CAPSTONE PROJECT – WHERE TO MOVE DUE TO BREXIT?

IBM / COURSERA CERTIFICATION

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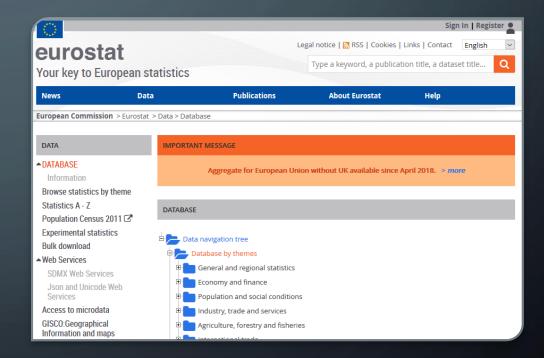
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BUSINESS PROBLEM

- This project deals with the following question:
 - Banks with their HQ in the UK (especially London) consider moving their HQ to cities which belong to EU countries. This is due to the Brexit, which will implement some substantial hurdles for banks to make business in the EU market, if their HQ is located in the UK.
 - The question now is: "which EU city, which has a relevant stock exchange located in its city area, is similar to London?"
 - The target audience consists of decision makers at the banks.

DATA

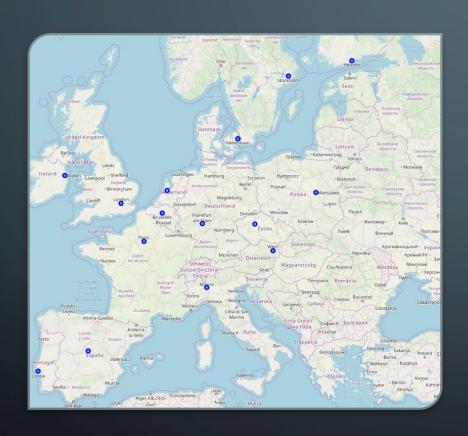
- The data used for this investigation was retrieved from the eurostat database, which offers publicly available data on various topics related to the EU (https://ec.europa.eu/eurostat/data/d atabase).
- The following parameters / cities were identified to be relevant for the project scope



DATA - PARAMETERS

- The percentage of country inhabitants with an education level of 5-8 acc. the International Standard Classification of Education (ISCED)(2018)
- The labor costs in the respective country [€] (2018)
- The average monthly rent in the candidate city [€/m^2] (2018)
- Consumer prices acc. to the Harmonized Index of Consumer Prices (HICP) (2018)
- Crime rate / 100'000 inhabitants for the respective country
- The number of universities in the city area
- The difference in time zones compared to London
- The life satisfaction index (2018) for the respective country
- The number of active companies for the respective country (2017)

DATA — EVALUATED CITIES



- Northwest Europe:
 - Dublin, Ireland
- Southwest Europe :
 - Madrid, Spain / Lisbon, Portugal
- Northeast Europe :
 - Stockholm, Sweden / Helsinki, Finland / Warsaw, Poland
- Central Europe:
 - Frankfurt, Germany / Paris, France / Brussels, Belgium / Amsterdam, Netherlands / Copenhagen, Denmark / Vienna, Austria / Prague, Czech Republic
- South Europe:
 - Milan, Italy

METHODOLOGY

- In this project we will try to find an alternative city, to which banks with their current HQ in London / UK can move to, in order to avoid negative consequences due to the upcoming Brexit. To do so, we followed the steps below:
- 1. We first imported a prepared data set through the cloning of my git repository, and transformed it into a pandas DataFrame
- 2. We created a second DataFrame, and store the geographical coordinates of the evaluated cities in it
- 3. A first map is created, to visualize the geographical locations of the cities
- 4. 2 different clustering algorithms are tested on the first Dataframe: KMeans & DBScan
- 5. The results of the 2 cluster analyses are shown on separate maps, in order to make it easier to identify the alternative candidates

	<u>-</u>		
0	Paris, France	48.856610	2.351499
0	Warsaw, Poland	52.233717	21.071411
0	Madrid, Spain	40.416705	-3.703582
0	Lisbon, Portugal	38.707751	-9.136592
0	Stockholm, Sweden	59.325117	18.071093
0	Helsinki, Finland	60.167409	24.942568
0	Milan, Italy	45.486800	9.190500
0	Brussels, Belgium	50.843671	4.367437
0	Amsterdam Netherlands	52 374540	4.897978

