CAPSTONE PROJECT

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Introduction

THE DATA SCIENCE PROFESSIONAL CERTIFICATE CULMINATES WITH A CAPSTONE PROJECT WHERE PARTICIPANTS APPLY ALL THE SKILLS AND KNOWLEDGE GAINED FROM THE NINE COURSES. THE FINAL PROBLEM AND ANALYSIS ARE OPEN-ENDED, ALLOWING LEARNERS TO EXPLORE AND DECIDE ON THEIR OWN. UTILIZING FOURSQUARE'S LOCATION DATA THROUGH ITS API, PARTICIPANTS CAN CREATE A UNIQUE PROBLEM TO SOLVE OR COMPARE CITIES AND NEIGHBORHOODS ACCORDING TO THEIR PREFERENCES.

Business Problem

IN THE DYNAMIC LANDSCAPE OF TECHNOLOGY AND EVOLVING INDUSTRIES, AI IS POISED TO PLAY A DOMINANT ROLE, RESHAPING THE WORLD AS WE KNOW IT. AMIDST THIS BACKDROP, THE QUESTION ARISES: WHICH OF THE TWO BUSIEST CITIES IN THE WORLD WOULD BE THE IDEAL CHOICE FOR STARTING AN AI BUSINESS? FACTORS SUCH AS PRICING, MULTICULTURALISM, LANGUAGE BARRIERS, AND MORE WILL SIGNIFICANTLY IMPACT THIS CRUCIAL DECISION-MAKING PROCESS..

Data

Paris-Dataset Shown

	Place Name	State	County	City	Latitude	Longitude
0	Paris 01 Louvre	Île-de-France	Paris	Paris	48.8592	2.3417
1	Paris 02 Bourse	Île-de-France	Paris	Paris	48.8655	2.3426
2	Paris 03 Temple	Île-de-France	Paris	Paris	48.8637	2.3615
3	Paris 04 Hôtel-de-Ville	Île-de-France	Paris	Paris	48.8601	2.3507
4	Paris 05 Panthéon	Île-de-France	Paris	Paris	48.8448	2.3471

