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SOFTWARE IMPLEMENTATION OF THE HUFF GRAVITY MODEL FOR OPTIMAL SPATIAL PLACEMENT OF URBAN SERVICE FACILITIES

The article analyzes software methods for modeling the optimal placement of service facilities using optimization algorithms, geostatistics, and machine learning. The software ArcGIS, QGIS, MapInfo Professional, Tango Geospatial Platform which offer tools for spatial analysis and allow the integration of various datasets, such as demographic information and infrastructure layouts, has been analyzed. The main limitations of using ArcGIS and QGIS relate to high cost, performance, learning curve, and integration capabilities. ArcGIS is commercial software with high licensing costs that may not be affordable for small organizations. Processing large amounts of data can be slow in ArcGIS. Optimization algorithms, such as the k-means clustering and facility location problem (FLP) models, help in determining the most effective placement. Machine learning techniques, particularly in spatial data science, can also predict optimal locations based on patterns in statistical historical data. Efficient placement of service facilities, such as healthcare centers, retail stores, or public services, significantly impacts accessibility, customer satisfaction, and operational efficiency.

Software for spatial modeling of optimal placement of service facilities using Google Maps API data is proposed, which can be used for the needs of modern urban planning and business logistics. For the software implementation of the gravity Huff model, libraries and modules of the Python programming language were used: Requests, Numpy, Geopy.distance, Geodesic, Folium, MarkerCluster.

By leveraging geospatial data from Google Maps API, proposed method enables accurate analysis of location patterns, population density, and travel routes, leading to data-driven decisions. This approach not only enhances service coverage and reduces costs but also supports sustainable urban development by optimizing resource distribution and minimizing travel times.

Key words: *software, gravity Huff model, spatial modeling of optimal placement, Python programming language, regression analysis, Google Maps API.*

Introduction. Problem statement. The choice of location for a retail zone is one of the key decisions for retail companies. The store's location affects the number of potential customers and sales volume, as well as the costs associated with renting or purchasing land, which can vary significantly depending on the site. The location shapes the store's image and the image of the entire retail network. While the cost of rent and construction rights are usually known in advance, sales turnover can only be forecasted, making this step the most challenging. The demand for goods and services in a retail zone is determined by geography. Entrepreneurs seek to place their stores not only where there are many customers but where there are customers that match their target audience. The importance of the location lies in the fact that it is a unique factor that provides a competitive advantage and requires significant capital investment. The store's location influences customer attraction, as well as the supply and distribution of goods. To assess a location's potential, it is necessary to determine the maximum distance customers are willing to travel, the population within that radius, and the number of competitors in the region. Entrepreneurs should follow certain steps: market analysis, evaluation of demographic indicators, market potential assessment, and selecting alternative locations. Software can automate these processes, helping to choose the optimal store location, while also providing users with information about the nearest stores.

The main goal of the article is software development for spatial modeling of optimal placement of service facilities in the city using the Huff gravity model and analysis of Google Maps API data.

Related research. The research article [1] explores the concept of food deserts in urban areas, focusing on the intersection of public transportation and food accessibility. The authors employ geo-big data analysis to examine the relationship between transit routes, social inequality, and food access. The research aims to provide urban planners with insights on how to address food deserts and promote healthy eating habits in urban populations. The research

[2] explored the use of a geographically weighted regression (GWR) model instead of the traditional global ordinary least squares (OLS) model in the Huff model for retail distribution. By accounting for spatial nonstationarity in parameters, the local model provided more accurate results. The research demonstrated that the local model offered a better fit than the global OLS model, especially in capturing store performance and customer preferences.

The study [3] validated the Huff gravity model using a large-scale transactional dataset, marking the first real-data validation of the model. The researchers found that the Huff model accurately represents customer shopping behavior across various categories, such as grocery stores, clothing stores, gas stations, and restaurants. The model can be easily applied to different regions and merchant categories. Regression analysis revealed that factors like gender and marital status diversity improved the model's validation, offering deeper understanding into customer behavior. The research [4] presents a new method to uncover urban functions by aggregating human activities using mobile phone positioning and social media data. It identifies homes, workplaces, and other activities (e.g., shopping, schooling, entertainment) through a hidden Markov model and analyzes the diurnal dynamics of urban functions. In a case study of Shenzhen, China, the results show that urban areas may serve multiple functions throughout the day, despite being labeled with a single land-use type. The approach offers valuable findings into citywide human activity patterns, aiding both short-term urban decision-making and long-term policy planning.

