Objective Monitoring and Analysis of the Obesogenic Behaviour in Relation to the Local Environment

A Tool Facilitating Decisions by Public Health Authorities

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Obesity is a threat for health and economy

<table>
<thead>
<tr>
<th></th>
<th>2002</th>
<th>2007</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obese</td>
<td>356 million</td>
<td>523 million</td>
<td>704 million</td>
</tr>
<tr>
<td>Overweight</td>
<td>1.4 billion</td>
<td>1.5 billion</td>
<td>2.3 billion</td>
</tr>
</tbody>
</table>

Overweight, body mass index (BMI) ≥25 kg/m²; obese, BMI >28 kg/m² (Asian) or >30 kg/m². James WP. J Intern Med. 2008;263(4):336–352.
Obesity is a threat for health and economy

- 2.8 million deaths per year in the EU result from causes associated with overweight and obesity

(Source: European Association for the Study of Obesity, easo.org)
Current Public health actions

- Are not tailored to the needs of local communities
- Are limited to single-element strategies
Big Data Againsts Childhood Obesity

- H2020 funding
  → 2016-2020

- 13 organizations
  → Universities
  → Schools
  → Obesity clinics
  → Technical companies
  → Telecommunications provider
  → Public Health Authorities

- 5 countries
Big Data Againsts Childhood Obesity

- Allow evidence based, pre-assessed, more effective policy choices, all the way from the prevention front to the point-of-care level for already obese individuals.

- Teach young European citizens about the principles of Voluntarism, Citizen Science and Public Participation.

- Increasing the awareness about healthy living, introducing students to the health-in-all-things mentality.
Need of multi-level approaches

- **Obesity risk** depends on:
  - The way we eat
  - What we eat
  - How we move
  - The way we sleep

- These decompose into a long list of personal **behavioral patterns**

- Highly correlated, in a causal way, with the conditions of **local** urban, social, regulatory and economic **environment**

Based on Davison KK, Birch LL. Childhood overweight: a contextual model and recommendations for future research. Obesity reviews. 2001 Aug 1;2(3):159-71
Causality hierarchy

Local Extrinsic Conditions (LECs) = The environment
- Urban
- Social
- Financial
- Regulatory

Personal Behavioural Patterns
Causality hierarchy

Personal Behavioural Patterns = our *habits*
- The multiplicity of them

Behavioural Risk Factors
Causality hierarchy

**Behavioural Risk Factors =**
- How one eats
- What one eats
- How one sleeps
- How one moves

**Child BMI**

**Obesity Prevalence**
BigO = extract evidence, locally!

- **Aetiology**
  - Why bad habits are being adopted
  - Not in general! Here, at a local level

- **Prediction**
  - What is the effect of an adopted policy
    - Estimate it before it is adopted
    - Quantitatively
Aetiology: the “Policy Advisor”

- **What** makes the population of a specific neighborhood of Athens scarcely use public means of transportation?
  → An easy one

- **What** makes the population of a specific neighborhood of Dublin exercise less than average?
  → More interesting

- **Why** students at IEGS eat their lunch too fast?

**Local Extrinsic Conditions (LECs)** = The environment
- Urban
- Social
- Financial
- Regulatory

**Personal Behavioural Patterns**
Prediction: the “Policy Planner”

- What is the effect of adding a bus line to the use of public means of transportation from the population of a specific neighborhood of Athens?  
  → Not that easy to quantify

- What is the effect of reducing the availability of high sugar sweetened beverages in metro stations to the calorie intake of students?

Local Extrinsic Conditions (LECs) = The environment
- Urban
- Social
- Financial
- Regulatory

Personal Behavioural Patterns
Big Data is the key!

- Large-scale data
  - behavioural patterns
  - local environment variables
- Statistically significant associations
Which big data

- Thousands of children
  → Schools
  → Clinics

- Behavioural data
  → Personal Behavioural Patterns
  → Behavioural Risk Factors

- Local Environment Conditions from relevant areas
Citizen-scientist model

- **Primary incentives**
  - Offer my data for my neighborhood
  - Be a scientist
  - Participatory design paradigm

- **Part of school courses/projects**
  - Need the support of school teachers / administration
  - Produce material easy to integrate in school classes
    - Math, Physical Education, Physics, Social Education, ...
BigO Community

Reaching out to more than 23,000 school children to become BigO citizen scientists and share their behavioural data
Engage ~7,000

Engaging more than 2,000 children at 3 obesity clinics
BigO Data collection

Location – GPS
Photos - Food & Ads
Sleep
Barcode Scanning – Food
Physical Activity
Self-reporting
The BigO System
Measuring behavior: Devices + Apps

Use smartphones/smartwatches to measure accelerometry + position
Measures of behavior: Activity Counts & Steps

- Measure activity per minute
  - Activity counts
  - Steps

- 3D Accelerometer recordings at 10 up to 100 Hz

- Smartphone or Smartwatch

- Use signal processing algorithms
Measures of behavior: Activity Counts
Measures of behavior:
Activity Type Classification

