# Multivariate analysis and complex networks

## 5: Complex networks for data-driven medicine

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Ischia, May 2017

# Introduction

Motivation: Mining knowledge from Medical Records

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| Methods: | Network Analysis for Case-Features dataset |
| Case-study: | Childhood orthodontics |

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The aim is to generate knowledge

“”Machine Science” James Evans and Andrey Rzhetsky

Science **329**. no. 5990, pp. 399 (2010)

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- *network science* looks globally at the relations among the components of a system
- complex network analysis reveals new conceptual classes *emerging due to the the interaction among the data*

# Data

medicine: clinical cases - clinical features

2d cromatography: experiment - substance is (not) detected

test/marketing pools: people - answer to question

human geography people - locations

coauthoring: author - publication

textual co-occurrence: word - query/sentence/paragraph/book

community matrices: taxa - sample

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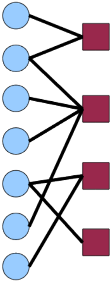
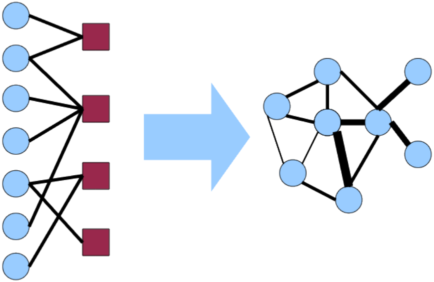
BIPARTITE GRAPH / BINARY MATRICES

# Methodology



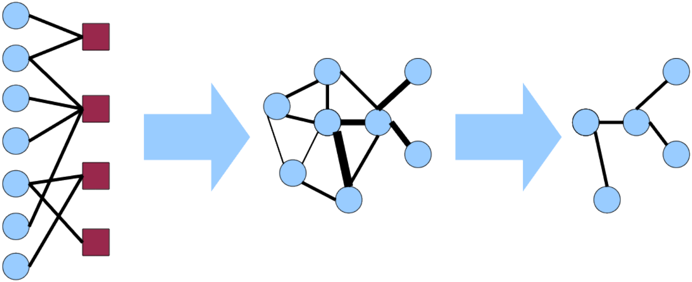
**DATA**

# Methodology



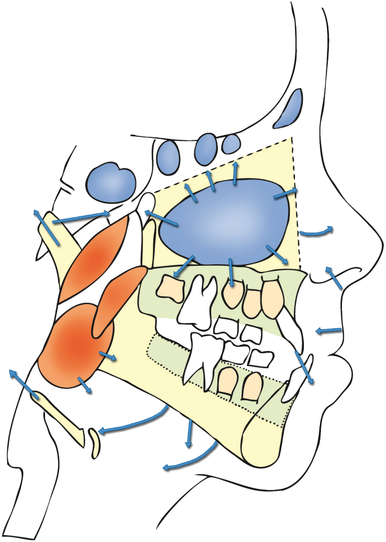
PROJECT

# Methodology



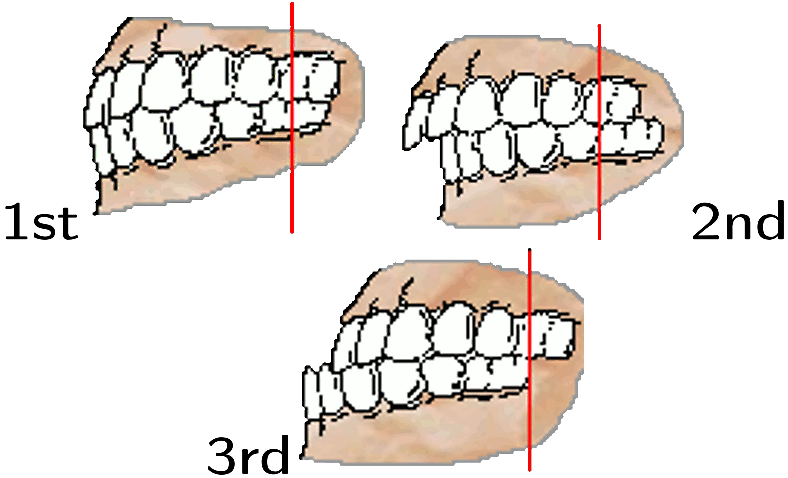
SELECT

# The Complex Oro-Facial System



- components
- relations
- interactions
- dynamics

# Dental Classes



## Cases

- 97 subjects (49 males, 48 females)
- age 8-13 (mean 10.2)
- 28 1st class, 44 2nd class, 25 3rd class patients
- Uniform age and gender