Data

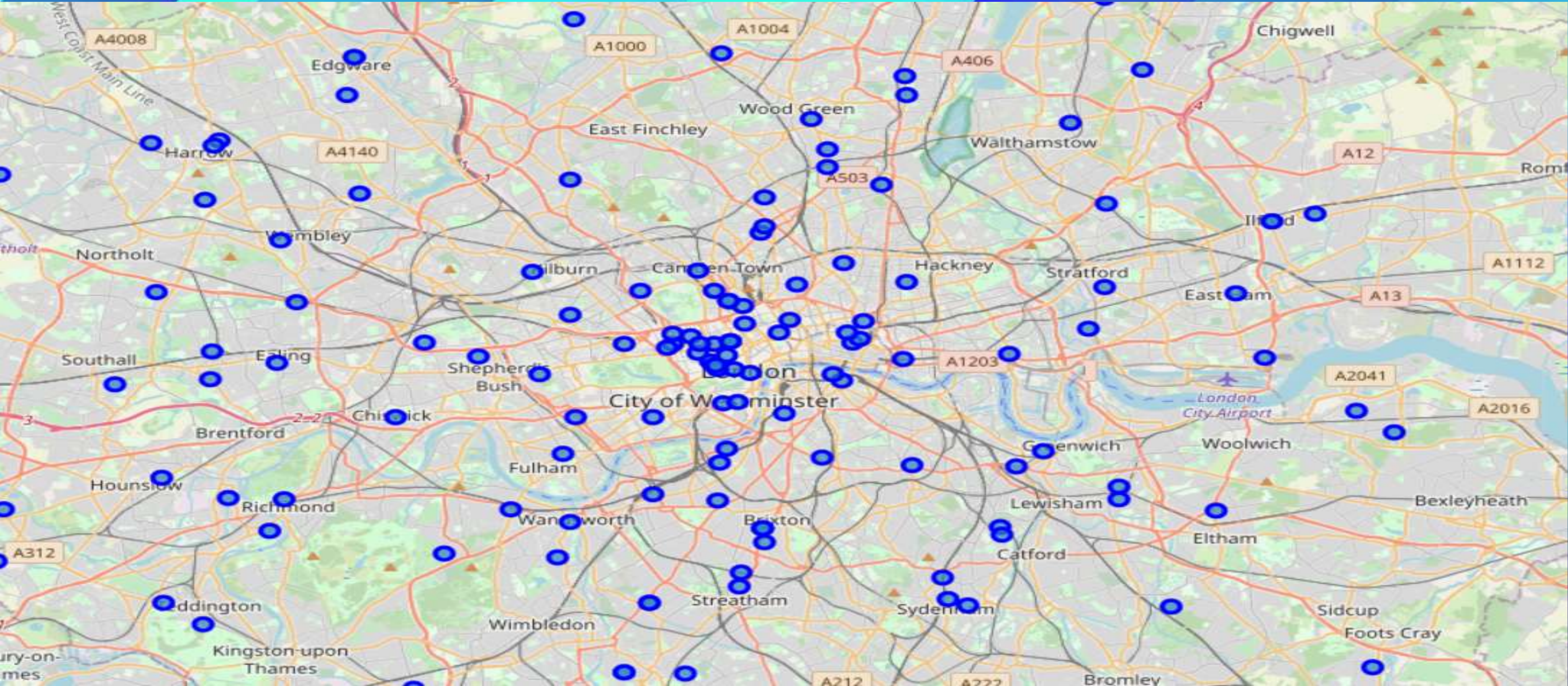
London- Dataset shown below

	Postcode	Country	County	District	Latitude	Longitude
0	BR1 1AA	England	Greater London	Bromley	51.401546	0.015415
1	BR1 1AB	England	Greater London	Bromley	51.406333	0.015208
2	BR1 1AD	England	Greater London	Bromley	51.400057	0.016715
3	BR1 1AE	England	Greater London	Bromley	51.404543	0.014195
4	BR1 1AF	England	Greater London	Bromley	51.401392	0.014948

