



# Capstone Project

BREXIT RELOCATION SCENARIO

# Business Problem

- ▶ Due to UK's vote to leave EU, trading conditions for financial services companies headquartered in UK will change for the worse
- ▶ Client's only European office is in London, despite considerable portfolio of assets deployed in the EU
- ▶ Companies already moved \$1tn+ of assets and resources from UK to EU since vote
- ▶ All this leads to one inevitable question: "Where do we move the London office to?"

# Business Problem

- ▶ Lack of other EU roots means client has free choice to move where it finds most desirable
- ▶ Through iteration of requirements, the question has evolved from:
- ▶ “Where do we move the London office?” to:
- ▶ “Given the top 50 most populous EU cities to choose from, compile a shortlist of cities to which a move makes sense economically and culturally”

# Analytic Approach

- ▶ It was decided that this list was to be compiled with the help of a clustering model
- ▶ The objective would then be to feed various economic and cultural variables to the model for all candidate cities + London, then extract the cluster London goes in as the presumed best fits
- ▶ Candidate cities were the top 50 most populous EU urban areas, minus any without an int'l airport or a stock exchange due to client requirements – this narrowed the list to 27

# Data Requirements

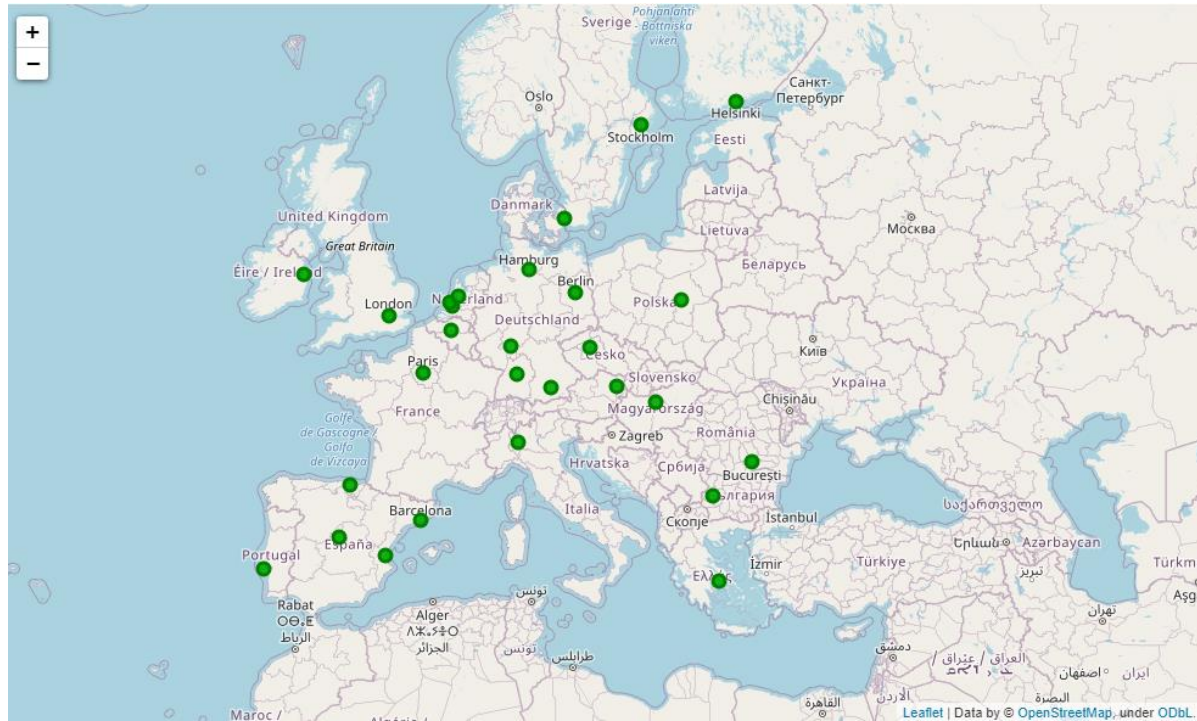
The following data was targeted for collection:

- ▶ Straight line distance to London
- ▶ Fact-sheet data (population and density)
- ▶ Percentage of English speakers, according to [an EU Commission report on second languages](#) - assumed 100% in Ireland as English is official language
- ▶ Average commercial rental cost, sourced mostly from [this Statista dataset](#)
- ▶ Average rental cost and income, sourced mostly from [this Kaggle dataset](#) (missing records searched individually at the source in Numbeo)
- ▶ [HDI of country](#)
- ▶ Venue data from Foursquare for the cultural fit requirement