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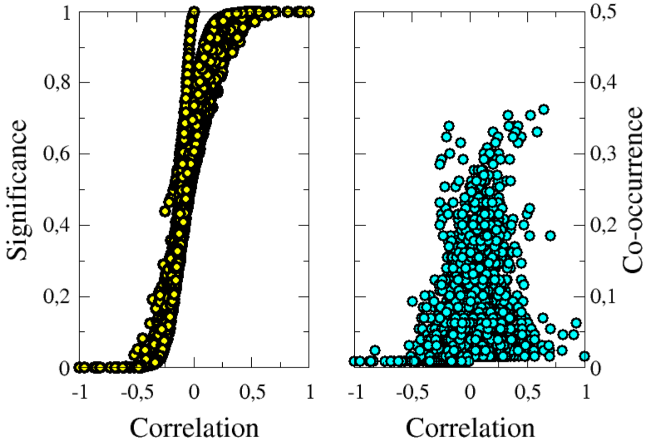
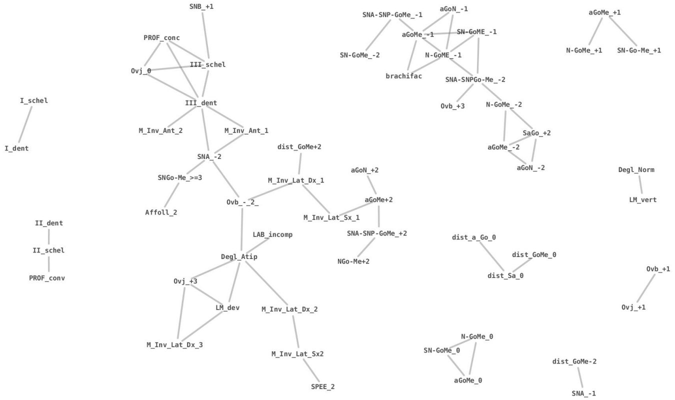
## Features

- 33 clinical, anatomic, functional and radiographic features
- 16 landmarks on the cephalograms
- 17 functional and clinical signs or oral habits
- score from -3 to + 3 = standard deviations from the mean