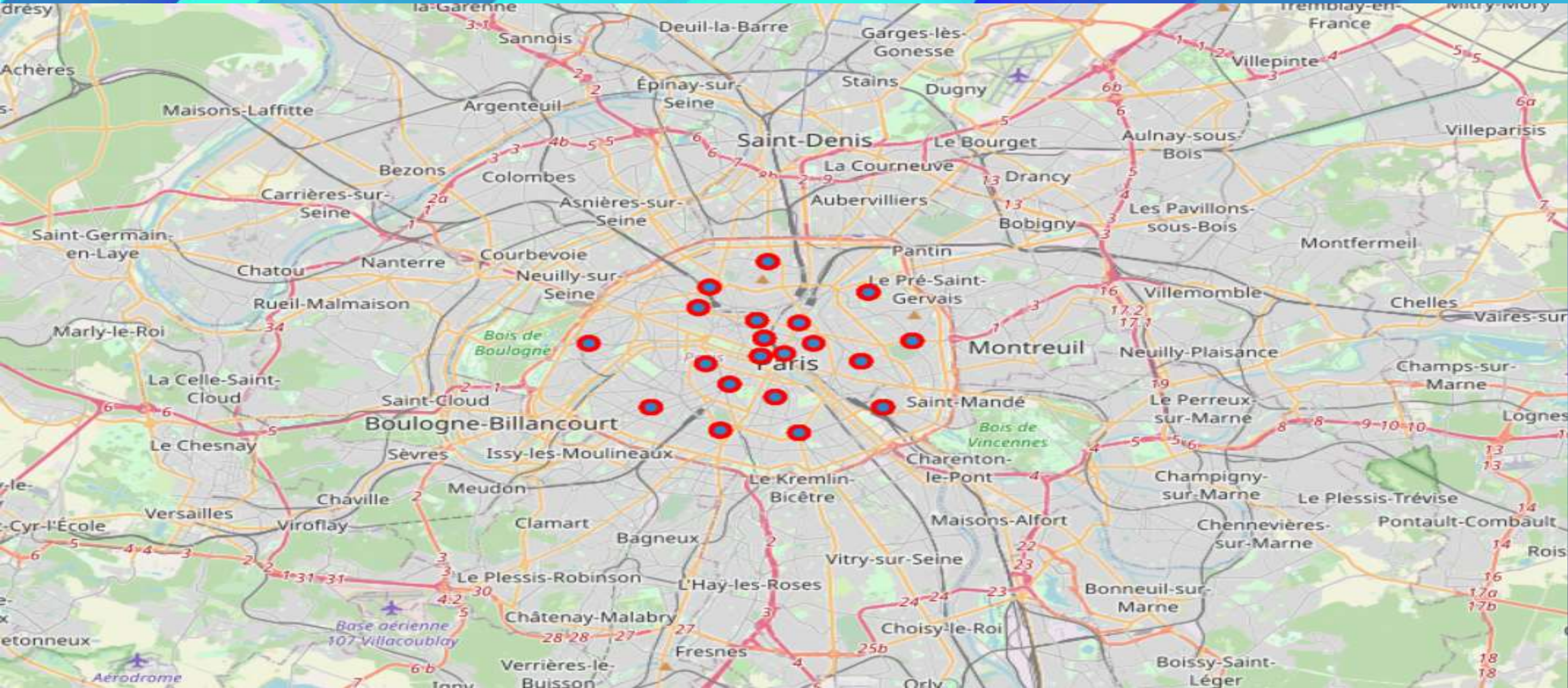
Methodology

EXTENSIVE RESEARCH HAS BEEN CONDUCTED ON THE DATASET, DELVING INTO A COMPREHENSIVE ANALYSIS OF VARIOUS FEATURES AND METHODOLOGIES TO ACHIEVE THE HIGHEST POSSIBLE MODEL ACCURACY. TO STREAMLINE THE DATA FRAME, CERTAIN FEATURES WERE REPLACED WITH MORE RELEVANT DATA THROUGH A REDUCTION PROCESS. SUBSEQUENTLY, CLUSTER ANALYSIS WAS PERFORMED TO IDENTIFY THE OPTIMAL CLUSTERS FOR BOTH PARIS AND LONDON. FURTHER COMPARISONS BETWEEN THE TWO CITIES WERE MADE USING CORRELATION AND VARIOUS VISUAL GRAPHS, PROVIDING VALUABLE INSIGHTS INTO THEIR SIMILARITIES AND DIFFERENCES.

Let’s see the Map of London



Let’s see the Map of Paris



➢ Venues

London-data displayed

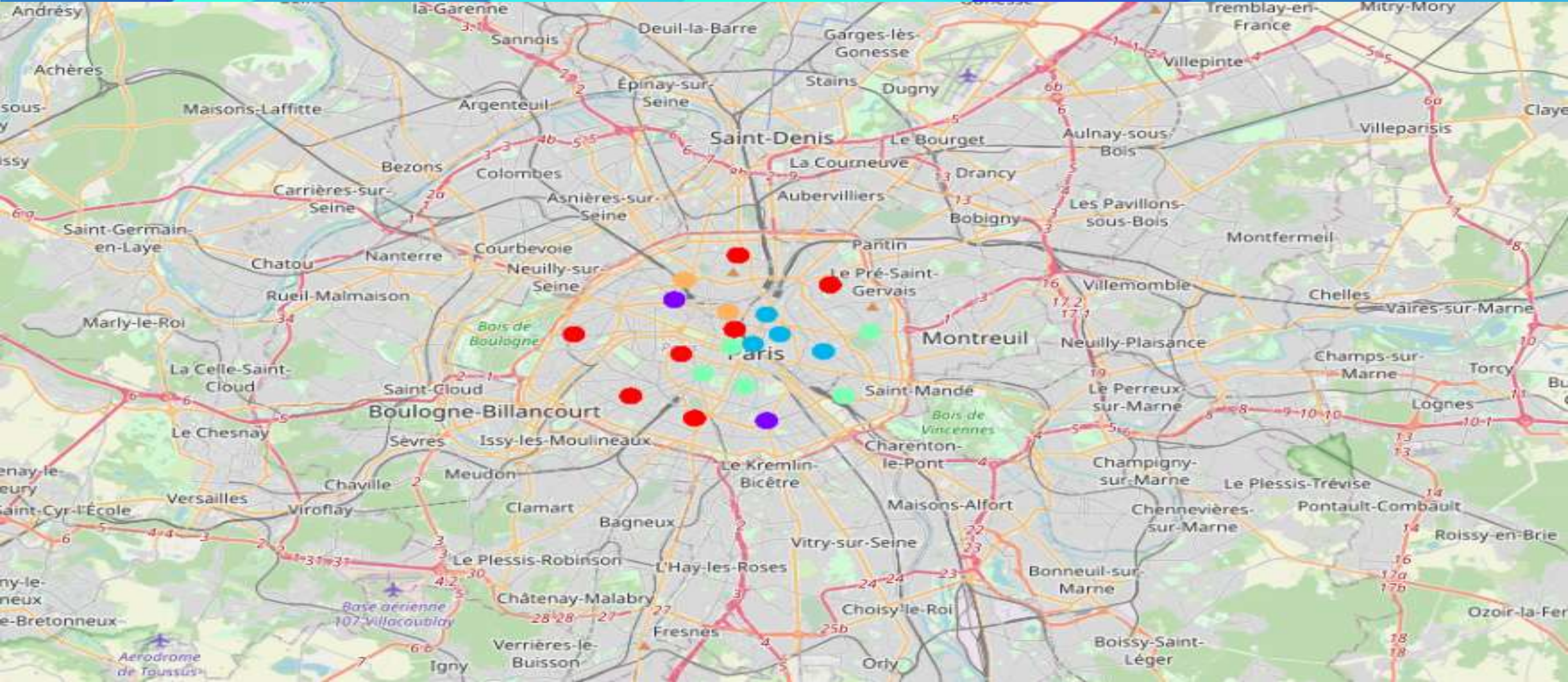
	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Barnet	Turkish Restaurant	Italian Restaurant	Sushi Restaurant	Grocery Store	Indian Restaurant	Bakery	Deli / Bodega	Portuguese Restaurant	Coffee Shop	Gym / Fitness Center
1	Brent	Pub	Coffee Shop	Park	Platform	Indian Restaurant	Eastern European Restaurant	Supermarket	Food Truck	Japanese Restaurant	Deli / Bodega
2	Bromley	Pizza Place	Supermarket	Coffee Shop	Grocery Store	Pub	Stationery Store	Indian Restaurant	Fish & Chips Shop	Pharmacy	Café
3	Camden	Japanese Restaurant	Pizza Place	Coffee Shop	Beer Bar	Italian Restaurant	Tapas Restaurant	Malay Restaurant	Market	Hotel	Mexican Restaurant
4	City of London	Boxing Gym	Hotel	Burrito Place	Steakhouse	Department Store	Pizza Place	Indie Movie Theater	Event Space	French Restaurant	Botanical Garden