- Decide Activity Type per minute
  - Walking, running, bicycling, sitting, standing, etc

- 3D Accelerometer recordings at 10 up to 100 Hz

- Smartphone or Smartwatch

- Signal processing + machine learning
Measures of behavior: Determining “Lifespace”

- Determine Points of Interest visited
  - Home
  - Frequently visited locations
  - Public POIs
- GPS recordings per minute
- Smartphone or Smartwatch
- Cluster locations
  - DBSCAN
Measures of behavior: Determining “Lifespace Graph”

- Derive the graph of lifespace
  - Places visited
  - How and when ones moves from node-to-node

- Add labels to places
  - Restaurant/Fast food/Bus station/School/Gym/....
  - Access Google/Foursquare for this
Measures of behavior: Food type and quantity

- Determine the type of food

- Quantify food
  - Volume
  - Main ingredients

- Pictures

- 3D computer vision
Measures of behavior: Analyze meal microstructure

- Detect bites during meals
- In the wild
- Smartwatch captures accelerometry + gyroscope data
- Signal Processing + Deep Learning
Measures of behavior: Analyze meal microstructure
Measures of behavior: Analyze sleep

- Sleep Duration, Fragmentation, Efficiency, ...

- Smartwatch

- 3D accelerometer + HRV sensor

- In the wild

- Signal Processing + Deep Learning
Eating activity indicators (indicative)

<table>
<thead>
<tr>
<th>Name</th>
<th>Units</th>
<th>Sensors involved</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eating fast food /outside</td>
<td>Occurrence</td>
<td>L, P, U</td>
</tr>
<tr>
<td>Fast-food eating frequency</td>
<td>Times/week</td>
<td>L, P, U</td>
</tr>
<tr>
<td>Eating dinner outside of the home?</td>
<td>Occurrence</td>
<td>L, P, U</td>
</tr>
<tr>
<td>Eating at home</td>
<td>Occurrence</td>
<td>L, P, U</td>
</tr>
<tr>
<td>Food type</td>
<td>Categorical</td>
<td>U, P</td>
</tr>
<tr>
<td>Meal type (breakfast, lunch, dinner, snack)</td>
<td>Categorical</td>
<td>L, P, U</td>
</tr>
<tr>
<td>Meal frequency (e.g., breakfast)</td>
<td>Occurrence</td>
<td>U, P</td>
</tr>
<tr>
<td>Soda or fizzy drinks (sugar added)</td>
<td>Occurrence</td>
<td>U, P</td>
</tr>
<tr>
<td>Diet soda/Juice/water/milk</td>
<td>Occurrence</td>
<td>U, P</td>
</tr>
<tr>
<td>Eating occurrences</td>
<td>Occurrence</td>
<td>U</td>
</tr>
<tr>
<td>Eating/snacking frequency</td>
<td>times/day</td>
<td>U</td>
</tr>
<tr>
<td>Eating late at night</td>
<td>Times/week</td>
<td>U</td>
</tr>
<tr>
<td>Eating schedule obedience</td>
<td>sec (std)</td>
<td>U</td>
</tr>
</tbody>
</table>
### Physical activity - Sleep indicators (indicative)

<table>
<thead>
<tr>
<th>Name</th>
<th>Units</th>
<th>Sensors involved</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy expenditure (at minute intervals)</td>
<td>Categorical</td>
<td>A</td>
</tr>
<tr>
<td>Activity type (minute)</td>
<td>Categorical</td>
<td>A</td>
</tr>
<tr>
<td>Activity intensity</td>
<td>Categorical</td>
<td>A</td>
</tr>
<tr>
<td>Activity level</td>
<td>Categorical</td>
<td>A</td>
</tr>
<tr>
<td>Steps</td>
<td>Integer</td>
<td>A</td>
</tr>
<tr>
<td>Activity counts</td>
<td>Counts/minute</td>
<td>A</td>
</tr>
<tr>
<td>Exercise frequency</td>
<td>Times/week</td>
<td>A</td>
</tr>
<tr>
<td>Frequency of 10 min bouts of consecutive mod-vigorous activity</td>
<td>Times/week</td>
<td>A</td>
</tr>
<tr>
<td>Hours of sleep per night</td>
<td>Hours</td>
<td>A, U</td>
</tr>
<tr>
<td>Sleep/wake-up times per night</td>
<td>Timestamp</td>
<td>A</td>
</tr>
<tr>
<td>Interruptions of sleep</td>
<td>Number</td>
<td>A</td>
</tr>
<tr>
<td>Duration of each interruption</td>
<td>Minutes</td>
<td>A</td>
</tr>
<tr>
<td>Movement during sleep</td>
<td>Categorical</td>
<td>A</td>
</tr>
</tbody>
</table>
Measuring Environment: External Sources

- Maps
  → Incl. Google, Foursquare

- Statistical Authorities
  → Finest spatial scale
  → Microdata (?)
Measuring Environment: Deep Learning

