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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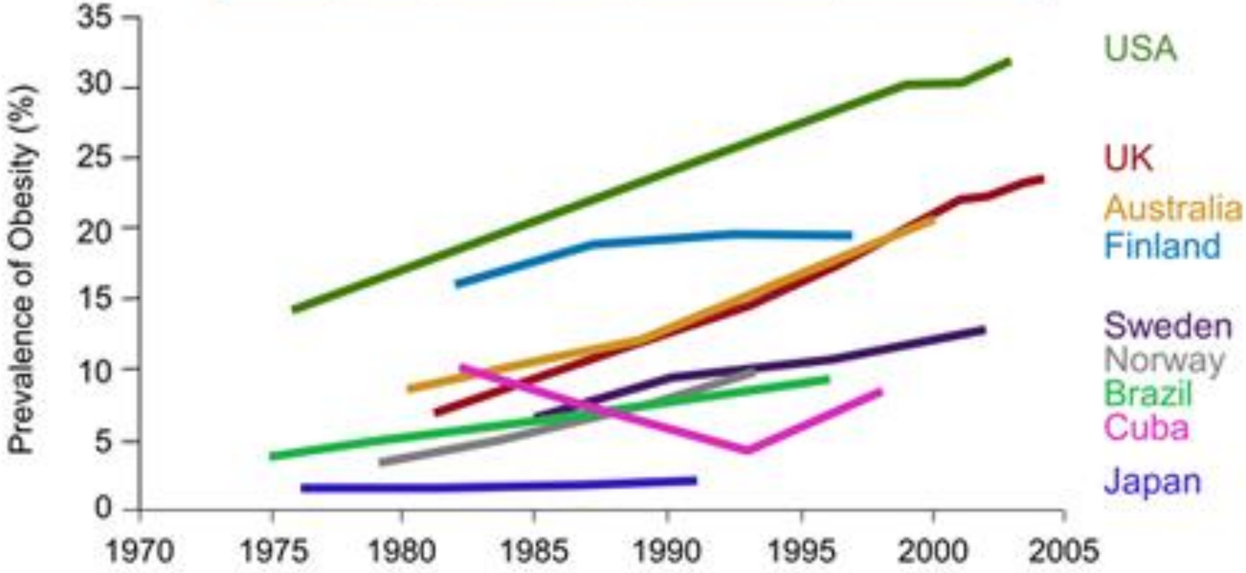
Obesity is a threat for health and economy

	2002	2007	2015
Obese	356 million	523 million	704 million
Overweight	1.4 billion	1.5 billion	2.3 billion



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.

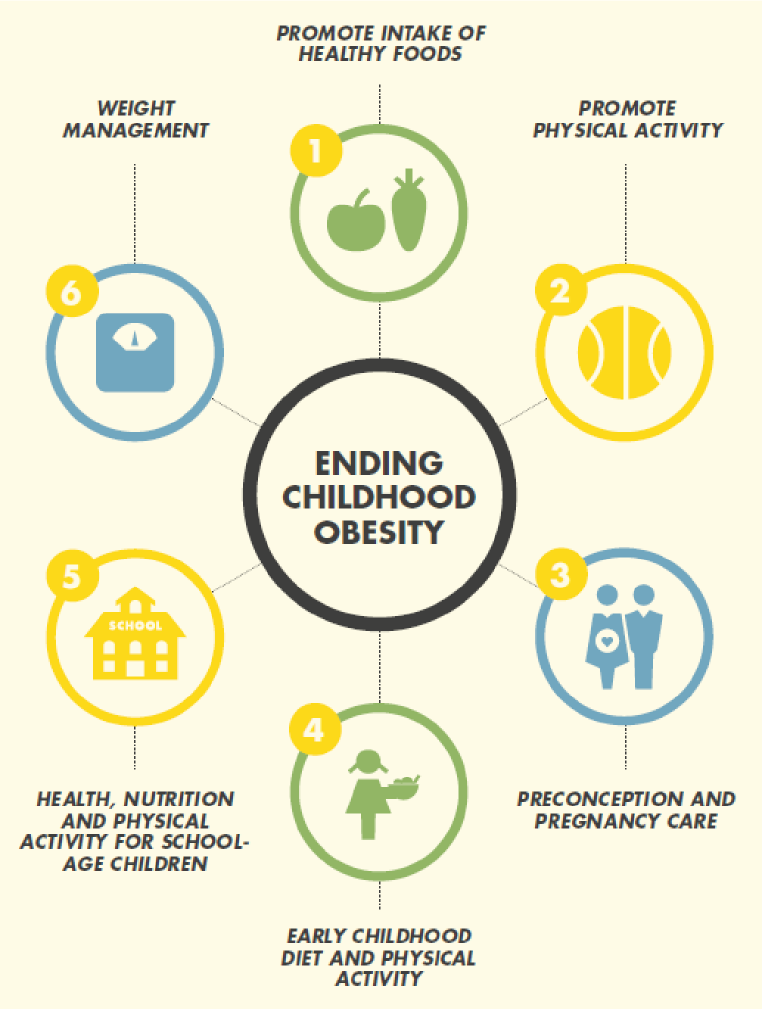
Obesity is a threat for health and economy