In the article [5] authors analyze trade area delimitation using social media data. In a case study of Beijing, the city was divided into grid cells, and activity centers for social media users were extracted. Ten sample sets were created by selecting users based on retail locations they visited, and distance and visitation frequency were calculated for each grid cell. These values were input into a Huff model to delimit trade areas. Results indicate that aggregating user activity centers improves delimitation accuracy, and differences in trade area distribution and intensity were observed. The research article [6] examines human spatial convergence and divergence using large-scale mobile phone data. Researchers developed a method to identify spatiotemporal patterns of human movement and extracted eight distinct patterns. These patterns were analyzed in relation to urban functional regions. The research results offer understanding into how human mobility patterns evolve over time and their connection to the urban environment, which can support urban policy, planning, and traffic management.

The study [7] examines the relationship between mixed-use development and neighborhood vibrancy using new data sources like mobile phone data and Points of Interest (POI). Traditional measures, such as Shannon entropy, are found inadequate to capture the multidimensional aspects of mixed use. Using Hill numbers, the study developed new indicators for mixed use and analyzed how they relate to neighborhood vibrancy, represented by mobile phone user activity over 24 hours. The results showed that POI richness significantly improves vibrancy, while POI density and entropy explain only a small portion. The study highlights the limitations of traditional metrics and the importance of mixing complementary POIs for better neighborhood design and planning.

The research article [8] introduces a time-aware dynamic Huff model (T-Huff) for analyzing location-based market share, calibrated using large-scale mobile phone location data from the 10 most populated U.S. cities. By comparing hourly visit patterns for supermarkets and department stores, the T-Huff model proved more accurate than the original Huff model in predicting market share over time. The research also revealed that people in metropolitan areas with developed transit systems are less sensitive to long-distance visits. Socioeconomic and demographic factors, like median household income, were identified as influencing visit decisions. In the article [9] authors analyze how web analytics can be used to determine optimal locations for new recreational facilities in cities. By analyzing user search data, reviews, and the popularity of existing institutions, a probabilistic model was developed to identify the best places for new facilities. The model considers factors like territorial characteristics, competitor influence, and user needs. Authors propose a new software solution that leverages online data to simulate optimal placement for future recreational establishments.

Existing software solutions analysis

MapInfo Professional (Fig. 1) is a software developed by Pitney Bowes Software (formerly MapInfo Corporation) that is used for mapping and location analysis. It enables users to visualize, analyze, edit, interpret, and output data in a user-friendly format to discover relationships, patterns, and trends. MapInfo allows users to explore spatial data, symbolize features, and create maps.

MapInfo Pro is a 64-bit Geographic Information System (GIS) application used by GIS engineers and business analysts [10]. Areas of MapInfo Professional application are next.

– Risk analysis related to environmental or natural hazards such as floods, tornadoes, hurricanes, or crime.

– Assessing environmental impacts like pollution, erosion, invasive species, and climate change, including human-caused environmental shifts.

– Collaborating with local planning and engineering groups on construction projects.

– Utilizing geographic intelligence to identify marketing regions.

– Determining the optimal location for opening or closing retail facilities (e.g., stores, factories, depots) based on customer and employee locations, demographics, purchase patterns, and transportation links.

– Systematic analysis of spatial data to identify patterns and trends in crime and disorder.

– Visualization of spatial data such as drill holes, soil samples, geophysical surveys, lease boundaries, and cadastral data.

Tango Geospatial Platform offers predictive analytics for customers and locations, providing tailored GIS and location development in a single package (Fig. 2). Key features include location data management, high-quality location data, geocoding. Stores information on locations, including shops, sites, rental data, and competitors, along with geographic information such as trade zones, regions, markets, and

