A mixt data/knowledge-driven data science approach for complex decision making

Mental Health policy-making in LAMIC at WHO

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[6] Working Group Clinical Management of the Spanish Society of Psychiatry

Data Council Barcelona 2019. UTOPIA 126, October 2-3th, 2019

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UPC, ANU, WHO, Manzonni, UB, SEP

- ***WHO is the directing and coordinating authority for health within the United Nations system (www.who.int)***
- WHO is responsible for:
  - providing leadership on global health matters
  - shaping the health research agenda
  - setting norms and standards
  - articulating evidence-based policy options
  - providing technical support to countries
  - monitoring and assessing health trends.

Gibert, K., L. Salvador-Carulla, J. Morris, A. Lora, S. Saxena (2017) The data mining approach as the starting point for Mental Health policy-making in low and middle income countries at World Health Organization, In Proc ISI 2017, Marrakesh, Morocco.

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Guide mental health policies in low and middle income countries

Gibert, K., L. Salvador-Carulla, J. Morris, A. Lora, S. Saxena (201
point for Mental Health policy-making in low and middle income countries at W
Proc ISI 2017, Marrakesh, Morocco.

Understanding mental health systems in LAMIC

Mental Health System:

"structure and all the activities whose primary purpose is to promote, maintain or restore mental health. The MHS includes all organizations and resources that focus on improving mental health"

Collaboration WHO, Geneva, Switzerland

Guide mental health policies in low and middle income countries

WHY?

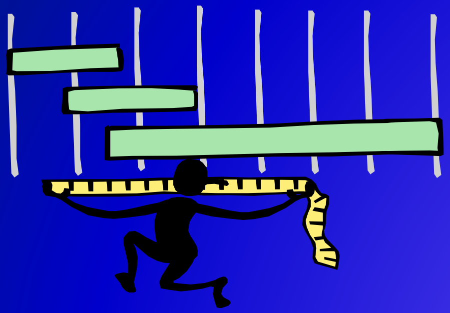
Major depression of young mothers in LAMIC important cause of neonatum mortality

First step: *Understand how mental health is in LAMIC*

Learn from WHO-AIMS DB

APA (2000): *Diagnostic and Statistical Manual of Mental Disorders*. DSM-IV-TR. Washington: APA (American Psychiatric Association).

WHO-AIMS Project



Data on mental health system compiled from 42 selected LAMIC countries between Feb 2005-Feb 2008

Countries referred by their WHO Regional Advisers as those that would benefit for a WHO assessment

WHO-AIMS v2.2 instrument: 22 facets, 155 items, 256 variables

- ***policy and legislative framework***
- ***mental health services***
- ***mental health in primary care***
- ***human resources***
- ***public information and links with other sectors***
- ***monitoring and research***

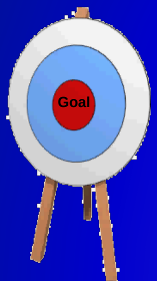
+ some additional (decisional) composite indicators by WHO

+ prior expert knowledge

Janca A, Kastrup M *et al.* (1996)]: The WHO Short Disability Assessment Schedule...*Soc Psychiatry Psychiatr Epidemiol* 31: 349-54.

Profiling mental health systems
Methodology

Use WHO-AIMS DB to learn a **typology** of MHS in LAMIC



- Easy **understanding** of reality
- Assessment to countries
- Intervention design: guidelines, mental health policies....

Clustering (ClBR)

Postprocessing CPG, TLP

Experts combine items in 19 composite decisional indicators

- A 21,43% of **missing** data in original Data Base
- Missings propagate to indicators
- Difficult decision-making

Missing imputation (MIMMI)

The data mining process

Preprocessing

Feature Selection
Missings: MIMMI
Outliers: Unnecessary
Transformations: No
New variables: expert indicators

DataMining

Clustering based on rules

Post-processing

Class interpretation
- CPGs
- Termometer
- TLPs
- Maps

Inputs

Data sources:
- WHO-AIMS
- WHO data
- World Bank

Knowledge sources:
- Experts

New Knowledge

Dimensions of MHS

Typology of MHS

Ontology of MHS

Gibert, K. J. Izquierdo, M. Sànchez-Marrè, S. (H) Hamilton, I. Rodríguez-Roda, G. Holmes (2018) Which method to use? An assessment of Data Mining Methods in Environmental Data Mining. Environmental Modelling and Software. Elsevier