Venues

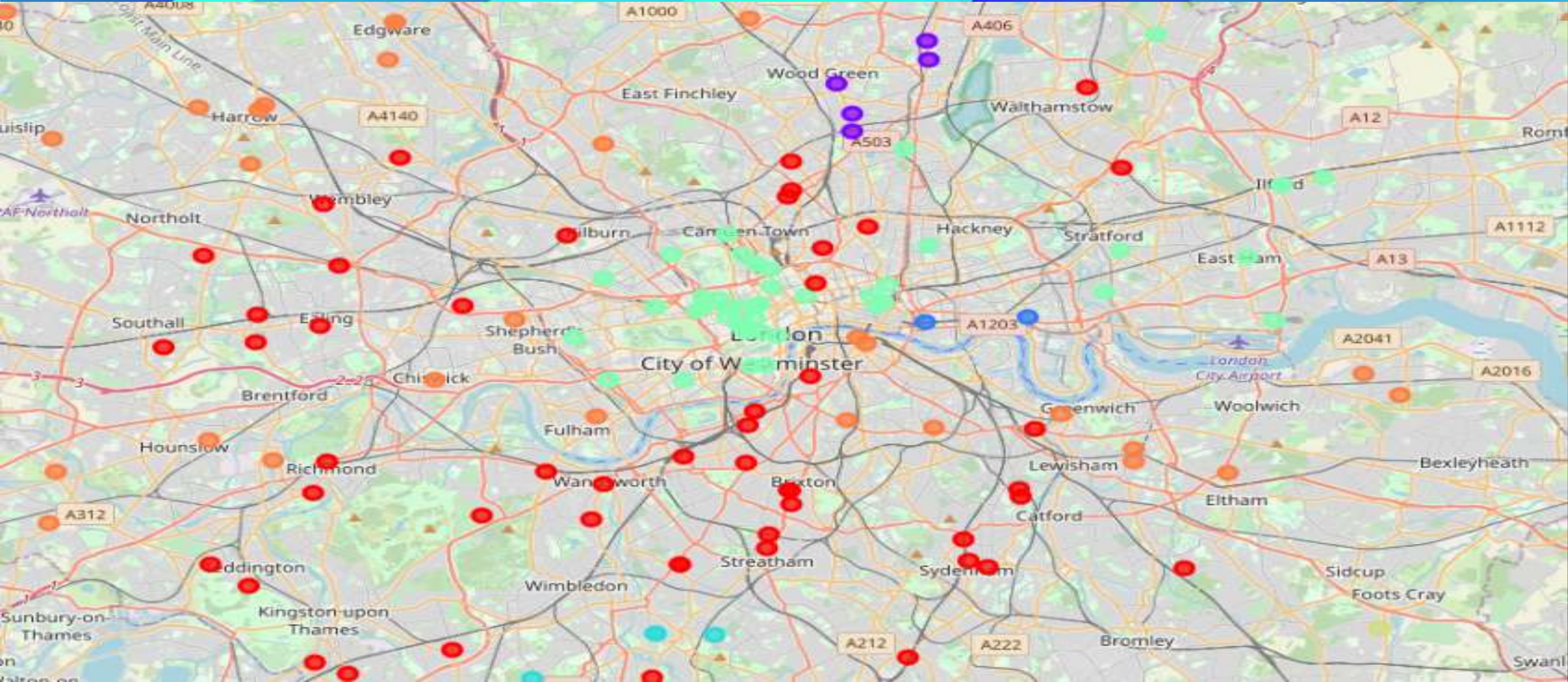
Data of Paris Displayed

	Cluster Labels	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	3	Paris 01 Louvre	Plaza	French Restaurant	Cocktail Bar	Church	Pedestrian Plaza	Chinese Restaurant	Park	Coffee Shop	Art Gallery	Garden
1	0	Paris 02 Bourse	French Restaurant	Plaza	Bakery	Ramen Restaurant	Restaurant	Souvlaki Shop	Perfume Shop	Bookstore	Farmers Market	Coffee Shop
2	2	Paris 03 Temple	Sandwich Place	Wine Bar	Park	Tea Room	Burger Joint	Restaurant	Cocktail Bar	Seafood Restaurant	Farmers Market	Wine Shop
3	2	Paris 04 Hôtel-de-Ville	Ice Cream Shop	Souvenir Shop	Art Gallery	Art Museum	Cocktail Bar	Fountain	Gourmet Shop	Lebanese Restaurant	Pub	Alsatian Restaurant
4	3	Paris 05 Panthéon	Plaza	French Restaurant	Bar	Korean Restaurant	Monument / Landmark	Science Museum	Ice Cream Shop	Bakery	Creperie	Grocery Store