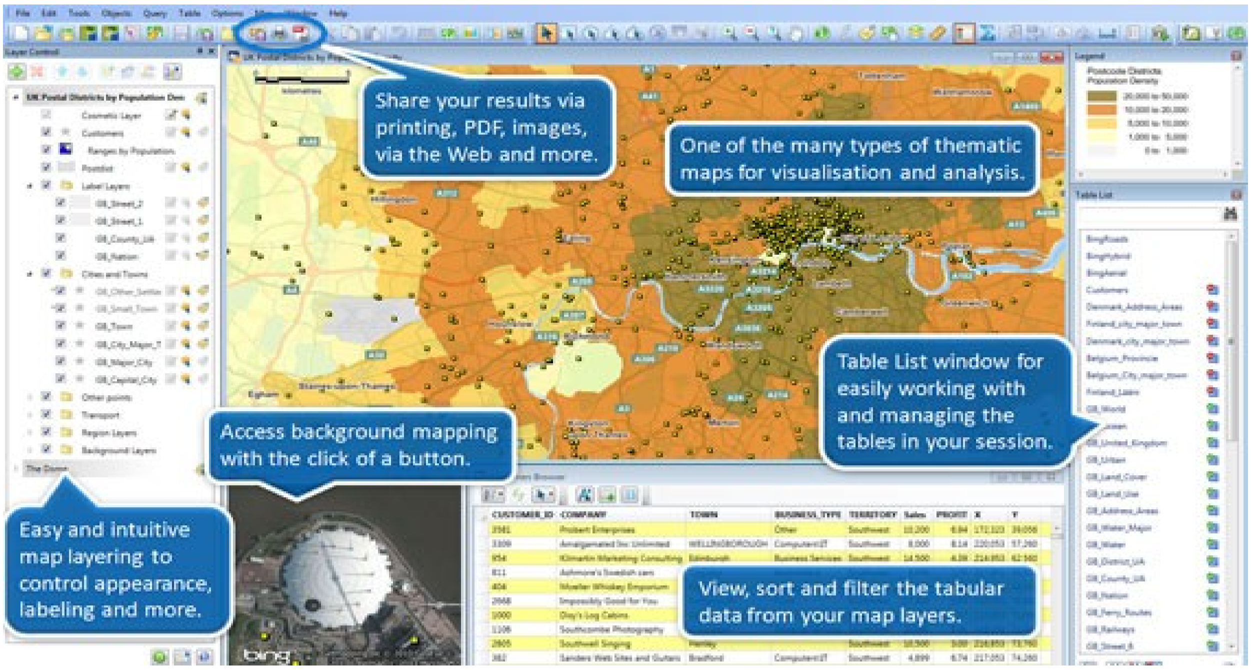

Fig. 1. Example of Pitney Bowes MapInfo in use

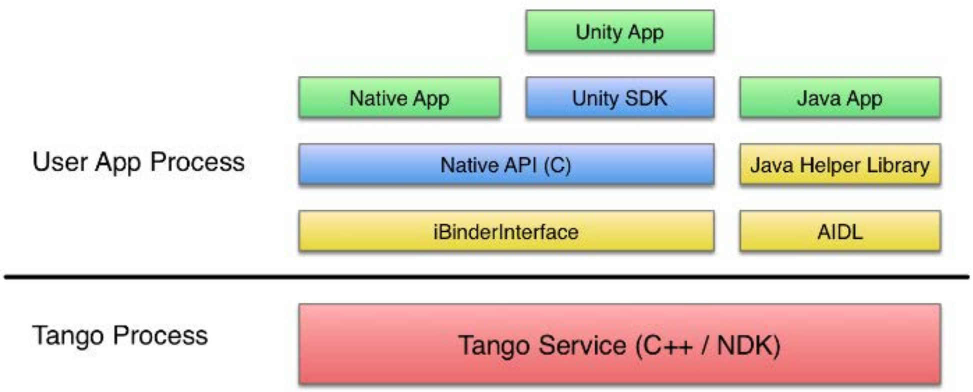

Fig. 2. Overview of Tango's API

territories. Built-in processes and tools help identify new data and detect anomalies in existing data, ensuring accuracy throughout the system. Converts address data into latitude and longitude [11].

Oracle Locator is a feature in all editions of the Oracle Database (Standard Edition, Standard Edition One, and Enterprise Edition), enabling the handling, querying, and analysis of positional data through standard SQL. It serves as a foundation for business applications that use location data, allowing developers to integrate spatial data into their apps easily. Oracle Locator ensures high levels of security, performance, scalability, and manageability provided by Oracle D. Each Oracle database includes built-in location functionality, enabling any business application to integrate location information and gain competitive advantages [12].

Oracle Spatial, an additional feature in Oracle Database 10g Enterprise Edition, offers utilities for processing spatial data used in GIS applications and location-based services. It supports all types of geospatial data, including vector, raster, topological, and network models, meeting GIS needs such as land management, utilities, and security [13].

Maptitude Mapping Software is a powerful Geographic Information System (GIS) designed for mapping and spatial analysis. It enables users to visualize, analyze, and manipulate geographic data for business, urban planning, and market analysis, among other fields (Fig. 3).