Preprocessing

Mixed Intelligent-Multivariate Missing Imputation *[Gibert 2012]*

- Select a small number of quasi-full relevant variables
- Use ***intelligent inputation*** on that reduced data matrix
  - *(expert-based inputation)*
- Multivariate clustering using the inputed variables
- Determine a partition of the data and compute local means for ALL variables
- Inpute the missing data of the remaining variables with computed local means

Trade-off
Accuracy/required time

Gibert, K (2013) Mixed Intelligent-Multivariate Missing Imputation, International Journal of Computer Mathematics 91(1):85-96

Preprocessing

MIMMI method on WHO-AIMS database

Selection of 16 core variables

WHO-AIMSname	Meaning	KLASSname
polplanr	Presence of policy or plan	polplanr
legisl	Presence of legislation	Legisl
d1f5i5rec	Affordability of anitpsychotic medicine	d1f5i5rec(antipsych)
d1f5i6rec	Affordability of anitdepressant medicine	d1f5i6rec(antidepr)
D2F1I2	Oragnization of services	D2f1i2(orgServices)
cbusrate	Community based inpatient units per 100,000 population	cbusrate
mhrate	mental hospitals per 100 000 population	mhrate
outpfrate	outpatient facilities per 100 000 population	outpfrate
daytrfrate	day treatment facilities per 100 000	daytrfrate
D4F1I11	psychiatrists per 100 000	d4f1i11(psychi)
D4F1I12	other doctors per 100 000	D4F1I12(doctors)
D4F1I13	nurses per 100 000	D4F1I13(nurses)
D4F1I14	psychologists per 100 000	D4F1I14(psycho)
D4F1I15	Social workers per 100 000	D4F1I15(socWorK)
d3f1i3	availability of treatment and assessment manuals	d3f1i3(manuals)
d5f2i51	formal collaborative relationship with department of primary care	d5f2i51(relprimcare)
D6F1I1	formally defined min data set	D6F1I1(mindataset)

Preprocessing
MIMMI method

Selection of 16 core variables:

- Characteristic information of the whole 6 domains
- Related with decisional variables (composite indicators)
- Low tax of missing data

KLASSname	nMissing
outpfrate	1
D4F1I12(Other)	1
D4F1I13(nurses)	1
D4F1I14(psycho)	2
D4F1I15(socWorK)	1
d3f1i3(manuals)	1
d5f2i51(relprimcare)	1

Complex process

time consuming

applicable in real projects with experts

total of 8 missing cells to be inputed

- Intelligent inputation of 8 missing values

Preprocessing (MIMMI)

Intelligent inputation of 8 missing values

Country	Missing variable and imputed value
South Africa	outpfrate = 2.0
China	D4F1I12(Other) = 1.20
India	D4F1I13(nurses) = 0.15
China	D4F1I14(psycho) = 0.16
Paraguay	D4F1I14(psycho) = 1.4
Nepal	D4F1I15(socWorK)= 0.15
Moldova	d3f1i3(manuals) = B
Azerbaijan	d5f2i51(relprimcare) = N

Two Strategies

Preprocessing (MIMMI)

Intelligent inputation of 8 missing values

Country	Missing variable and imputed value
South Africa	outpfrate = 2.0
China	D4F1I12(Other) = 1.20
[illegible]	D4F1I13(nurses) = 0.1[illegible]
[illegible]	D4F1I14(psycho) = 0.16[illegible]
Paraguay	D4F1I14(psycho) = 1.4
Nepal	D4F1I15(socWorK)= 0.15
Moldova	d3f1i3(manuals) = B
Azerbaijan	d5f2i51(relprimcare) = N

Vertical Imputation

Rate of "other medical doctors" in China
Very institutional system.
Higher than other Asian countries.
Between Vietnam and Thailand.

Two Strategies

Preprocessing (MIMMI)

Intelligent inputation

Vertical inputation:

use the value of the same variable in other similar individuals

- South Africa (Outpatient Facility):

  better developed outpatient facility net than other African countries.

  But less developed than other upper middle income countries.

Chose a value higher than the African countries but lower than Chile (a UMIC).

- China (rate of "other medical doctors“):

  higher than other Asian countries. Very institutional system.

  Choose a value in the middle between Vietnam and Thailand.

- Paraguay (psychologists):

  are more prevalent in Latin American countries.

  Choose a high value.