- 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)

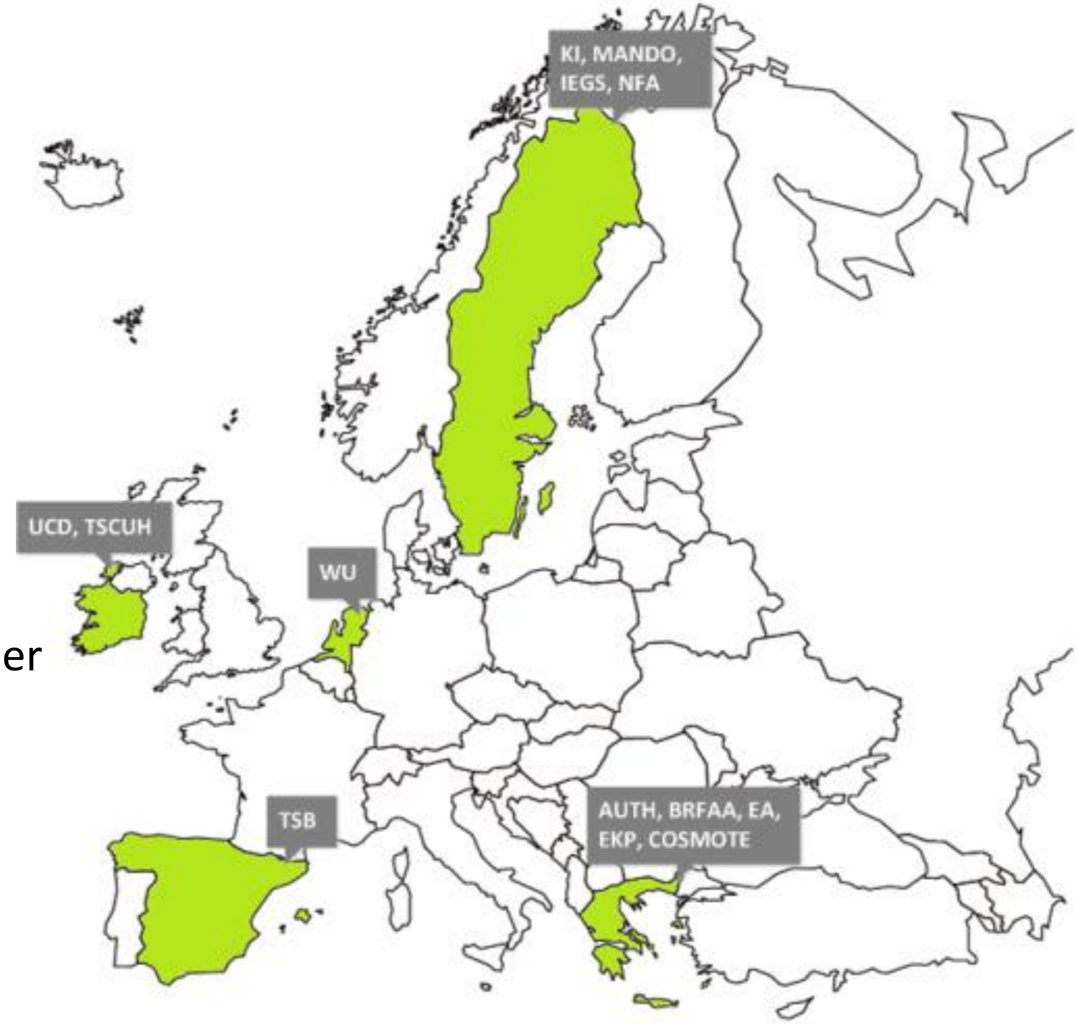
Current Public health actions

- Are not tailored to the needs of local communities
- Are limited to single-element strategies



Big Data Agains Childhood Obesity

- H2020 funding
  - → 2016-2020
- 13 organizations
  - →Universities
  - →Schools
  - →Obesity clinics
  - →Technical companies
  - →Telecommunications provider
  - →Public Health Authorities
- 5 countries