Maptitude offers extensive tools for demographic mapping, location analysis, and creating reports from spatial data, making it suitable for professionals without extensive GIS experience. Its drawbacks include a steep learning curve for beginners, limited compatibility with other GIS platforms, and a user interface that some may find outdated compared to newer GIS software. It also lacks certain advanced features found in more specialized GIS tools like ArcGIS.

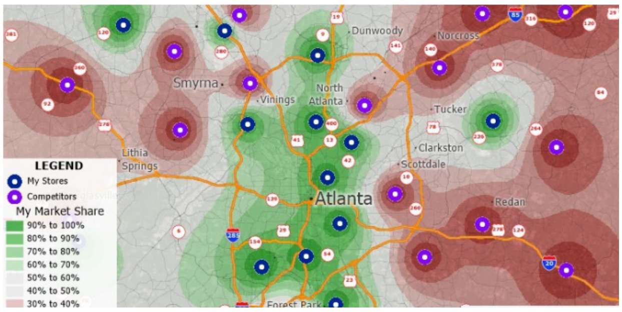

Fig. 3. Maptitude Mapping Software

ArcGIS Spatial Analyst provides a wide range of powerful spatial modeling and analysis functions (Fig. 4). It allows users to create, query, and analyze raster data; perform integrated raster/vector analysis; extract new information from existing data; run multi-layer data queries, and fully integrate raster data with traditional vector data sources. The latest version is fully integrated with Python but lacks a mobile version. The application has some drawbacks: from a software perspective it requires high-end hardware and manual data entry, which may be unfamiliar to the user; from a user perspective: the interface can be complex, requiring some expertise to use effectively [14].

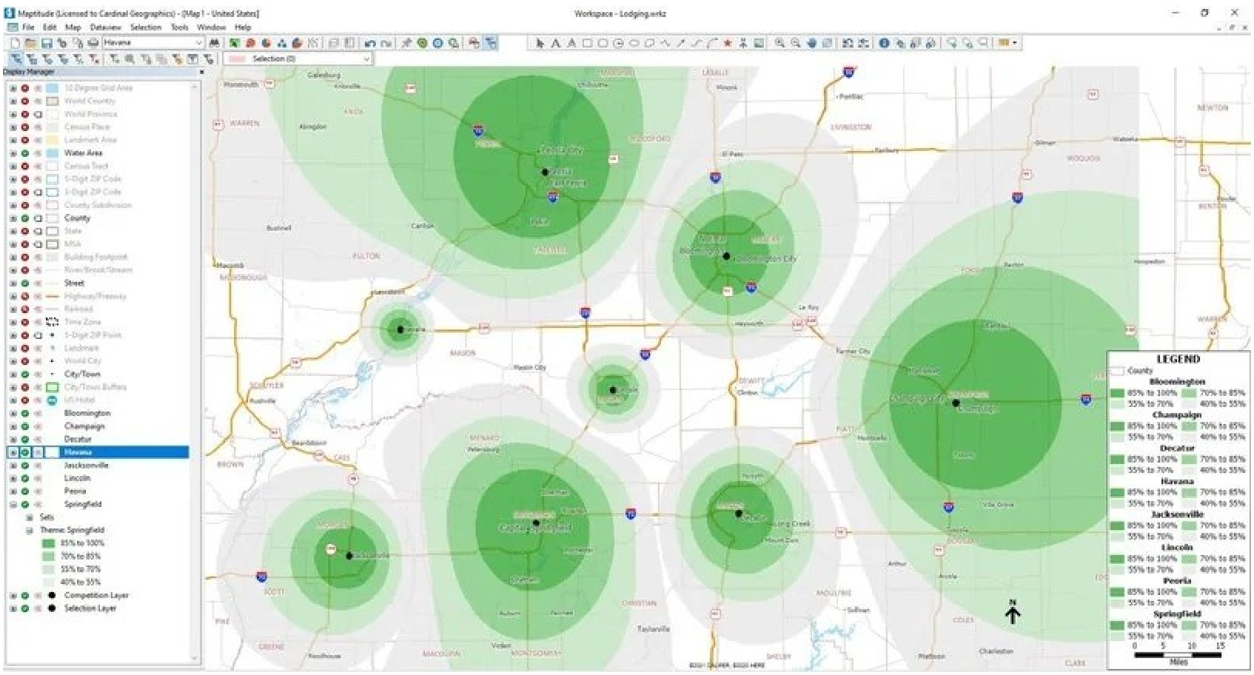

Fig. 4. Result of determining the best retail location

Key factors for service facility building

After reviewing the existing software solutions drawbacks, the following key factors must be taken into account when constructing service facility in the Kyiv city:

– Facility size.