- Nepal (Social workers):

  similar to Sri-Lanka

Expert Knowledge based

Preprocessing (MIMMI)

Intelligent inputation of 8 missing values

Country	Missing variable and imputed value
[illegible]	outpfrate = 2.0
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Horizontal Imputation

India-Uttaranchal (nurses rate)
High where hospitals are.
India do not has mental hospital

Choose a low value

Two Strategies

Preprocessing (MIMMI)

Intelligent inputation of 8 missing values

Horizontal inputation:

check other variables of the same individual as predictors

- India (Uttaranchal) (nurses)

  high where hospitals are. India do not has mental hospital

  Choose a low value for the rate of nurses

- China (rate of psychologists):

  Mental health system medical based

  Choose a very low rate of psychologists

- Azerbajan (relation with primary care):

  The country declared to have no treatment manuals available and few referrals between primary care and mental health services.

  Choose No

- Moldova (Manuals):

  comparing their data with their re… ar items.

Expert Knowledge based

Preprocessing MIMMI

Inputation:

Complete the 42x16 data matrix

Clustering the full matrix

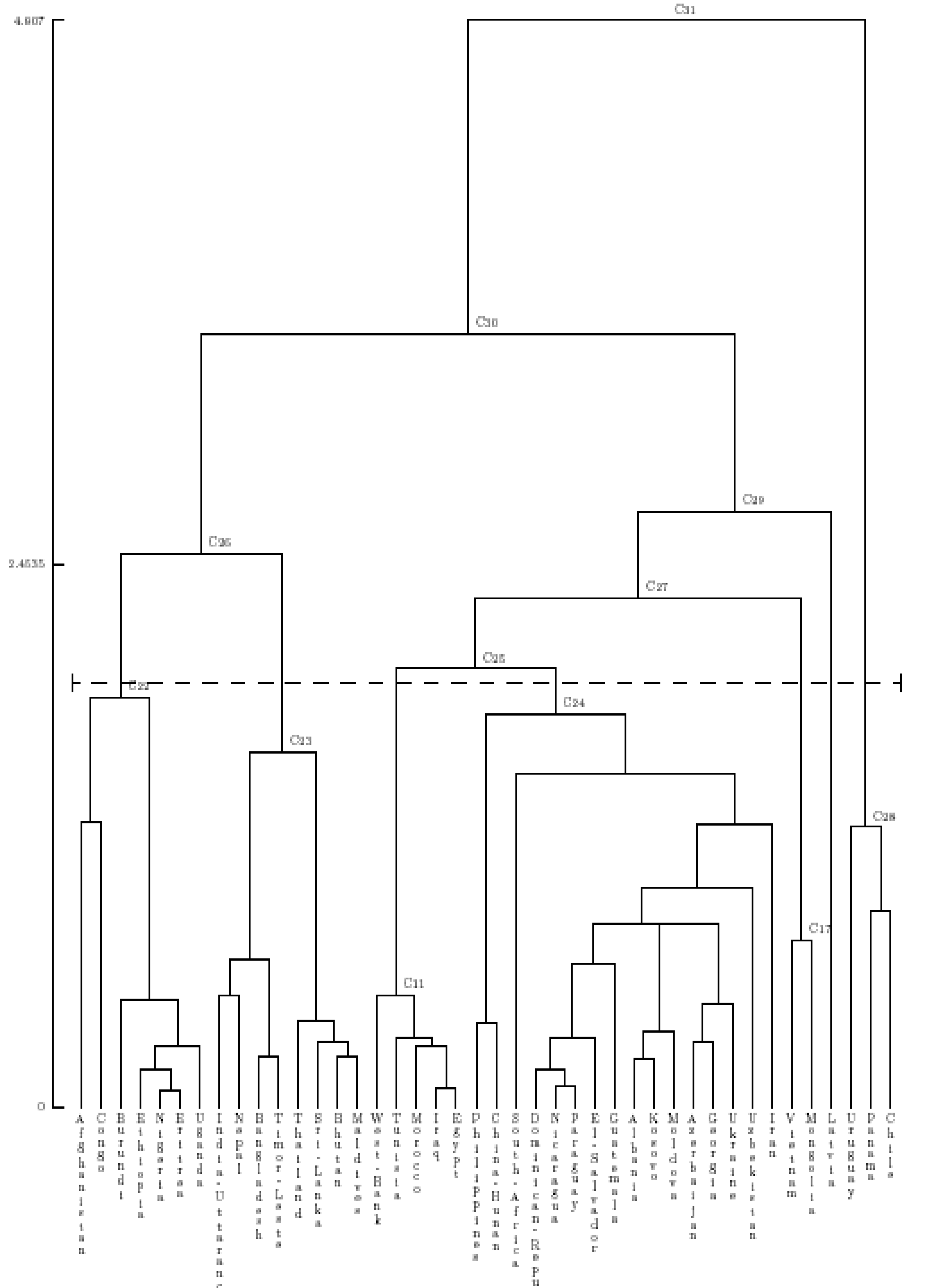
Hierarchical

Ward criterion

Gibert's mixed metrics [Gibert 96]