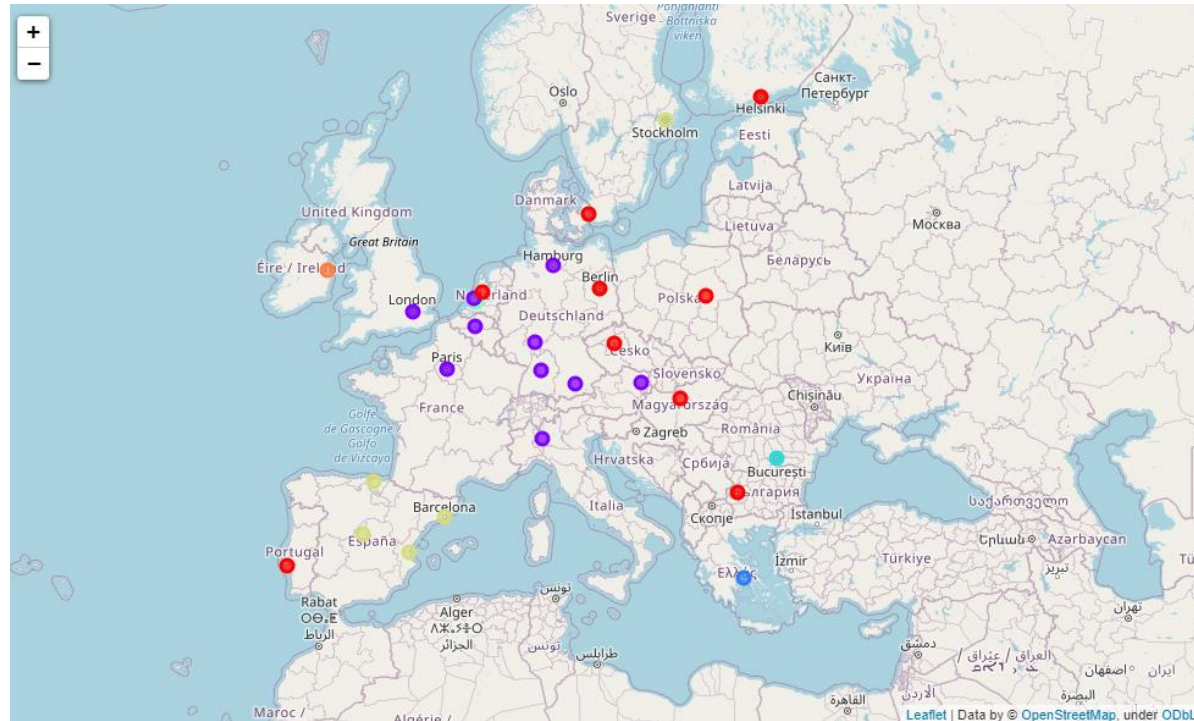
# Data Collection

- ▶ All target data was collected, with the exception of commercial rental averages for some cities
- ▶ Decision was made to cull the whole column as it wasn't material to model success
- ▶ Model can be re-run once this data is publically available or the client seeks out this information for target office buildings

# Potential Locations + London before clustering



# Potential Locations + London after clustering





# Candidate cities after clustering

## an overview

- ▶ Paris
- ▶ Milan
- ▶ The Hague
- ▶ Brussels
- ▶ Hamburg
- ▶ Munich
- ▶ Frankfurt
- ▶ Vienna
- ▶ Stuttgart

- ▶ Contains the traditional finance powerhouse cities in continental Europe
  - ▶ High average income (€2304.05 vs €1626.53 rest of sample, both net p/m), which tracks well with London's being higher than all 27 initial candidate cities
  - ▶ High average population (3.10m vs 2.15m rest of sample), which again tracks well as London clears 9m
  - ▶ Healthier income-to-rent ratio than London's, which is terrifyingly low (2.38 vs London's 1.37 – you'll want to use that to get staff onside)
- (all cluster average figures minus London)

# Conclusion and future directions

- ▶ The model did its job – split up cities in Europe according to their features and return a list of cities that are similar to London in stature, economy and culture
- ▶ A few outlier clusters were returned, so maybe reduce the number of clusters in future iterations
- ▶ What to do next depends on how happy the list makes the client – now the model is built, it's possible to go back and include more variables or tweak how they're treated, for instance:
  - ▶ Include the commercial rental field that was cut during data collection
  - ▶ Collect data on employee/board sentiment of all destinations on the shortlist and add it in
  - ▶ Weight variables more heavily if the client wishes to prioritise them i.e. make proximity to current location more important and cultural fit less so