– Number of nearby competitors.

– Environmental factors (e.g., nearby polluting factories).

– Accessibility for visitors from different parts of Kyiv.

Several tools are available that analyze all these factors, often incorporating terrain analysis and 3D modeling for a more detailed view. Existing software tools go beyond determining optimal retail locations, offering features like route planning and terrain analysis. They have limitations: most do not support the Ukrainian language and can be costly. ArcGIS requires powerful hardware and manual data input. The tools from Oracle, ArcGIS, and Tango Geospatial Platform often have complex interfaces, requiring users to study documentation thoroughly before use. Pitney Bowes MapInfo offers a more user-friendly interface, but it only supports 64-bit operating systems. After analyzing the market of existing software products, several limitations were identified. Based on these findings, the main requirements for the new application were defined: an intuitive interface, up-to-date data, and the ability for users to input only the desired area.

The Huff gravity model

The Huff gravity model states that the probability that a consumer will choose a particular location to purchase or visit depends on two main factors:

1. attractiveness of the location – characteristic that may depend on the size, services available, quality, or other attributes of the location.

2. distance to the location – the closer the location is to a potential customer, the more likely the customer is to choose it.

The basic equation for calculating the probability that a consumer from a given area (or point) will choose a particular location is as follows:

$$P_{ij} = \frac{U_{ij}}{\sum_{k=1}^{n} U_{ik}} = \frac{S_j^{\alpha} * D_{ij}^{\beta}}{\sum_{k=1}^{n} S_k^{\alpha} * D_{ik}^{\beta}} \quad (1)$$

where P_{ij} is the probability of a consumer from city i visiting point j; n is the set of competing points (or cities) in the region, U_{ij} is the utility of point j for an individual in i, S_j is the area of service facility j, D_{ij} is the distance between the consumer in i and point j, D_{ij} and β are the sensitivity parameters.

Stages of using the Huff model for spatial location modeling are next.

Stage 1. To apply the model, data is required on candidate locations for a new facility (building, service facility); distances between potential locations and customer residence areas and attractiveness of each existing and new facility (area, number of services, other factors).

Stage 2. For each location, the probabilities are calculated that customers from different areas will visit this facility. This allows to see which facility has the greatest potential number of visitors, based on distances and characteristics.

Stage 3. After calculating the probabilities, we can see which location is optimal for locating a new building or service facility, taking into account spatial competition with other locations.

Stage 4. Make informed decisions about where to locate new facilities, considering which location has the greatest potential to attract customers.

Research data

According to statistical data, around 60% of users consider reviews when choosing a leisure venue. The more reviews an service facility has, the better its popularity can be gauged. If a service facility has predominantly negative reviews, it is likely to attract fewer consumers. To obtain this information, users rely on mapping services like Google Maps, which allows reviews and ratings for visited places. Another crucial factor is website traffic. The assumption here is straightforward: the higher the traffic, the more popular the service facility. Consumers visit websites to gather various information, with studies showing that 29% of visitors check prices, 15% look at the service offerings, and 13% seek promotions. Website traffic is measured by two metrics: the number of visitors and the number of page views. Page views represent the total number of fully loaded pages over a specific period, while visitors refer to the number of unique users who have visited the website and loaded at least one page. The more pages a single user views, the better for the site. For example, if a user visits the site and views five pages, it adds one to the visitor count and five to the page view count.

The first criterion selected is the visitor rating of a given location, which can be obtained through a mapping service. Considering that consumers use the website to check pricing, service offerings, and promotions, the number of page views and site visitors became the next criteria. The size of the venue should be considered, as larger spaces are more likely to attract higher visitor numbers.

The research utilizes data from the Google Places API, including geographic coordinates, names, and types of existing restaurants in the target area, supplemented by tools such as geopy for distance calculations and *folium* Python library for interactive map visualization.

Software implementation of the Huff gravity model for optimal spatial placement of new restaurants

Consider the new software method for identifying optimal locations for new restaurants using data-driven analysis and visualization techniques. The process consists of the following steps.

Google Places API Query

The initial step involves sending requests to the Google Places API to retrieve data about existing restaurants in the target area. The API provides comprehensive information, including the geographical coordinates, names, and types of restaurants, forming the foundational dataset for analysis. The implementation utilizes the following libraries: *requests* for sending HTTP requests to the Google Places API to fetch restaurant data, *numpy* for array manipulation and mathematical operations, *geopy.distance* for calculating distances between geographic points, *folium* library for creating and visualizing interactive maps, and *MarkerCluster* for clustering markers on maps in densely populated areas.