Determine the classes (7)

Find partition

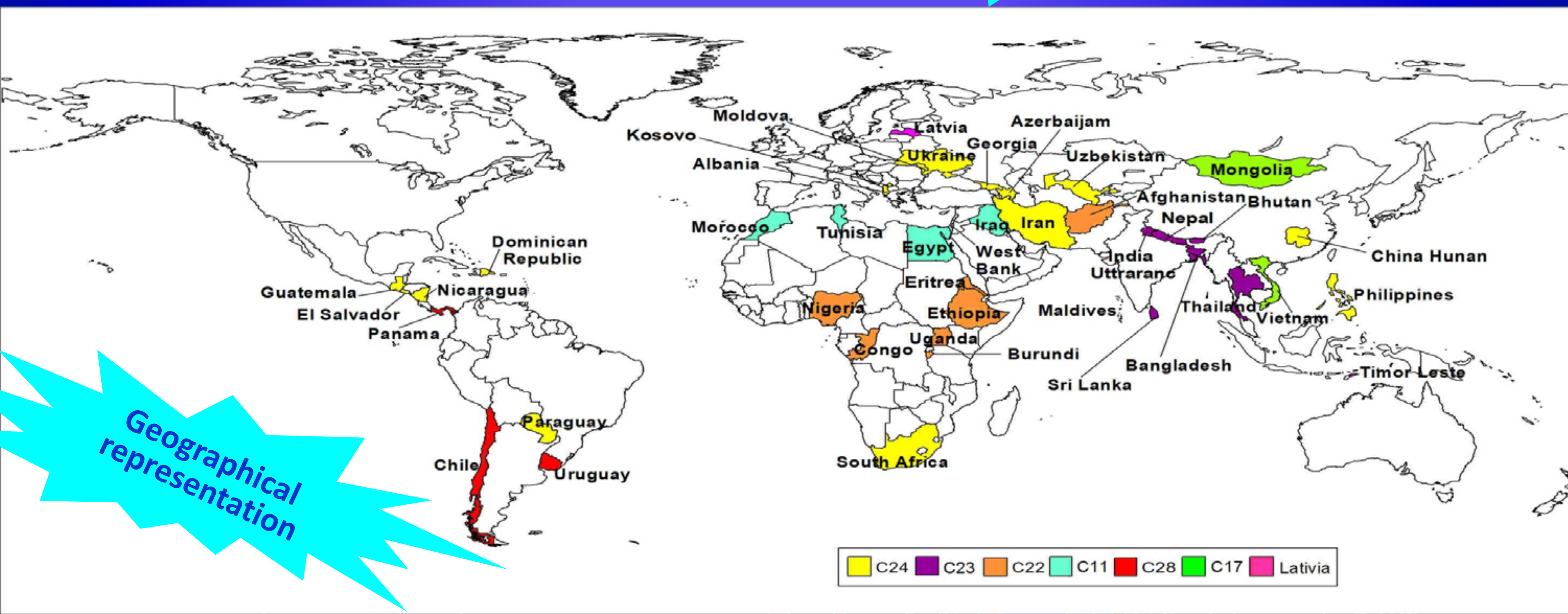


Preprocessing (MIMMI): preliminary partition

Seven classes recommended

- **C22:** Afghanistan, Burundi, Congo, Eritrea, Ethiopia, Nigeria, Uganda
- **C24:** Albania, Azerbaijan, China-Hunan, Dominican-Repu, El-Salvador, Georgia, Guatemala, Iran, Kosovo, Moldova, Nicaragua, Paraguay, Philippines, South-Africa, Ukraine, Uzbekistan
- **C23:** Bangladeh, Bhutan, India-Uttaranc, Maldives, Nepal, Sri-Lanka, Thailan Ti -Leste
- **C28:** Chile, Panama, Uruguay
- **C11:** Egypt, Iraq, Morocco, Tunisia, West-Bank
- **Latvia**
- **C17:** Mongolia, Vietnam

