Big Data, GeoAnalytics and Systems Analysis

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Regulating the internet giants

The world's most valuable resource is no longer oil, but data

The data economy demands a new approach to antitrust rules

A NEW commodity spawns a lucrative, fast-growing industry, prompting antitrust regulators to step in to restrain those who control its flow. A century ago, the resource in question was oil. Now similar concerns are being raised by the giants that deal in data, the oil of the digital era. These
“Big Data” are data and processes whose scale, distribution, diversity and/or creation speed requires the use of new storage and analysis technologies to allow the capture of the value inserted in them (FRANCISCO, 2016, adapted from EMC, 2013)

1. Data Volume

- Billions of lines x billions of columns
- Increase of 44 times from 2009 to 2020 (0.9ZB to 35ZB)

2. Processing Complexity

- Data structures are constantly changing
- Need to analyze such data in real time

3. Data Structure

- Large variety (80-90% unstructured) to be analyzed
- These characteristics make it necessary to use parallel and parallel mass computing (MPP) systems

Source: EMC (2013)
Expanding at an increasing rate on three fronts (the first 3 Vs)
Expanding at an increasing rate on three fronts (the first 3 Vs)

+ **Veracity**
+ **Value**
Expanding at an increasing rate on three fronts (the first 3 Vs)

+ **V**elocity
  - real time, asynchronous
  - almost real time
  - recurrent
  - batch

+ **V**olume
  - MB
  - GB
  - TB
  - PB

+ **V**ariety
  - social media
  - images
  - tables
  - databases
  - web
  - audio
  - mobile
  - unstructured

+ **V**eracity
+ **V**alue
+ **V**ariability
+ **V**isualization
Big Picture

Big Data, GeoAnalytics and Systems Analysis
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Challenges for Systems Analysis in the Big Data Era

• Big Data, Data Science, Analytics ...
• Challenge in the integration of analytical techniques
  • AI, Neuroscience applied to marketing and business, spatial statistics, behavioral models
  • Models to handle stakeholders’ relationships
• Computational Challenge
• Challenge in the adoption of AI and Data Science by companies and public organizations
  • Adoption of forceps, apart from core management
  • Analytical Sandbox vs. IT Policy
• Cultural challenge - new skills of analytical teams and managers

Use of alternative information (non-structured “Big” data) in the generation of indicators
• Open Data - API or Web Scrapping
• Sectoral Reports, Management Reports, Integrated Reports - Web Scrapping
• Interpretation of Images
• Data Enrichment by Geo-Analysis and Spatial Statistics
### Serious Implications for Scientific Research in Applied Social Sciences

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<th>Classic (Inferential) Statistics</th>
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Source: OLLION, 2018
Framework: Adaptive Business Intelligence and Big Data

Source: LETOUZÉ, 2017; MICHALEWICZ et al., 2006; GisBI, 2015
Inferring socio-demographic indicators

Scientific Prize and Ethics Mention: Construction of socio-demographic indicators with digital breadcrumbs
F. Bruckschen (1), T. Schmid (2), T. Zbiranski (3)

We show that socio-demographic indicators such as population, age, literacy, poverty, religion, ethnicity, electricity supply and others can be estimated in unprecedented detail and virtually ad-hoc using antenna-to-antenna traffic data only. We offer a uniform approach that can be easily extended to other variables. Results are tested for spatio-temporal robustness and visualized as heat maps.

(1) Humboldt Universität Berlin, Germany - (2) Freie Universität Berlin, Germany

Source: LETOUZÉ, 2017
**OBJ:** Analyze the relationship between household income and electricity consumption

Create an income indicator based on electricity

**Prediction Model:**

Electricity Consumption + Household Income

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**Traditional OLS Regression:**

\[ \hat{y} = \beta_0 + \beta_1 x \]

R² = 86.6%

**SAR (Spatial Auto-Regressive):**

\[ \hat{y} = \beta_0 + \beta_1 x + \rho Wy \]

R² = 94.4%

**GWR (Geographically Weighted Regression):**

\[ \hat{y}_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i) x_i \]

R² = 96.8%
Microcredit Score and Socio-Economic Indicators based on Electric Energy

Consumo Residencial de Energia Elétrica (kWh)

Microcredit Score

Renda Domiciliar (R$)

Source: FRANCISCO, 2011
• Development of an Indicator of Propensity to Energy Commercial Losses using Geospatial Statistical Techniques and Socio-Economic Data: the Case of AES Eletropaulo

FRANCISCO, E., FAGUNDES, E., PONCHIO, M., ZAMBALDI, F. - EnANPAD 2009

• Use of geospatial techniques for the design and operation of a fraud-prone indicator, and analysis (through GWR) of the association between this indicator and customer satisfaction

Source: FRANCISCO et al., 2009
Socio-Economic Indicators based on Electricity Consumption

- Should be published widely by the electricity distributors
- Support for strategy formulation and decision support
- Support for Customer Relationship Characterization and Management
- Support for Public Policies and Systems Analyses
- Socio-Economic Indicators based on Electricity Consumption

Managerial Implications

- Ad-hoc Studies
- Census Block
- Household Income Density
- Quadrats (1 square kilometer)
- Census Tracts (2,700,000 sq km)

Household Income Density

Managerial Implications
Health and Longevity Research and Study Platform

https://youtu.be/1ET4glwLAe0
Thank you!
¡Gracias!
Obrigado!