The function *get_restaurants_data* retrieves a list of restaurants within a specified radius from a given geographic point (latitude, longitude):

```
def get_restaurants_data(lat, lng, radius=500):
    url = f"https://maps.googleapis.com/maps/api/place/nearbysearch/json?key={API_KEY}&location={lat},{lng}&radius={radius}&type=restaurant&language=uk_UA"
    response = requests.get(url)
    if response.status_code == 200:
        return response.json().get('results', [])
    else:
        print("Error connecting to API")
        return []
```

It utilizes the Google Places API to fetch nearby restaurant data, including coordinates, names, ratings, and review counts. The function sends an HTTP request to the API endpoint and checks the response status code. If the request is successful (status code 200), it returns the restaurant data as a list. Otherwise, it prints an error message indicating a connection issue. This function streamlines the process of gathering localized restaurant information for further analysis and visualization.

Data Analysis Using Huff Model

The retrieved data is analyzed using the Huff model, which predicts the likelihood of customer attraction to a given location. This analysis incorporates factors such as distance, competition density, and population demographics to identify the most suitable site for a new restaurant. The results of the analysis are visualized on an interactive map: existing restaurants are displayed as green circles with a service radius of 1 km. The proposed location for the new restaurant is marked as a red circle with the same service radius of 1 km. This visualization allows stakeholders to intuitively assess the spatial relationships and service areas.

Consider the software implementation of the Huff model:

```
def huff_model(restaurants, user_location, beta=2):
    total_attractiveness = 0
    probabilities = []
    for restaurant in restaurants:
        location = restaurant['geometry']['location']
        rating = restaurant.get('rating', 0)
        reviews = restaurant.get('user_ratings_total', 1)
        attractiveness = rating * reviews
        distance = calculate_distance(user_location, (location['lat'], location['lng']))
        attractiveness_distance_ratio = attractiveness / (distance ** beta)
        total_attractiveness += attractiveness_distance_ratio
        probabilities.append({
            "restaurant": restaurant,
            "attractiveness_distance_ratio": attractiveness_distance_ratio
        })
    for probability in probabilities:
        probability['probability'] = probability['attractiveness_distance_ratio'] / total_attractiveness
    return probabilities
```

The *huff_model* function implements the probabilistic Huff model to assess the competitiveness of each restaurant based on its "attractiveness" and distance from a user-defined location. The attractiveness of a restaurant is calculated as the product of its rating and the number of reviews. This metric combines both qualitative (rating) and quantitative (review count) factors, providing a comprehensive measure of a restaurant's appeal to potential customers. The distance from the user's location to each restaurant is computed. This metric plays a critical role in determining the likelihood of a customer visiting a specific restaurant, as proximity often influences customer behavior. The probability of a customer visiting a given restaurant is derived as the ratio of the restaurant's attractiveness to the square of the distance.

A sensitivity parameter β in the formula (1) is introduced to control the model's responsiveness to distance, allowing for customization based on specific geographic or demographic contexts. This approach provides a robust framework for evaluating and comparing potential restaurant sites, integrating customer preferences, competition, and spatial factors into a unified probabilistic model.

We create a function to find the optimal location:

```
def find_optimal_location_for_new_restaurant(restaurants, user_locations):
    best_location = None
    best_probability = 0
    for user_location in user_locations:
        probabilities = huff_model(restaurants, user_location)
        total_competition = sum([p['probability'] for p in probabilities])

        if total_competition > best_probability:
            best_probability = total_competition
            best_location = user_location
    return best_location
```

The *find_optimal_location_for_new_restaurant* function calculates the overall probability of competitive viability for each proposed location, aiding in the identification of the most advantageous site for a new restaurant. For each candidate location, the function computes the total probability of customer visits to restaurants in the vicinity. This aggregate measure accounts for the cumulative attractiveness and accessibility of existing establishments in the area.

The location with the highest overall competitive probability is identified as the optimal choice. This selection maximizes the likelihood of attracting customers, balancing factors such as competition and proximity to potential clients. This method provides a data-driven approach to site selection, ensuring the proposed location is strategically positioned for maximum market competitiveness.

To implement this approach, users should obtain an API key from Google Places, as described in the setup documentation.