Burundi



Preprocessing (MIMMI)

Imputing Data Matrix

Conditional means wrt auxiliary class and variable

	CLASSE	C22	C24	C23	C28	C11	Latvia	C17
VARIABLE	$N = 42$	$n_c = 7$	$n_c = 16$	$n_c = 8$	$n_c = 3$	$n_c = 5$	$n_c = 1$	$n_c = 2$
totprofinh	$\bar{X}$	1.28	13.5507	5.1017	21.15	4.53	47.23	8.775
	S	0.9711	10.0276	6.0099	7.5041	2.6071		7.3468
	N*	0	2	2	0	1	0	0
treatpre	$\bar{X}$	192.22	1219.4614	59.7	1037.8201	547.0175	3490.75	1251.71
	S	121.1716	1447.8447	39.4424	519.8082	550.17	?	?
	N*	3	3	6	1	1	0	1
lundpararectrail	$\bar{X}$	1.09	0.9	0.49	1.2	1.1567	0.19	0.76
	S	0.7916	0.5622	?	0.0566	0.8864	?	?
	N*	3	7	7	1	2	0	1
comcarewor	$\bar{X}$	0.0314	0.0856	0.0197	0.0269	0.624	0.1991	0.1313
	S	0.0083	0.0196	?	0.0067			
	N*	5	10	7	1	4	0	1
usmhexperca	$\bar{X}$	0.2646	0.4961	0.2466	2.7995	0.4102	10.172	0.256
	S	0.5312	0.5059	0.2915	2.5926	0.2307		
	N*	0	1	1	0	1	0	1
d1f5i2exmhos	$\bar{X}$	0.7783	0.7954	0.7463	0.4963	0.5768	0.804	0.636
	S	0.2019	0.2121	0.1582	0.2051	0.1106		?
	N*	1	1	4	0	1	0	1

Data preparation

Expert-based feature selection

From 256 variables, 19 relevant decisional variables where selected

Expert-based creation of decisional indicators

Ex. Lund Parameter

external contacts/days hospital

Assess on "approach of a mental health system"
(hospital recovery vs social inclusion)

Gibert, K., M. Sànchez-Marrè, J. Izquierdo (2016) A Survey on Pre-processing Techniques in the Context of Environmental Data Mining. Artificial Intelligence in Communications, 29(6): 627-663, IOSPress DOI: 10.3233/AIC-160710

Lund, J. (1988). Psychiatric aspects of Down's syndrome. *Acta Psychiatrica Scandinavica*, 78(3), 369-374.

Profiling mental health systems
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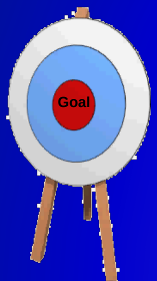

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Profiling mental health systems in LAMIC

Prior Expert Knowledge Acquisition

WHO-AIMS data

Rows: 42 LAMIC
Columns:
19 WHO-AIMS indicators
+ WHO-AIMS region
+ Income group
(World Bank classification)

KLASS

Clustering based on rules *[Gib'96]*

Ward's criterion
Gibert's mixed Metrics [Gib'97]

Prior Expert Knowledge

r0: Region=euro and income= lower
-> PreSoviet

r1: Region=AMR and income = lower
-> poorAmerica

r2: Region= SEAR and population < 10000000
-> ***smallAsia***

Gibert, K., Izquierdo, J., Sànchez-Marrè, M., Hamilton, S. H., Rodríguez-Roda, I., & Holmes, G. (2018). Which method to use? An assessment of data mining methods in Environmental Data Science. Environmental modelling & software, 110, 3-27.

