Hackathon 2024

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Trinity College Dublin

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Throughout the week we have looked into

 Population Distribution by ED's and visualising them by a histogram and fitting it to a power law curve

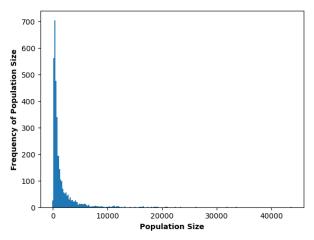
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- Applying Diffusion to non local population density

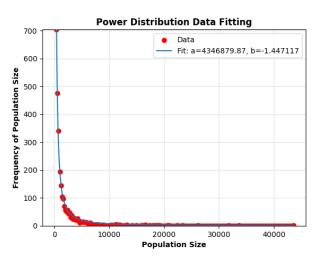
Population Distribution law

A histogram of the population data shows that most $\ensuremath{\mathsf{ED}}\xspace$'s have a small population



Population Distribution Law

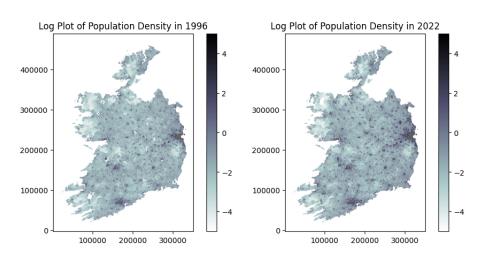
Fitting a power law to the data, ax^b



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- We attempted to model the internal migration of Ireland by taking inspiration from Density Functional Theory (DFT), a computational modelling method used in Condensed Matter Physics.
- In DFT, interactions between electrons are represented as potential energy functionals. As the name would suggest, these functionals are often dependent on electron density.
- We decided to see if we could do something similar with population density. Take a look at the plots on the following slide.



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- We used this idea of high population density being attractive to generate the following non-local potential matrix:

$$\rho_i = \frac{p_i}{A_i}$$

$$V_{ij}[\vec{p}, \vec{\rho}] = \beta \left(\frac{\rho_i - \rho_j}{p_j}\right) \left(\frac{\max(p_i, p_j)}{\min(\rho_i, \rho_j)}\right)$$

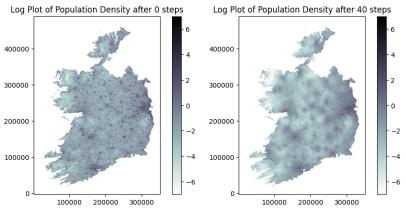
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• This matrix, when multiplied by the population vector, generates a $\Delta \vec{p}$ vector that has the condition that $\sum_i \Delta p_i = 0$, meaning that the total population doesn't change.

 We then combined this pseudo-potential functional with the diffusion equation (already coded by Cas) to account for the local dispersion of population from cities to the areas around them to obtain a working model for internal population migration.

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Modelling Internal Population Migration Population: Comparing to Census Data

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Figure: 2022 Census: pupulation movement out of Dublin by percentage

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- The highest percentage of people leaving Dublin were dispersing to nearby areas, as seen in the model
- The majority of people leaving Dublin for non surrounding areas were moving to other cities, i.e other areas of high population density

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 With this correlation matrix we can get a sense of what EDs are "topologically close".

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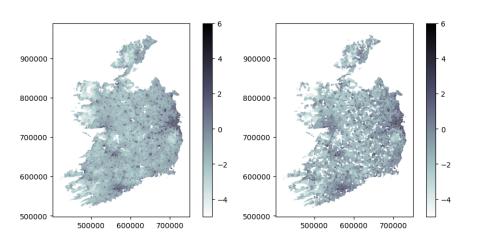
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- We can then use this with Electoral census data to create a new non-local adjacency matrix by having EDs within a certain topological distance of each other be connected.
- This new adjacency matrix can then be used with a simple diffusion model to allow the flow of population density from lower to higher density.



FINAL

Thanks for Listening!