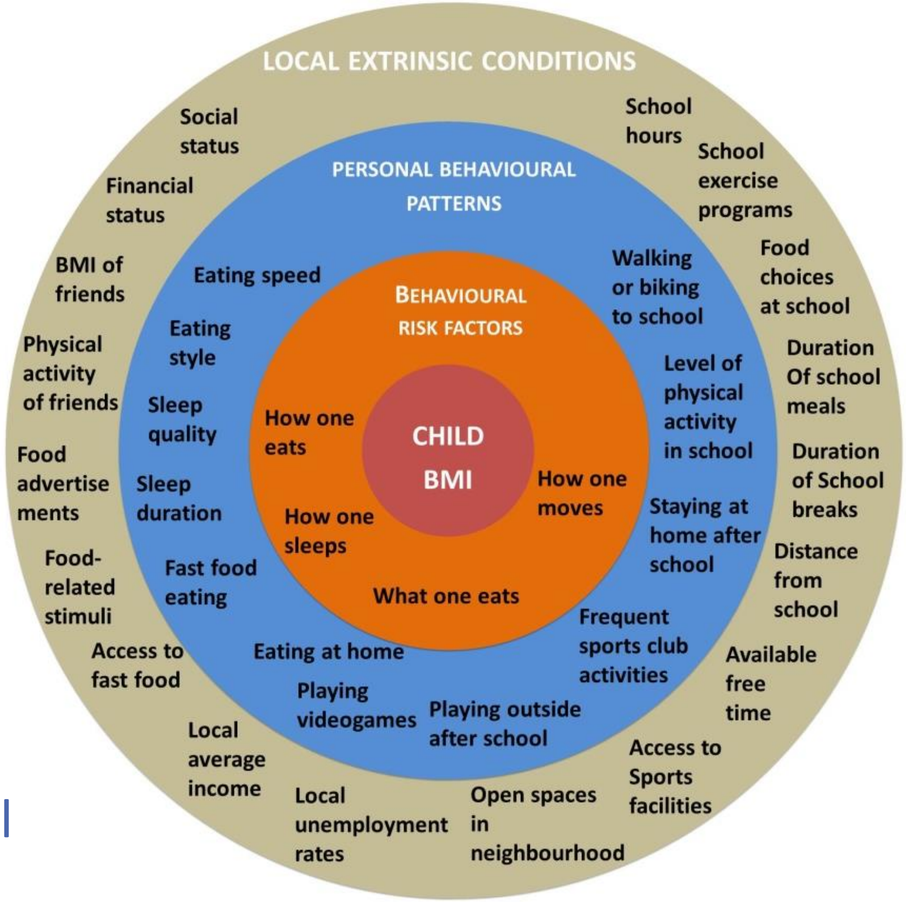


Big Data Agains Childhood Obesity

- 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

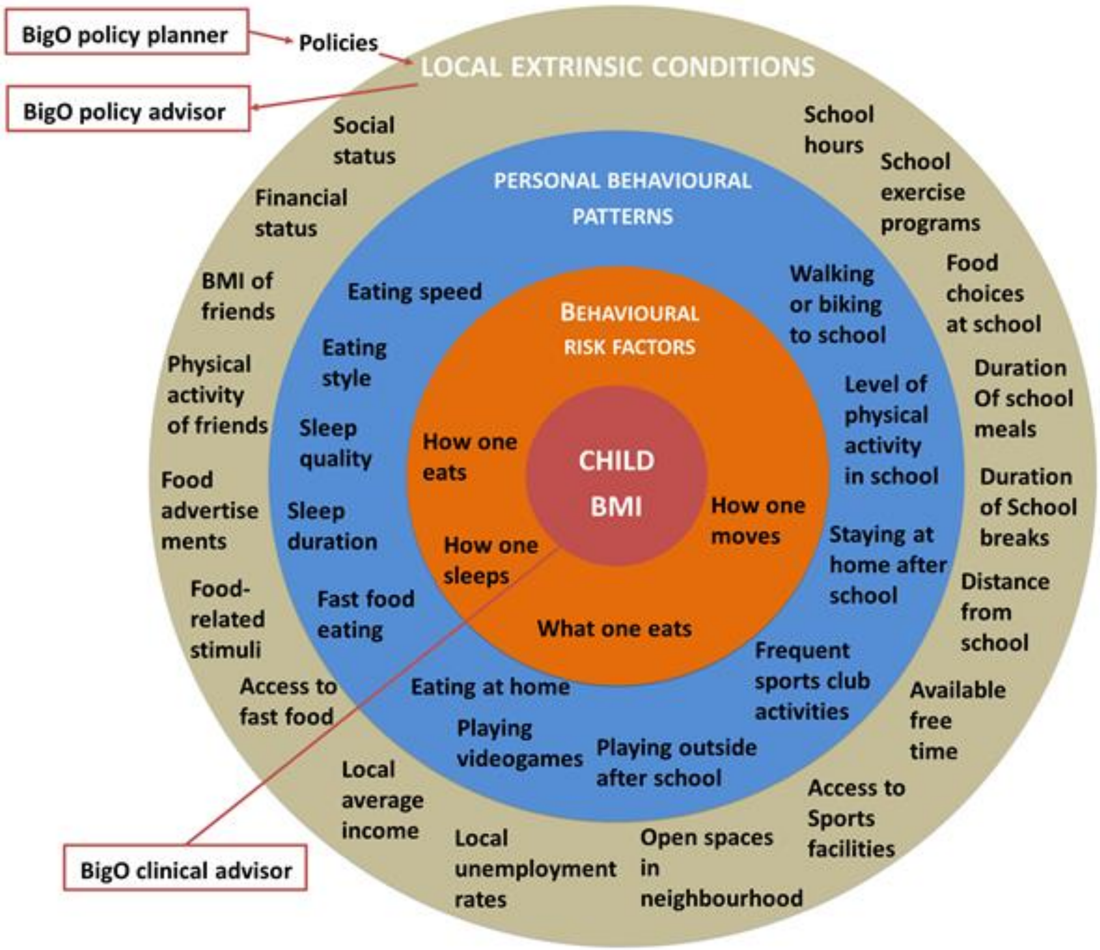
Need of multi-level approaches

- 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

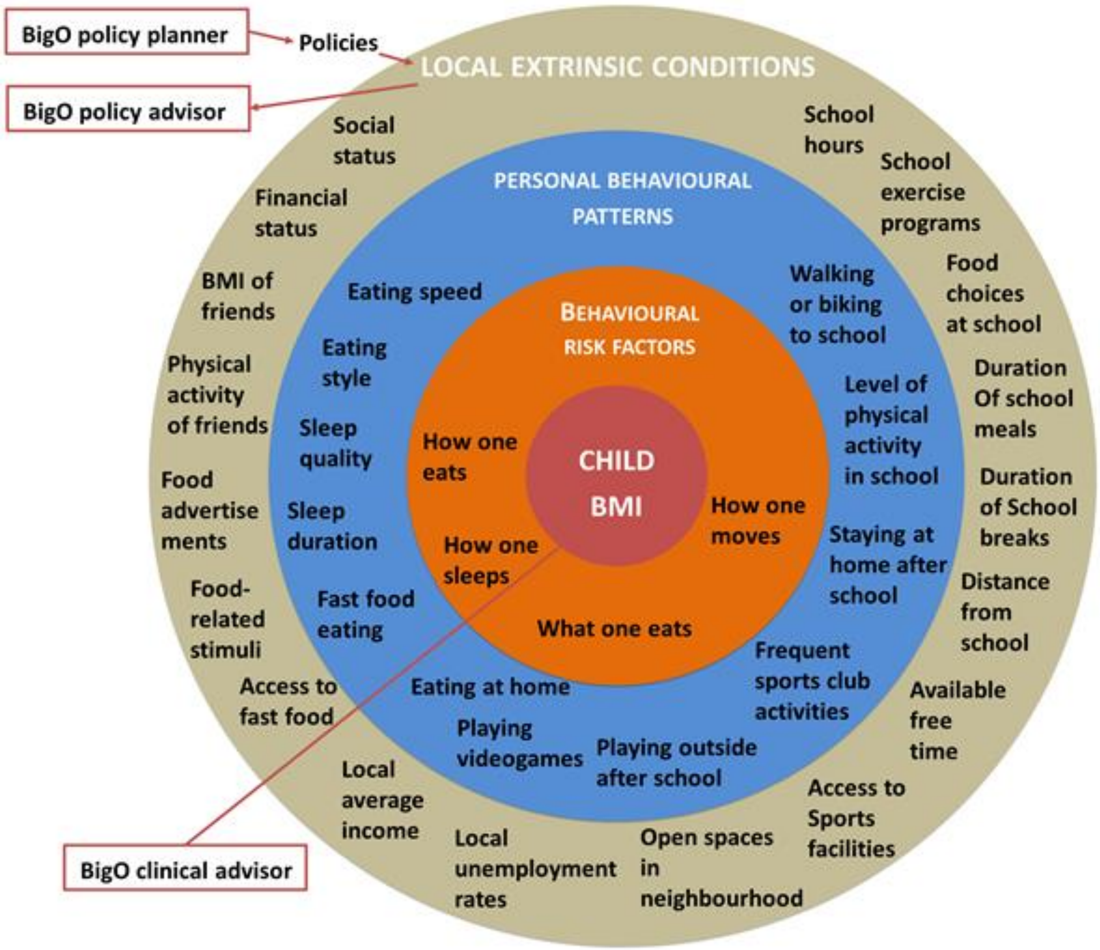