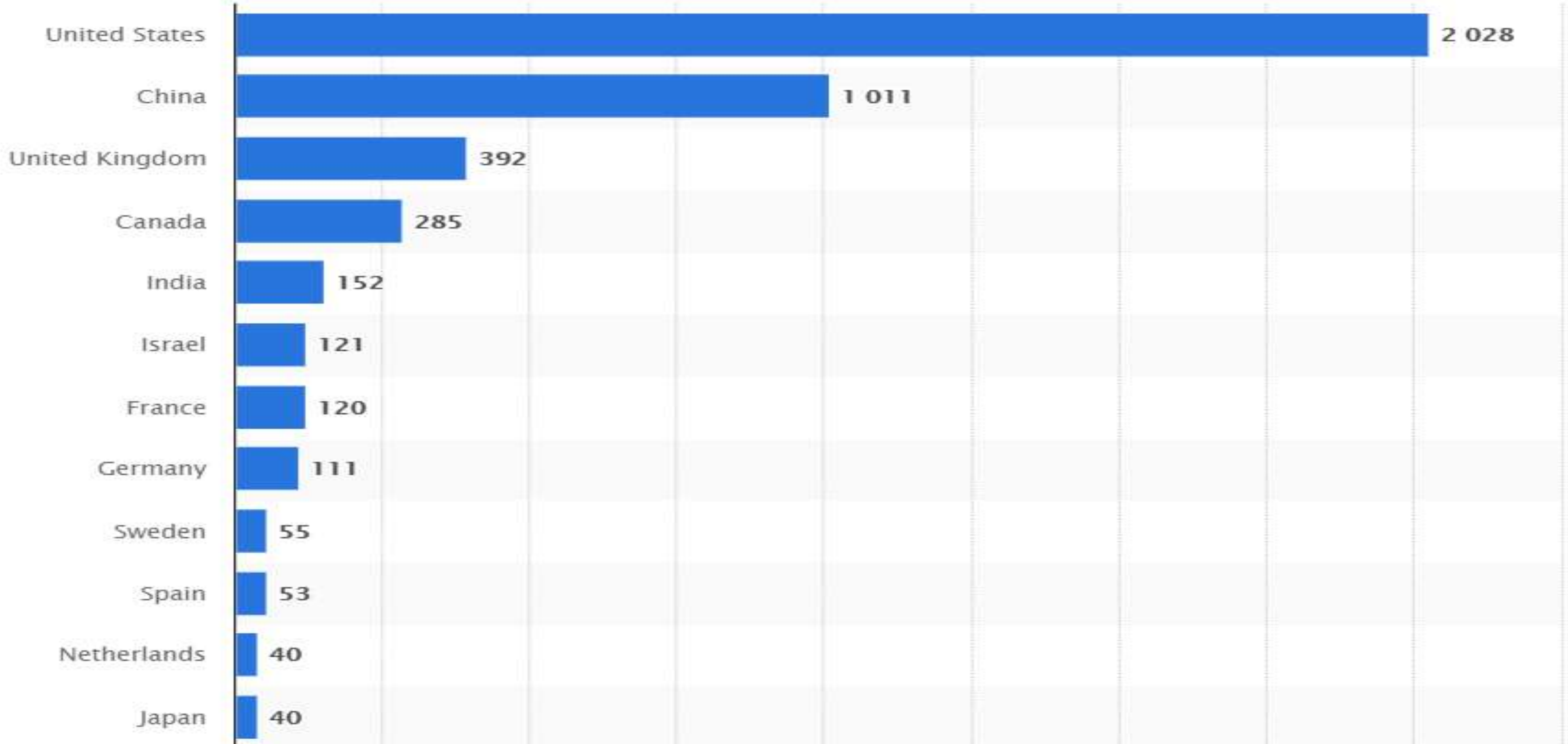
K Means Clustering Map - Paris



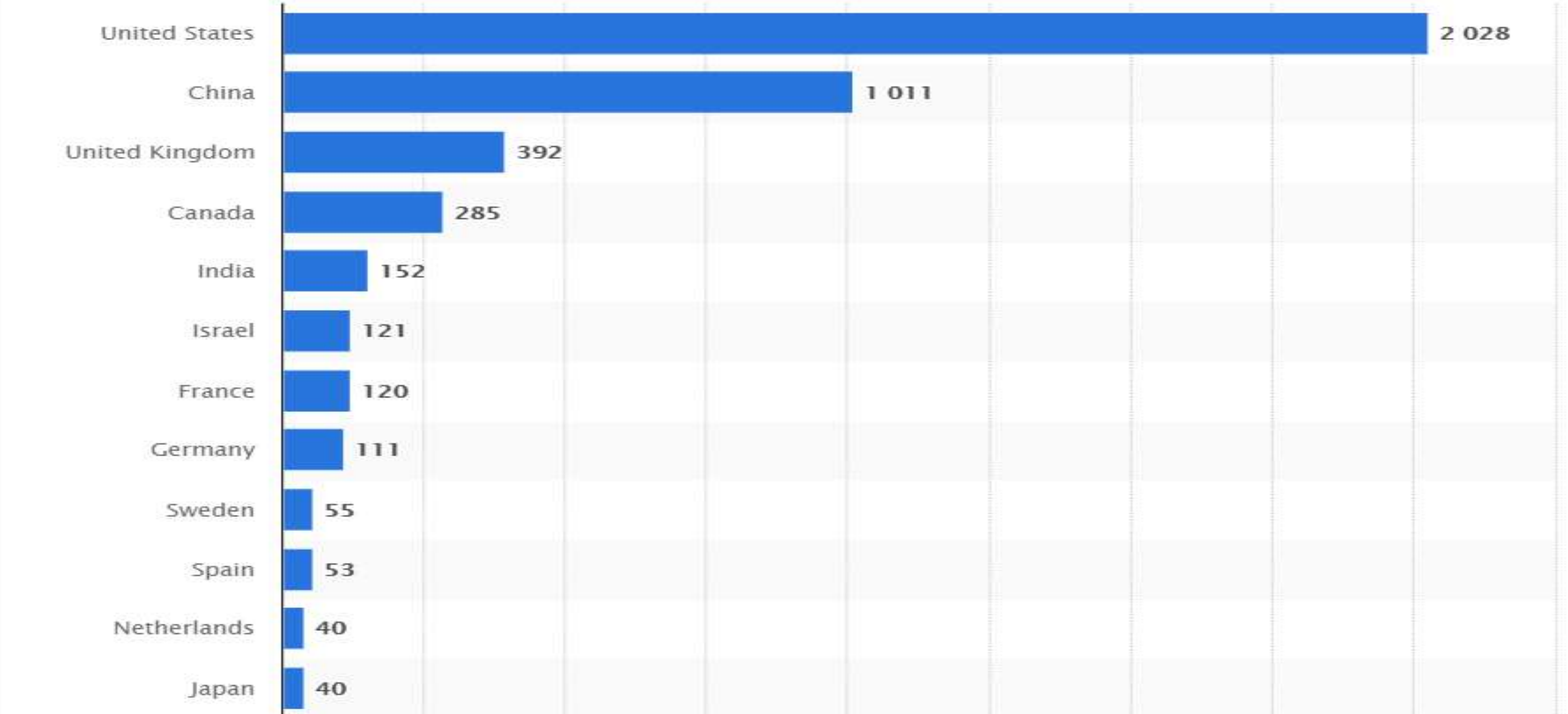
K Means Clustering Map - London



See the graph of Artificial Intelligence



Artificial Intelligence



Results and Discussion

SIMILARITIES:
BOTH PARIS AND LONDON STAND OUT AS MULTICULTURAL AND DIVERSE CITIES, EACH WITH ITS UNIQUE CULTURAL TAPESTRY AND HISTORICAL SIGNIFICANCE. A COMMON TREND THAT EMERGES IN BOTH CITIES IS THE PREVALENCE OF RESTAURANTS AS THE TOPMOST COMMON VENUE IN MANY RENOWNED NEIGHBORHOODS.

DIFFERENCES:
UPON EXAMINING THE CITY MAPS, A NOTICEABLE CONTRAST SURFACES BETWEEN PARIS AND LONDON IN TERMS OF THEIR SPATIAL LAYOUT. PARIS APPEARS MORE COMPACT, FACILITATING CONVENIENT AND UNHINDERED PEDESTRIAN MOVEMENT WITHOUT EXCESSIVE RELIANCE ON TRANSPORTATION. ON THE OTHER HAND, LONDON EXHIBITS A MORE SPRAWLING URBAN LANDSCAPE.

Results and Discussion

ARTIFICIAL INTELLIGENCE

Tech hub							
	2013	2014	2015	2016	2017	2018	Total
San Francisco	£418.08m	£1.83bn	£2.07bn	£4.46bn	£806.03m	£1.84bn	**£11.44bn**