- Example: Image processing + deep learning on Google Street View: *infer unemployment from car images*

- Deep Multiple Instance learning
  - Inexpensive
  - Good accuracy
  - Uses statistics of coarse spatial resolution during learning
  - Yields fine spatial resolution predictions
Estimates of local conditions: unemployment

Estimates of local conditions: unemployment

Local Environment Conditions (indicative)

<table>
<thead>
<tr>
<th>BUILT ENVIRONMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability of indoor facilities</td>
</tr>
<tr>
<td>Number of indoor facilities</td>
</tr>
<tr>
<td>Density of indoor facilities</td>
</tr>
<tr>
<td>Price of indoor facilities</td>
</tr>
<tr>
<td>Availability of outdoor facilities</td>
</tr>
<tr>
<td>Number of outdoor facilities</td>
</tr>
<tr>
<td>Density of outdoor facilities</td>
</tr>
<tr>
<td>Price of outdoor facilities</td>
</tr>
<tr>
<td>Recreational space within walking space of distance of home</td>
</tr>
<tr>
<td>School infrastructure that includes spaces for organised or individual exercise/activity</td>
</tr>
<tr>
<td>Affordability of organised sports: club fees and costs</td>
</tr>
<tr>
<td>Numbers of people who use recreational spaces</td>
</tr>
<tr>
<td>Availability of open spaces in neighbourhood</td>
</tr>
<tr>
<td>Number of public parks</td>
</tr>
<tr>
<td>Density of public parks</td>
</tr>
</tbody>
</table>
Local Environment Conditions (indicative)

<table>
<thead>
<tr>
<th>DIETARY ENVIRONMENT</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Density and type of food outlet in proximity to school</td>
<td></td>
</tr>
<tr>
<td>Density and type of food outlet in proximity to home</td>
<td></td>
</tr>
<tr>
<td>Density and type of food outlet along school commute</td>
<td></td>
</tr>
<tr>
<td>Tracking data on portion sizes in fast-food outlets, other restaurants and single-serving snacks</td>
<td></td>
</tr>
<tr>
<td>The pricing environment of foods</td>
<td></td>
</tr>
<tr>
<td>Range and diversity of food retail outlets</td>
<td></td>
</tr>
<tr>
<td>Number of fast food advertisements within the community</td>
<td></td>
</tr>
<tr>
<td>Advertisements in proximity of schools</td>
<td></td>
</tr>
<tr>
<td>% of processed food items with clear and accurate front of pack labelling</td>
<td></td>
</tr>
<tr>
<td>Food advertising at specific times</td>
<td></td>
</tr>
<tr>
<td>Digital exposure to food advertising</td>
<td></td>
</tr>
<tr>
<td>Availability of fresh fruit and vegetables</td>
<td></td>
</tr>
<tr>
<td>Retail environment within supermarkets</td>
<td></td>
</tr>
<tr>
<td>Density and type of food outlet in proximity to school</td>
<td></td>
</tr>
<tr>
<td>Density and type of food outlet in proximity to home</td>
<td></td>
</tr>
</tbody>
</table>
## Local Environment Conditions (indicative)

### SOCIOECONOMIC ENVIRONMENT / HEALTH INEQUALITIES

<table>
<thead>
<tr>
<th>Category</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education level statistics</td>
<td></td>
</tr>
<tr>
<td>Employment status or socio-economic status of family</td>
<td></td>
</tr>
<tr>
<td>Local deprivation indices</td>
<td></td>
</tr>
<tr>
<td>Area based food poverty statistics</td>
<td></td>
</tr>
<tr>
<td>Number of households experiencing food poverty</td>
<td></td>
</tr>
<tr>
<td>Unemployment levels</td>
<td></td>
</tr>
<tr>
<td>Child and family – living on public assistance</td>
<td></td>
</tr>
<tr>
<td>Health literacy</td>
<td></td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
</tr>
<tr>
<td>Family structure</td>
<td></td>
</tr>
<tr>
<td>Availability and access to universal primary health services</td>
<td></td>
</tr>
<tr>
<td>Availability and access to school meals schemes</td>
<td></td>
</tr>
<tr>
<td>Level of referrals</td>
<td></td>
</tr>
<tr>
<td>UNICEF deprivation index</td>
<td></td>
</tr>
</tbody>
</table>
Privacy preservation

- **Pseudonymization**
  - Real names out of the system
  - Analytics on Geohashes not on persons

- **Innovative handling of location data**
  - votes to elements of \{geohashes\} x \{behaviors\}
    - Cecilia was walking fast on Odengatan street of Stockholm at 9:15 am
    - increase votes(u6sce5, ‘walk fast’, 9) by one
    - k-anonymity
      - Cast the vote to all subareas of u6sce if less than k votes
Challenges

- Engagement
- Privacy
- Discreet operation
- Scalability
- Accuracy
- Validity
Thank you