Local Extrinsic Conditions (LECs) = *The environment*

- Urban
- Social
- Financial
- Regulatory

Personal Behavioural Patterns

Causality hierarchy

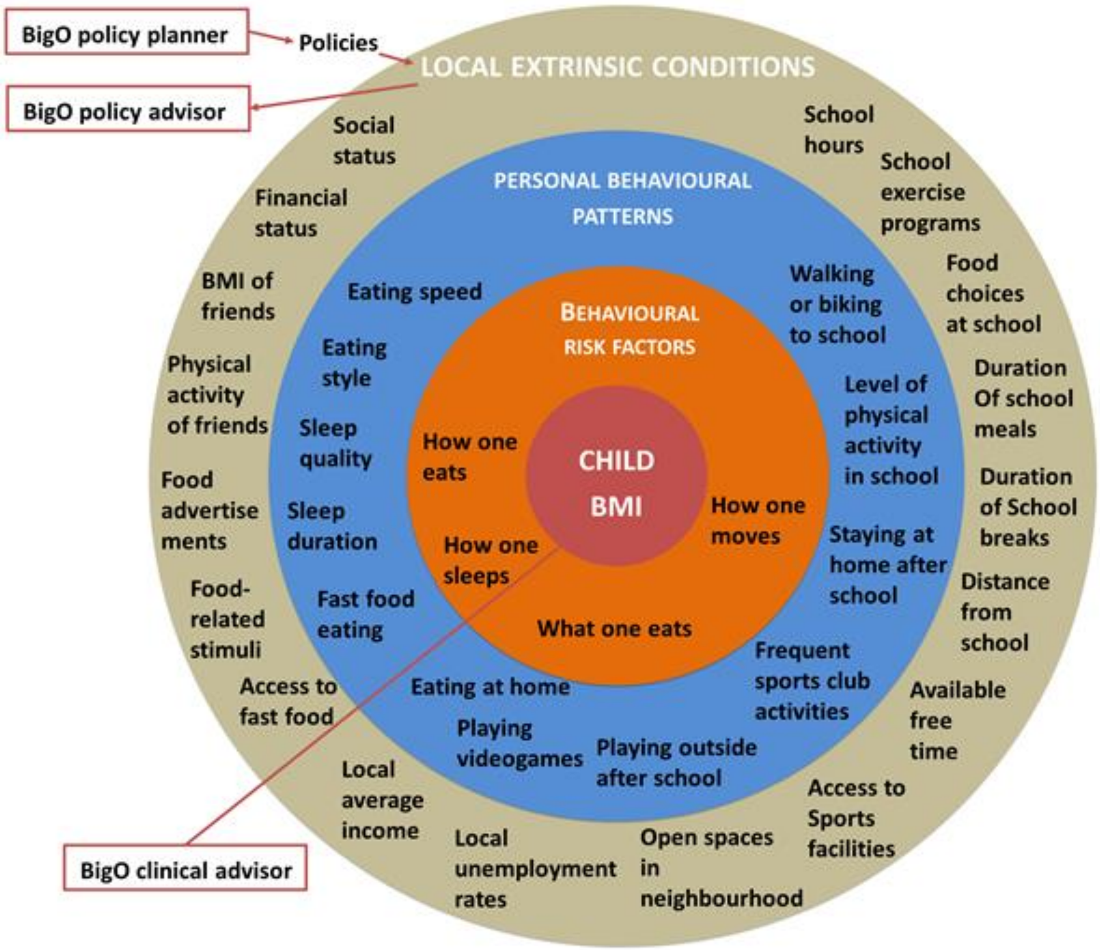


Personal Behavioural Patterns = our *habits*

– The multiplicity of them

Behavioural Risk Factors

Causality hierarchy



Behavioural Risk Factors =

A *structured profile*

- How one eats
- What one eats
- How one sleeps
- How one moves

Child BMI

or

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
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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