The *visualize_restaurants_on_map* function generates an interactive map using folium, displaying existing restaurants and their service areas alongside the optimal location for a new restaurant, if identified:

```
def visualize_restaurants_on_map(restaurants, new_location, user_locations):
    m = folium.Map(location=[50.4501, 30.5234], zoom_start=12)
    marker_cluster = MarkerCluster().add_to(m)
    for restaurant in restaurants:
        location = restaurant['geometry']['location']
        name = restaurant['name']
        rating = restaurant.get('rating', 0)
        folium.CircleMarker(
            location=[location['lat'], location['lng']],
            radius=10,
            color='green',
            fill=True,
            fill_color='green',
            fill_opacity=0.6,
            tooltip=f"{name} (Rating: {rating})"
        ).add_to(marker_cluster)
        folium.Circle(
            location=[location['lat'], location['lng']],
            radius=1000,
            color='green',
            fill=True,
            fill_opacity=0.1
        ).add_to(m)
    if new_location:
        folium.CircleMarker(
            location=new_location,
            radius=12,
            color='red',
            fill=True,
            fill_color='red',
            fill_opacity=0.8,
            tooltip="New Restaurant (Optimal Location)"
```

The map is centered on Kyiv city, with existing restaurants represented by green circular markers and a 1 km service radius. The optimal location for the new restaurant is highlighted with a red marker and an accompanying 1 km service radius. By clustering markers using *MarkerCluster*, the function ensures a clean and interactive visualization, enabling users to explore restaurant distribution and service coverage intuitively. For each candidate location, the function computes the total probability of customer visits to restaurants in the vicinity. This aggregate measure accounts for the cumulative attractiveness and accessibility of existing establishments in the area. The location with the highest overall competitive probability is identified as the optimal choice. This selection maximizes the likelihood of attracting customers, balancing factors such as competition and proximity to potential clients.

Research results

The optimal service area for a restaurant depends on several factors: type of restaurant, population density, competition, accessibility. Fast-food outlets typically have smaller service radii (up to 1 km), whereas fine-dining establishments may attract customers from a broader area (up to 3-5 km). In densely populated urban areas, the service radius may be limited to 0.5–1 km, while less populated regions may require a broader reach. A higher concentration of competitors in the vicinity may necessitate a smaller service radius due to increased competition.

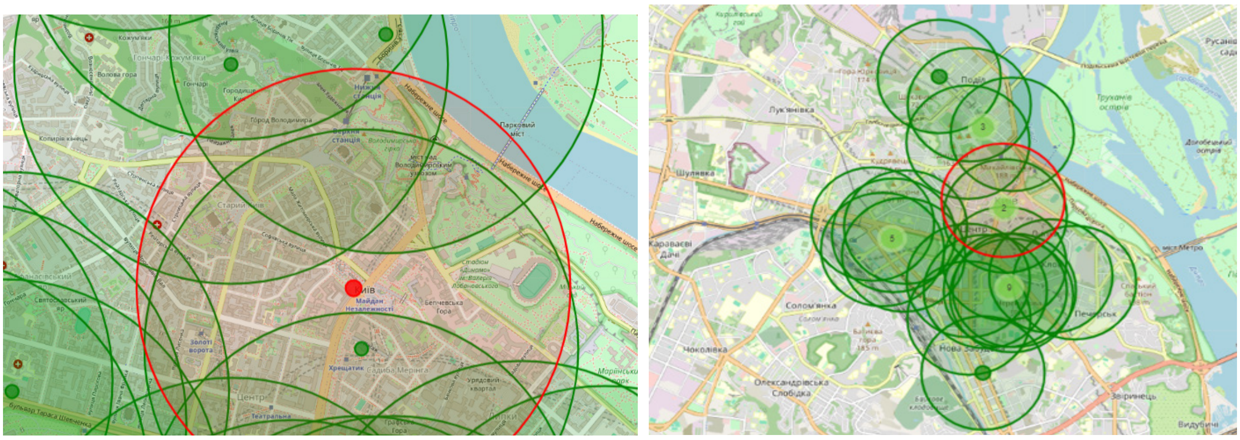

Fig. 5. Density map of existing restaurants in Kyiv with 1 km service radius (the red circle marks the optimal location for 1 new restaurant)

Factors such as transportation availability and parking convenience influence how far customers are willing to travel. For urban areas service radii generally range from 0.5 to 1 km. For suburban areas service radii can extend to 2–3 km, depending on population density. For rural areas due to lower population densities, the service radius may expand to 5–10 km.

The visualization represents a density map of existing restaurants in the city of Kyiv, marked by green circles with a 1 km service radius. The red circle highlights the optimal location for a new restaurant, as determined by the analysis (Fig. 5).