Beijing	£11.66m	£53.75m	£197.32m	£599.56m	£1.63bn	£1.07bn	**£3.57bn**
New York	£79.43m	£165.62m	£318.28m	£667.51m	£593.85m	£1.2bn	**£3.05bn**
Shanghai	—	£1.28m	£400.93m	£16.10m	£1.6bn	£453.61	**£2.47bn**
London	£9.85m	£41.16m	£67.04m	£166.04m	£228.97m	£326.90m	**£839.96m**
Paris	£1.92m	£2.83m	£23.49m	£61.49m	£99.45m	£132.40m	**£321.48m**
Singapore	£13.76m	£13.89m	£70.92m	£55.59m	£106.52m	£30.81m	**£291.49m**
Tel Aviv	£14.80m	£17.12m	£5.49m	£39.04m	£112.25m	£89.01m	**£277.71m**
Berlin	£7.09m	£0.79m	£23.60m	£17.41m	£17.67m	£21.06m	**£87.62m**
Bangalore	£1.31m	£32.29m	£45.75m	£1.96m	£36.71m	£18.65m	**£136.67m**

Results and Discussion

ARTIFICIAL INTELLIGENCE

THE DATASET FOR THE ARTIFICIAL INTELLIGENCE WASN'T READILY AVAILABLE AND SO HAD TO BE SCRAPPED FROM MULTIPLE SOURCES WHICH OFTEN LEADS TO INCONSISTENCY HAPPENING AS WELL AS ERRORS.

THE DISTRICTS HAVE TOO COMPLEX GEOMETRY WHICH WOULD BRING AN ERROR IN OUR ANALYSIS IF THE VENUES ARE TOO CLOSE TO EACH OTHER.