Physical Activity

Photos - Food & Ads

Barcode Scanning – Food

Sleep

Self-reporting

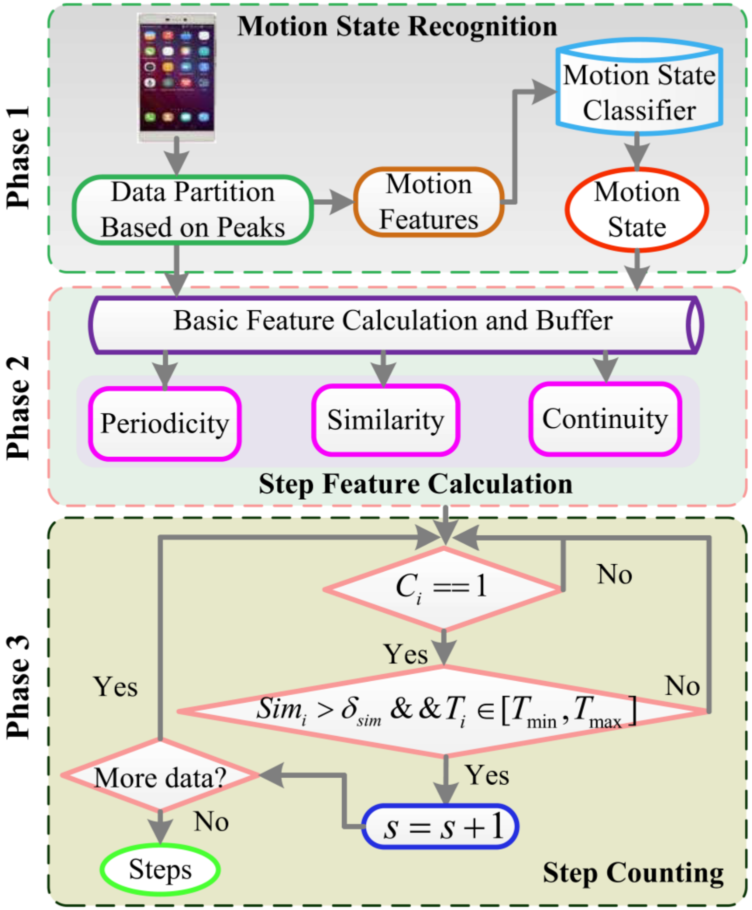
The BigO System

Measuring behavior: Devices + Apps

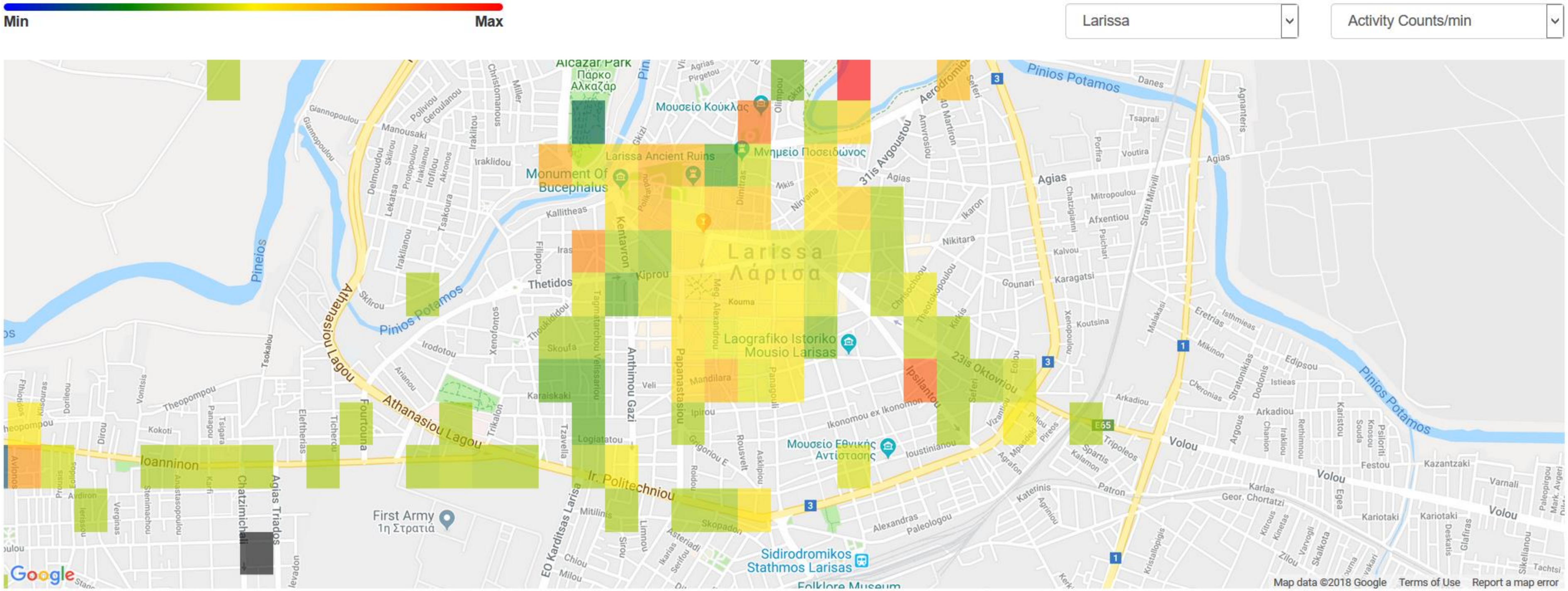
Use smartphones/smartwatches to measure accelerometry + position

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”