onLevel	LaborCost	A∨MonthlyRent	HICP	Crimes	NoUniversities	DiffTimeZones	Life SatisfactionIndex
.948718	0.517964	0.795322	0.904255	1.000000	1.000000	0.0	0.642857
.000000	0.658683	0.888304	0.000000	0.102203	0.148148	0.0	1.000000
.346154	0.733533	0.260819	0.567376	0.167737	0.037037	0.5	0.500000
.670940	0.769461	1.000000	0.496454	0.032920	0.925926	0.5	0.428571
.431624	0.000000	0.155556	0.319149	0.000000	0.555556	0.5	0.785714
.722222	0.338323	0.304094	0.471631	0.033625	0.037037	0.5	0.428571
.230769	0.122754	0.000000	0.460993	0.002395	0.888889	0.0	0.000000
.854701	0.793413	0.004678	0.765957	0.193409	0.222222	0.5	0.785714
.863248	0.703593	0.483626	0.287234	0.052930	0.111111	1.0	1.000000
.000000	0.541916	0.087719	0.301418	0.082759	0.037037	0.5	0.285714
.807692	0.886228	0.070175	1.000000	0.600960	0.407407	0.5	0.642857
.679487	0.772455	0.713450	0.393617	0.041654	0.037037	0.5	0.714286
.666667	1.000000	0.799415	0.177305	0.082741	0.000000	0.5	0.785714
.555556	0.715569	0.177193	0.817376	0.057598	0.518519	0.5	0.928571
.196581	0.074850	0.154971	0.762411	0.028409	0.851852	0.5	0.500000

ANALYSIS

REVIEW OF DATAFRAMES TO ENSURE DATA READINESS

Hordaland Oslo Tallinn Stockholm Eesti Vidceme 05/10cm Latvija Danmark United Kingdom København Lietuva Belfast Gdański Isle of Man. Гродно Беларусь Sheffield Bydgoszcz Szczecin Białystok Englard Birmincham Lublin Deutschland Луцык Wrocław Dresden Frankfurt Bruxelles Kraków Brussel Житомир : Guernsey Česko Nürnberg Львів Вінниця Luxembaura Boden-Slovensko Württemberg Кропи Rennes Centre-Österreich Nantes Schweiz/ Magyarország Cluj-Napoca Moldov Suisse/Svizzera/ Graz Svizra Slovenija România Ahone-Venezia Београд Aquitaine Bucuresti Cralova Bologna Hrvatska Genova Sarajevo Србија Monaco Oviedo / Constanta Occitanie Città di San Marino Vitoria-Gasteiz Marseille Erna Gora София В България Црна Гора Andorra Roma o Italia Castilla: la Vella Aragón Shqipëria Tekirdağ Napoli Θεσοαλονίκη Palma Portugali Balıkesir Li: boa Ελλάδα Palermo-Nurcia Sevilla . Andol icio Constantine Alger AX.510

ANALYSIS

- KMeans algorithm
- N° of clusters tested: 2-9
- Best cluster range from 3-5
- Below: no similar city
- Above: too many candidates

Enroyar Oppland Hedmark) Tallinn Stockholm Eesti. Пековская область. Latvija United Kingdom København Витебская Lietuva. Калининград Gdańsk Беларусь Groningen Bydgoszcz Szczecin Białystok England Poznań Birmingham verland) Magdeburg Lublin Deutschland Луцьк Dresden Wrocław Frankfurt Kraków Brussel Житомир» Nürnberg Львів Вінниця Luxembourg Slovensko Rennes Чернівці München Крив Centre Osterreich Nantes Schweiz/ Magyarország Cluj-Napoca Moldova Suisse/Svizzera/* Graz Одеса Slovenija Timișoara România Venezia Београд Craiova București Aquitaine Bologna Hrvatska Genova Sarajevo Србија Monaco Constanta Occitanie Città di San Marino Vitoria-Gasteiz Marseille Crna Gora / София в България Црна Гора Andorra Roma o Italia y Leg 1 Porto Istanbul Shqipëria Tekirdağ Sakarya Napoli España Θεσσαλονίκη Palma Valencia Portugal Balikesir Lisboa Palermo Ελλάδα Sevilla 9 Andolucio Alger AX.5+O

ANALYSIS

- DBSCAN algorithm
- Minimum of 2 samples per cluster defined
- Best configuration found for epsilon = 0.8 1.2
- Below: too many candidates
- Above: no candidate

RESULTS, DISCUSSION & CONCLUSION

- The analysis shows that the only candidate city which can be considered similar enough is Paris, France.
- Using the KMeans algorithm, various groupings can be obtained, with only a small range of k clusters giving reasonable results. For only 2 clusters, the cities of Lisbon, Madrid, Paris, Frankfurt, Milan, Prague ad Warsaw are considered to be similar to London. As this result is not helping a decision, it is not used for the decision process. Within the range of 3-5 clusters, only Paris is considered to be an alternative to London. For a number of clusters higher than 5, there is no similar city in the evaluated candidate group. Therefore the only reasonable configuration to use for the decision process is with 3-5 clusters.
- For DBSCAN, the amount of minimum samples was set to 2 samples, as this would be enough to provide at least one candidate city which is similar to London. Therefore the other parameter changed was the epsilon parameter. Reducing this parameter from 2 to 0.1 in steps of 0.05, it becomes clear that values above 1.2 do not provide a similar city. Between 0.8 and 1.2, again Paris is the only city being considered an alternative to London. At 0.75, the next city added to the potential locations is Dublin. Below 0.75, further cities are added to this list, so that a reasonable recommendation cannot be given.
- Given the results discussed above, only 2 cities can be considered a realistic alternatives compared to the current location in London: Paris and Dublin. This recommendation can be used for a in detail review of locations, involving other factors which were not included in this investigation, e.g. taxes to pay, infrastructure etc.