The map suggests that the selected area has high potential for market entry, likely due to favorable proximity to underserved zones or reduced competition. The clustering of markers demonstrates areas of restaurant saturation, while the red marker emphasizes a strategically advantageous location based on the Huff model's probabilistic competitiveness analysis.

One of the key advantages of this solution is its economic accessibility, as it relies on open data and uses free or publicly available libraries, such as *folium* for visualization and the Google Places API for data retrieval. This significantly reduces costs compared to commercial geo-analytical platforms, which often require expensive licenses and specialized equipment. The proposed approach is flexible and scalable: the algorithms can easily be adapted for analyzing other types of businesses or geographical areas, making it versatile for various scenarios. Interactive visualization of results on the map allows users to quickly assess spatial distribution and understand the competitive environment without requiring specialized expertise in geoinformation systems. The integration of the probabilistic Huff model enables consideration of important factors such as attractiveness and accessibility, providing a more accurate and justified selection of the optimal location than standard methods based solely on geographical positioning or population density.

Conclusions and future work. The probabilistic gravity-based Huff model is a powerful tool for modeling the spatial placement of new facilities, allowing for the maximum utilization of spatial data to predict customer or consumer distribution. The developed software is designed to search for restaurants and determine the optimal location for opening a new restaurant in the city of Kyiv using the probabilistic gravity-based Huff model. The code enables the visualization of results on an interactive map using the *folium* library. The Huff model estimates the probability that a customer will choose a particular restaurant, taking into account both its attractiveness and its distance. This model allows for identifying the optimal location for a new restaurant, where competition with others is minimized.

Further development of this software will allow for the inclusion of additional factors such as demographic data, pedestrian and vehicular traffic flows, as well as seasonal and socio-economic characteristics of the region, which will enhance the accuracy of predictions and facilitate more effective decision-making for business planning and the placement of commercial facilities.

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Олещенко Л.М. ПРОГРАМНА РЕАЛІЗАЦІЯ ГРАВІТАЦІЙНОЇ МОДЕЛІ ХАФФА ДЛЯ ОПТИМАЛЬНОГО ПРОСТОРОВОГО РОЗМІЩЕННЯ ОБ'ЄКТІВ ОБСЛУГОВУВАННЯ МІСТА

У статті проаналізовано програмні методи моделювання оптимального розміщення об'єктів обслуговування, які використовують алгоритми оптимізації, геостатистику та машинне навчання. Проаналізовано програмне забезпечення ArcGIS, QGIS, MapInfo Professional, Tango Geospatial Platform, що пропонує інструменти для просторового аналізу та дозволяє інтегрувати різні набори даних, такі як демографічна інформація та макети інфраструктури. Основні обмеження використання ArcGIS і QGIS стосуються високої вартості програмного забезпечення, продуктивності, кривої навчання, і можливостей інтеграції. ArcGIS є комерційним програмним забезпеченням з високою вартістю ліцензій, що може бути недоступним для невеликих організацій. Обробка великих обсягів даних може бути повільною в ArcGIS. Алгоритми оптимізації, такі як кластеризація k-середніх і моделі розташування об'єктів FLP допомагають визначити оптимальне розміщення нових об'єктів. Методи машинного навчання, зокрема в науці про просторові дані, дозволяють передбачати оптимальне розташування на основі шаблонів у історичних статистичних даних. Ефективне розміщення об'єктів обслуговування, таких як центри охорони здоров'я, роздрібні магазини чи громадські служби, значно впливає на ефективність їх роботи, доступність та задоволеність клієнтів.

Запропоноване програмне забезпечення для просторового моделювання оптимального розміщення об'єктів обслуговування з використанням даних Google Maps API може використовуватись для потреб сучасного містобудування та бізнес-логістики. Для програмної реалізації гравітаційної моделі Хаффа було використано бібліотеки та модулі мови програмування Python: Requests, Numpy, Geopy.distance, Geodesic, Folium, MarkerCluster.

Використовуючи геопросторові дані з Google Maps API, запропонований програмний метод дозволяє аналізувати моделі розташування, щільність населення та маршрути подорожей, що дає змогу приймати рішення на основі наявних даних. Цей підхід може покращити охоплення послугами та зменшити витрати, також підтримувати сталий розвиток міст шляхом оптимізації розподілу ресурсів і мінімізації часу на дорогу.

Ключові слова: *програмне забезпечення, гравітаційна модель Хаффа, просторове моделювання оптимального розміщення, мова програмування Python, регресійний аналіз даних, Google Maps API.*