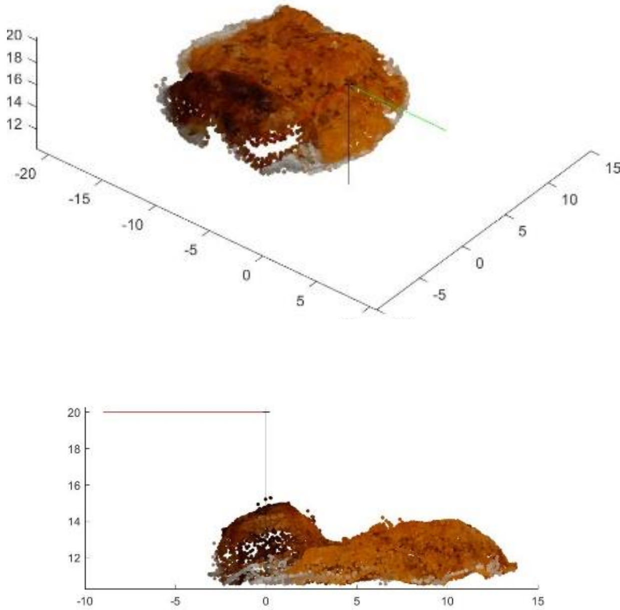
- Determine Points of Interest visited
  - →Home
  - →Frequently visited locations
  - →Public POIs
- GPS recordings per minute
- Smartphone or Smartwatch
- Cluster locations
  - →DBSCAN

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

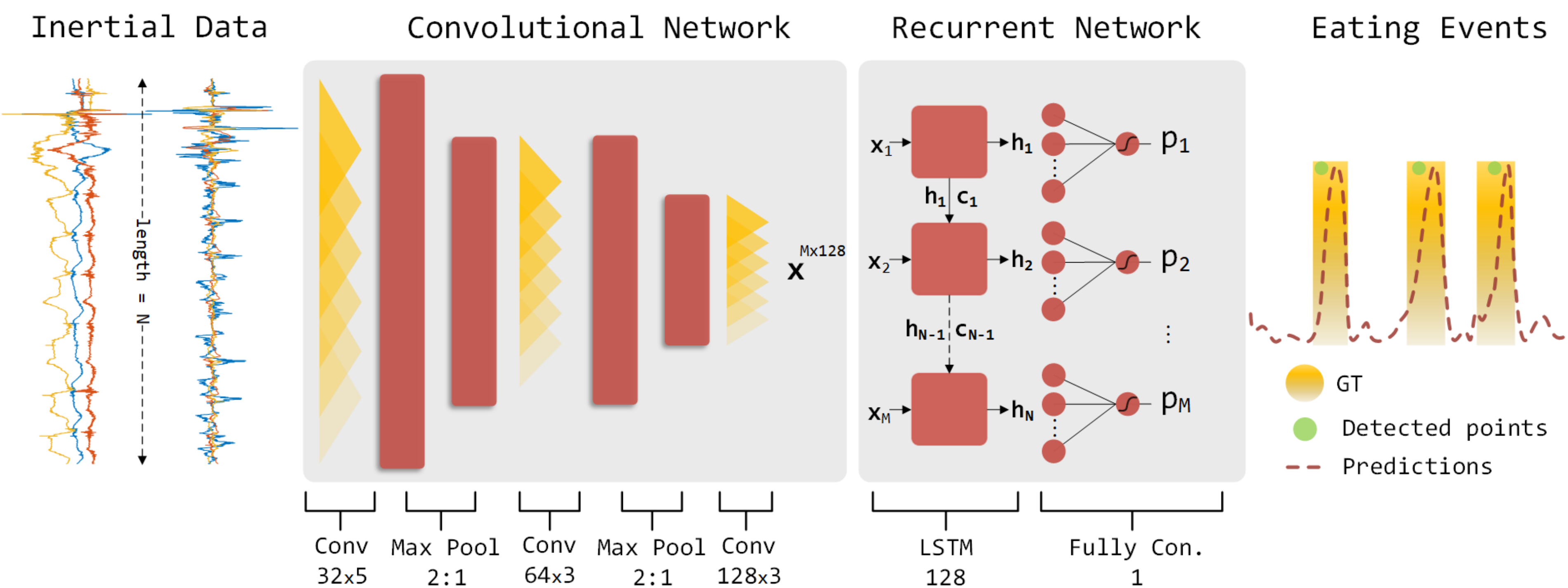
- Determine the type of food
- Quantify food
  - →Volume
  - →Main ingredients
- Pictures
- 3D computer vision



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)

Name	Units	Sensors involved (Location, Accelerometer, Photo, User answers)
Eating fast food /outside	Occurrence	L, P, U
Fast-food eating frequency	Times/week	L, P, U
Eating dinner outside of the home?	Occurrence	L, P, U
Eating at home	Occurrence	L, P, U
Food type	Categorical	U, P
Meal type (breakfast, lunch, dinner, snack)	Categorical	L, P, U
Meal frequency (e.g., breakfast)	Occurrence	U, P
Soda or fizzy drinks (sugar added)	Occurrence	U, P
Diet soda/Juice/water/milk	Occurrence	U, P
Eating occurrences	Occurrence	U
Eating/snacking frequency	times/day	U
Eating late at night	Times/week	U
Eating schedule adherence	sec (std)	U

Physical activity - Sleep indicators (indicative)