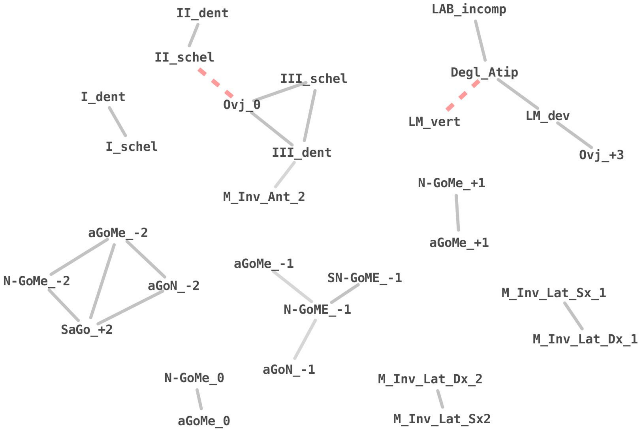
# Correlation vs Co-occurrence



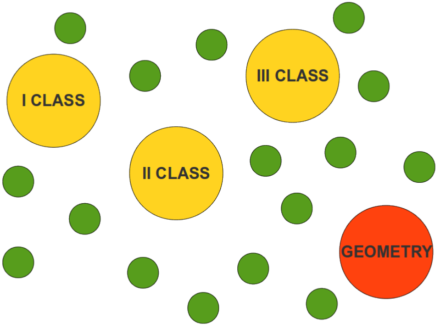
# Positive Correlations >40%



# All Together >50%



# Emergence of dental classes

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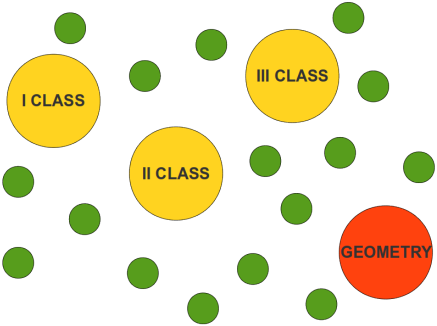
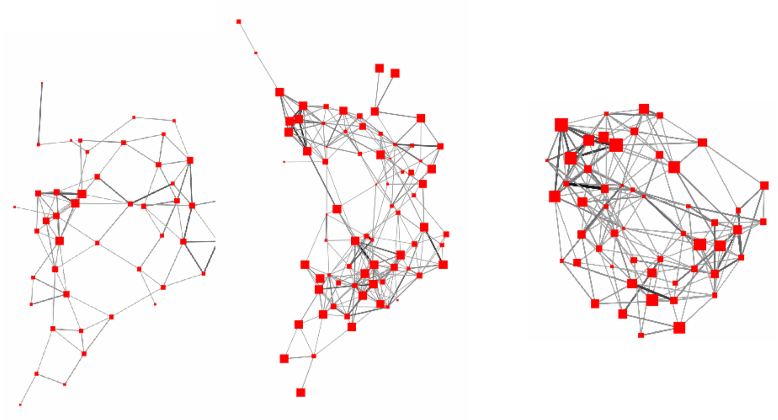



- Emergence of dental classes
- Emergence of geometrical constraints

# Networks for single Classes

$\varphi \geqq 30\%$ (treshold for medium & high correlations)



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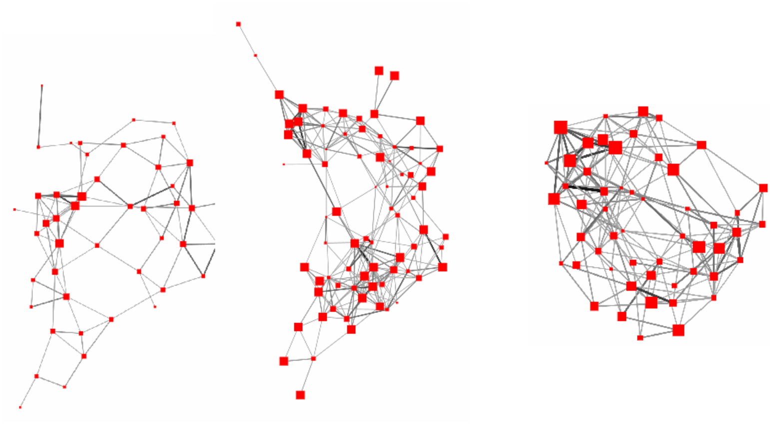

- 3rd class malocclusion strongly connected but devoid of distinctive peculiar hubs
- multiple therapeutic attack on the many highly connected nodes

# Networks for single classes

| | Average Degree | Clustering coefficient | Mean Shortest |
|---|---|---|---|
| 1st (normal) | 4.04 | 0.28 | 3.43 |
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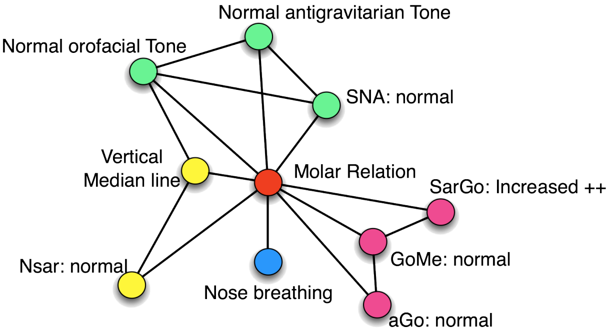
- 2nd and 3rd class features are more connected than those of the control patients.
- 3rd class patients shows a much higher connection and closeness: this topology allows a high transmission of the bite forces and neuromuscular inputs

# Hubs in 2nd Class

Network local picture (simplified)




- peculiar hubs as starting point for an orthodontic selective treatment
- hubs do not necessarily correspond to the most evident clinical signs

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- Features can be considered in the light of the appropriate network specific for a particular malocclusion
- Networks represent the system in a visually intuitive way, focus on most important features
- Valuable tool for evidence-based diagnosis in primary orthodontic care
- *Could also be applied to other clinical problems*

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Complex Networks can contribute to mine new knowledge

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  - clinical records
  - designing experiments

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**GOAL** infer syndromic phenotypes from clinical data via complex networks methods