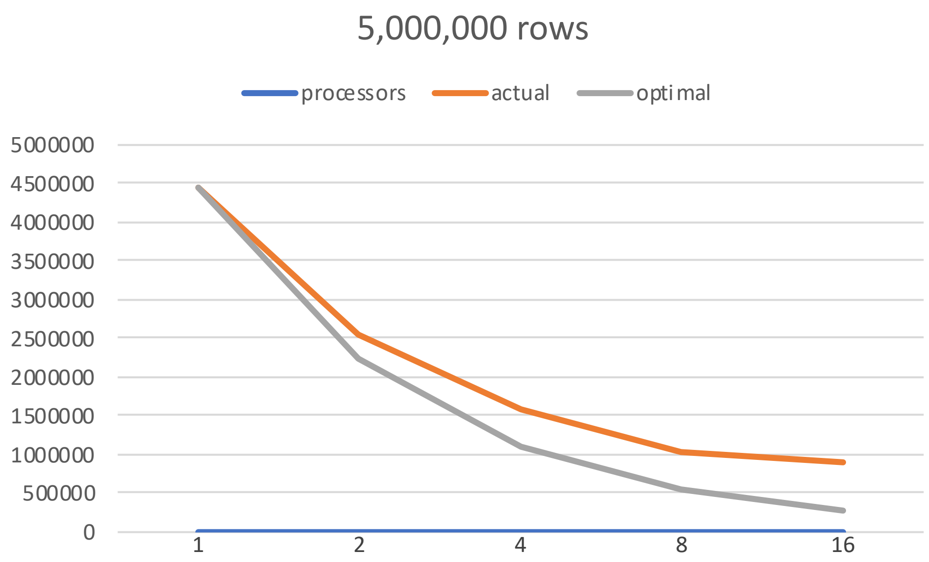


Test Environment

- OpenStack configuration with 16 GB disk space, 4 GB RAM, 4 vCPU per node
- Ran tests for k=100 over 1, 2, 4, 8 and 16 nodes
- Dataset sizes: 250,000 rows, 5 million rows and 10 million rows
- Spark and Java installed on every node
- Public/private keys added to every node and hosts file updated

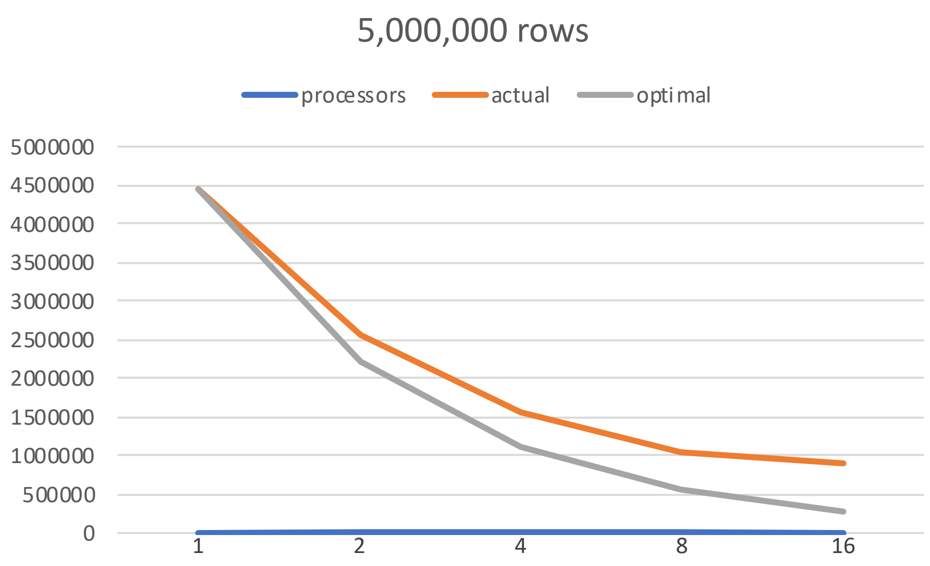
Test Results





Comparison with Original Paper

My Implementation



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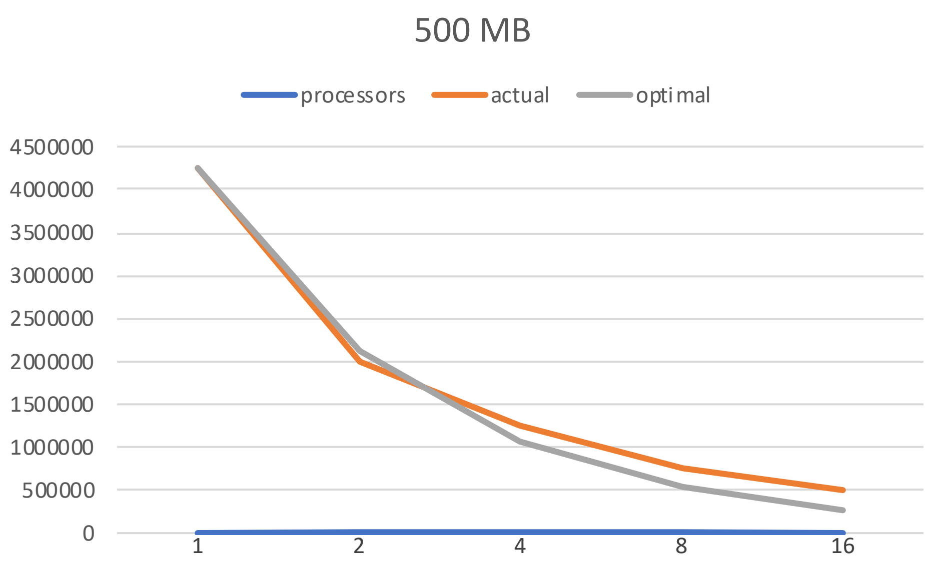

Questions

- What’s the difference between Quasi-Identifiers and Sensitive Attributes?
- What change contributed the most to performance improvement?
- What should be the number of partitions compared to number of processors?