Name	Units	Sensors involved (Location, Accelerometer, Photo, User answers)
Energy expenditure (at minute intervals)	Categorical	A
Activity type (minute)	Categorical	A
Activity intensity	Categorical	A
Activity level	Categorical	A
Steps	Integer	A
Activity counts	Counts/minute	A
Exercise frequency	Times/week	A
Frequency of 10 min bouts of consecutive mod-vigorus activity	Times/week	A
Hours of sleep per night	Hours	A, U
Sleep/wake-up times per night	Timestamp	A
Interruptions of sleep	Number	A
Duration of each interruption	Minutes	A
Movement during sleep	Categorical	A

Measuring Environment: External Sources

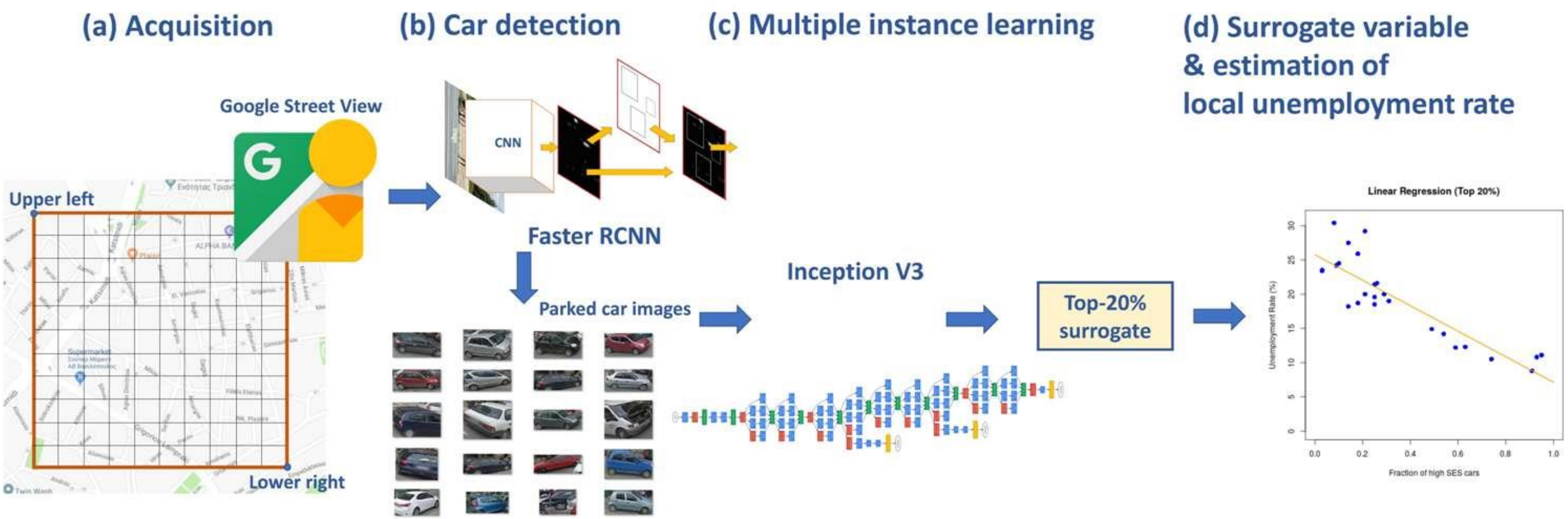
- Maps
  - →Incl. Google, Foursquare
- Statistical Authorities
  - → Finest spatial scale
  - → Microdata (?)

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



Diou, C.; Lelekas, P.; Delopoulos, A. Image-Based Surrogates of Socio-Economic Status in Urban Neighborhoods Using Deep Multiple Instance Learning. Preprints 2018, 2018080154 (doi: 10.20944/preprints201808.0154.v1)

Estimates of local conditions: unemployment

(a) Pylaia

(b) Panorama

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Local Environment Conditions (indicative)

BUILT ENVIRONMENT
Availability of indoor facilities
Number of indoor facilities
Density of indoor facilities
Price of indoor facilities
Availability of outdoor facilities
Number of outdoor facilities
Density of outdoor facilities
Price of outdoor facilities
Recreational space within walking space of distance of home
School infrastructure that includes spaces for organised or individual exercise/activity
Affordability of organised sports: club fees and costs
Numbers of people who use recreational spaces
Availability of open spaces in neighbourhood
Number of public parks
Density of public parks

Local Environment Conditions (indicative)

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

Local Environment Conditions (indicative)

SOCIOECONOMIC ENVIRONMENT / HEALTH INEQUALITIES
Education level statistics
Employment status or socio-economic status of family
Local deprivation indices
Area based food poverty statistics
Number of households experiencing food poverty
Unemployment levels
Child and family – living on public assistance
Health literacy
Ethnicity
Gender
Family structure
Availability and access to universal primary health services
Availability and access to school meals schemes
Level of referrals
UNICEF deprivation index

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**

6 digit geohashes in central Stockholm

Challenges

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

Thank you