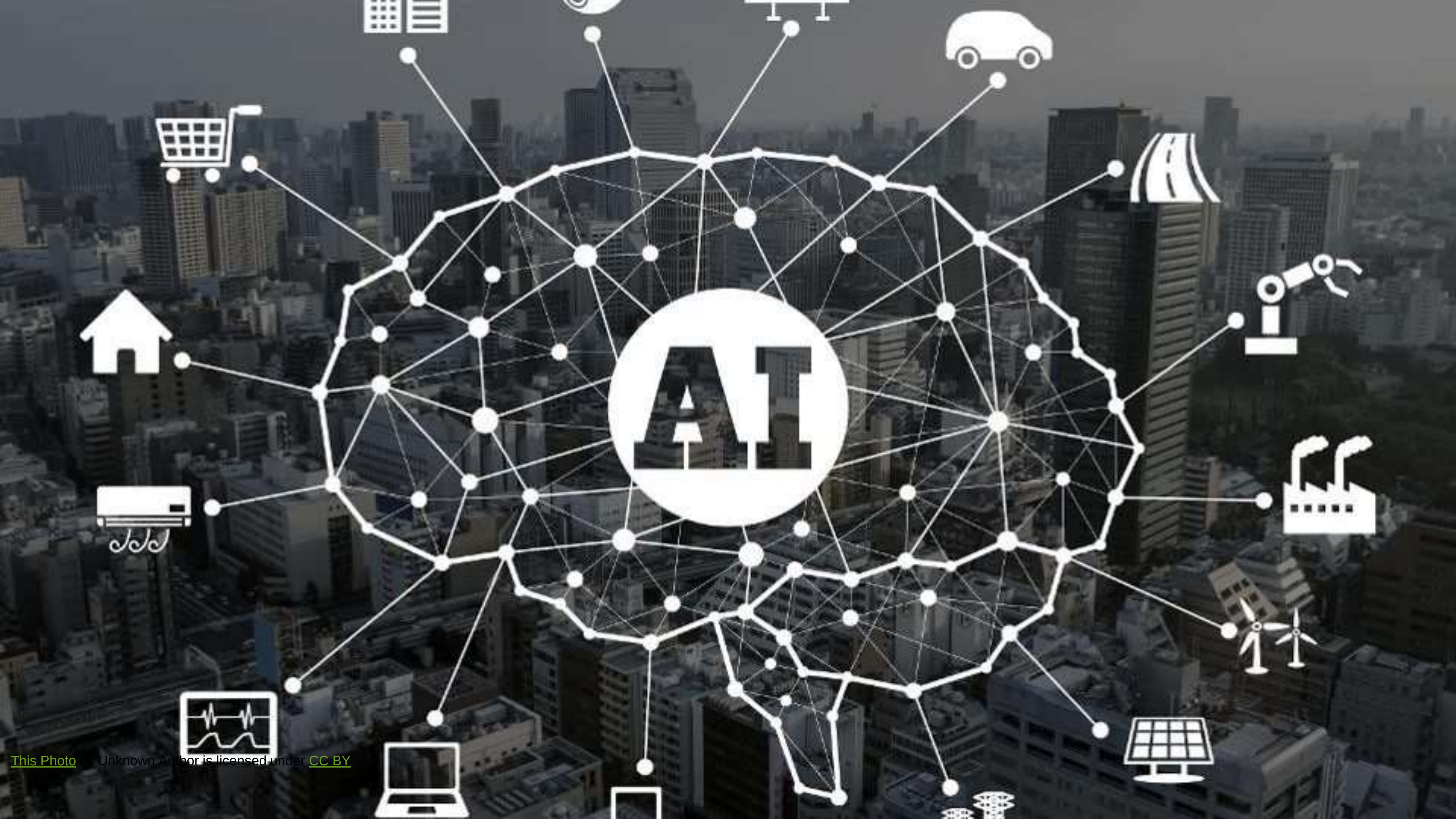
THE DATA OBTAINED THROUGH THE API CALLS WOULD RETURN DIFFERENT RESULTS EACH TIME ITS CALLED. MULTIPLE TRIALS AND ERROR RUNS ARE REQUIRED TO GET THE DESIRED RESULT.

Conclusion

ARTIFICIAL INTELLIGENCE (AI) HAS EMERGED AS A THRIVING AND HIGHLY SOUGHT-AFTER FIELD, ATTRACTING INCREASED INVESTMENTS FROM INDIVIDUALS AND COMPANIES ALIKE, PROMPTING THEM TO AUTOMATE THEIR OPERATIONS. BOTH CITIES PRESENT A PLETHORA OF OPPORTUNITIES FOR THOSE INTERESTED IN INVESTING IN AI OR ESTABLISHING THEIR AI-DRIVEN ENTERPRISES, AS WE HAVE EXPLORED THROUGH VARIOUS FACTORS. FURTHERMORE, THE QUEST FOR A SUPERIOR MODEL LED TO THE EXPLORATION OF ALTERNATIVE METHODS AND ROBUST MACHINE LEARNING ALGORITHMS LIKE KD TREE, WHICH SIGNIFICANTLY ENHANCE RUNTIME EFFICIENCY. ALTHOUGH CLUSTERING PROVED VALUABLE IN IDENTIFYING OPTIMAL VENUES AND AREAS, IT'S CRUCIAL TO ACKNOWLEDGE THAT CORRELATION DOES NOT IMPLY CAUSATION. CONSEQUENTLY, ANY CONCLUSIONS DRAWN FROM THIS ANALYSIS REMAIN SUBJECT TO CHANGE BASED ON ADDITIONAL TRENDS, DIVERSE OPINIONS, AND ALTERNATIVE DATASETS.

APPENDIX

BY PRACTISING DATA SCIENCE COURSE LAB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