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Profiling mental health systems in LAMIC

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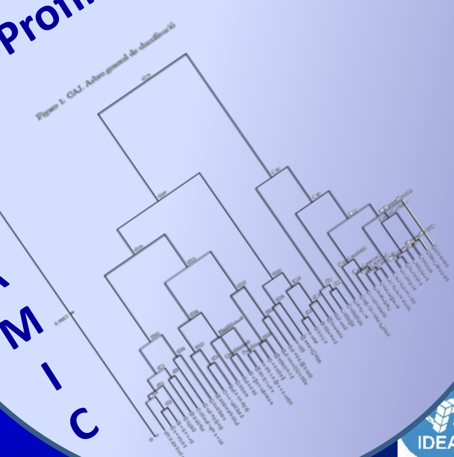
Profiles

MHS in LAMIC

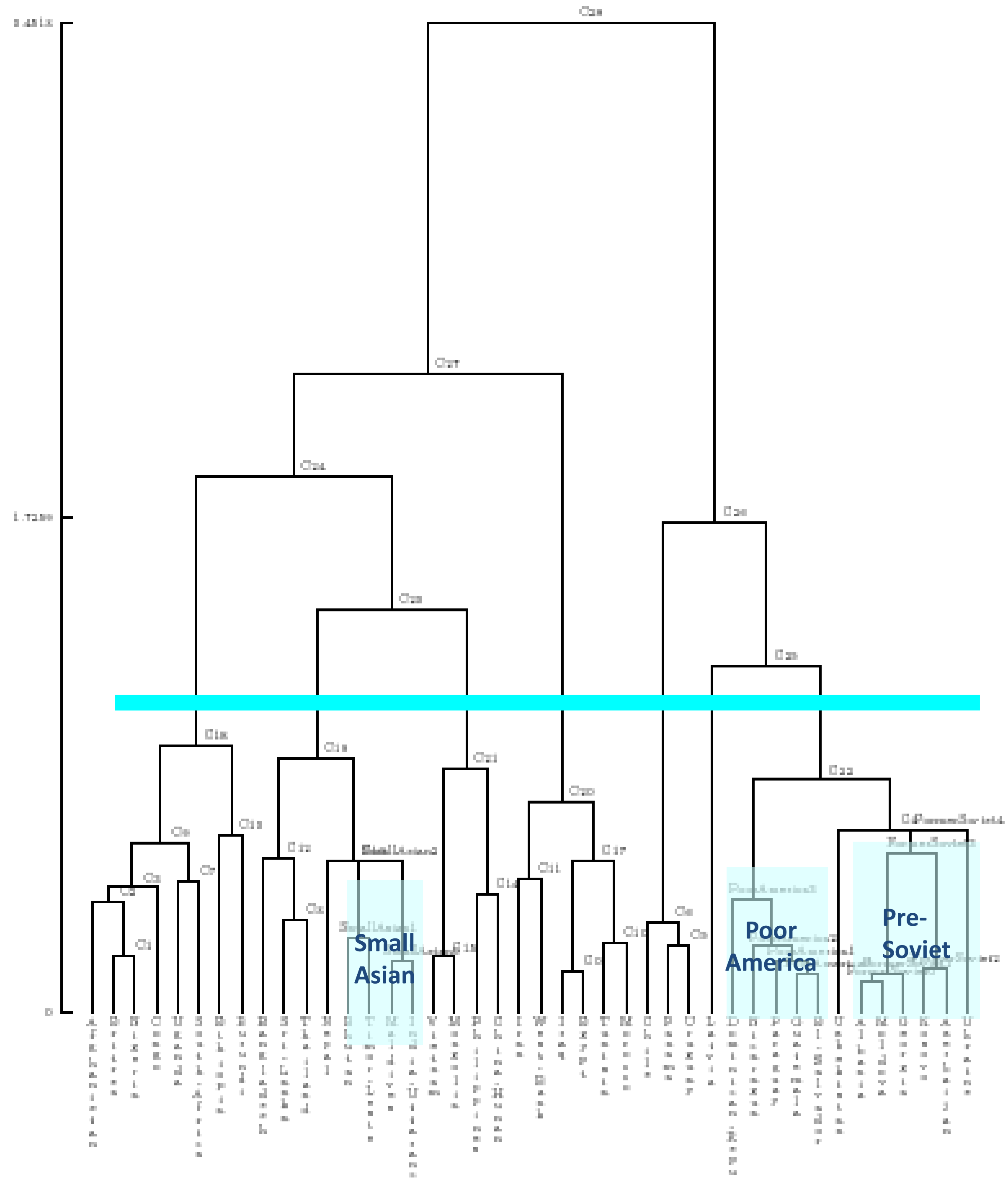


IDEAI

ClBR Dendrogram

Kalinski-Harabaz criterion
7 classes

Prior Knowledge base revisited



Profiling mental health systems
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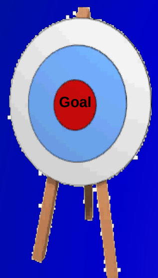

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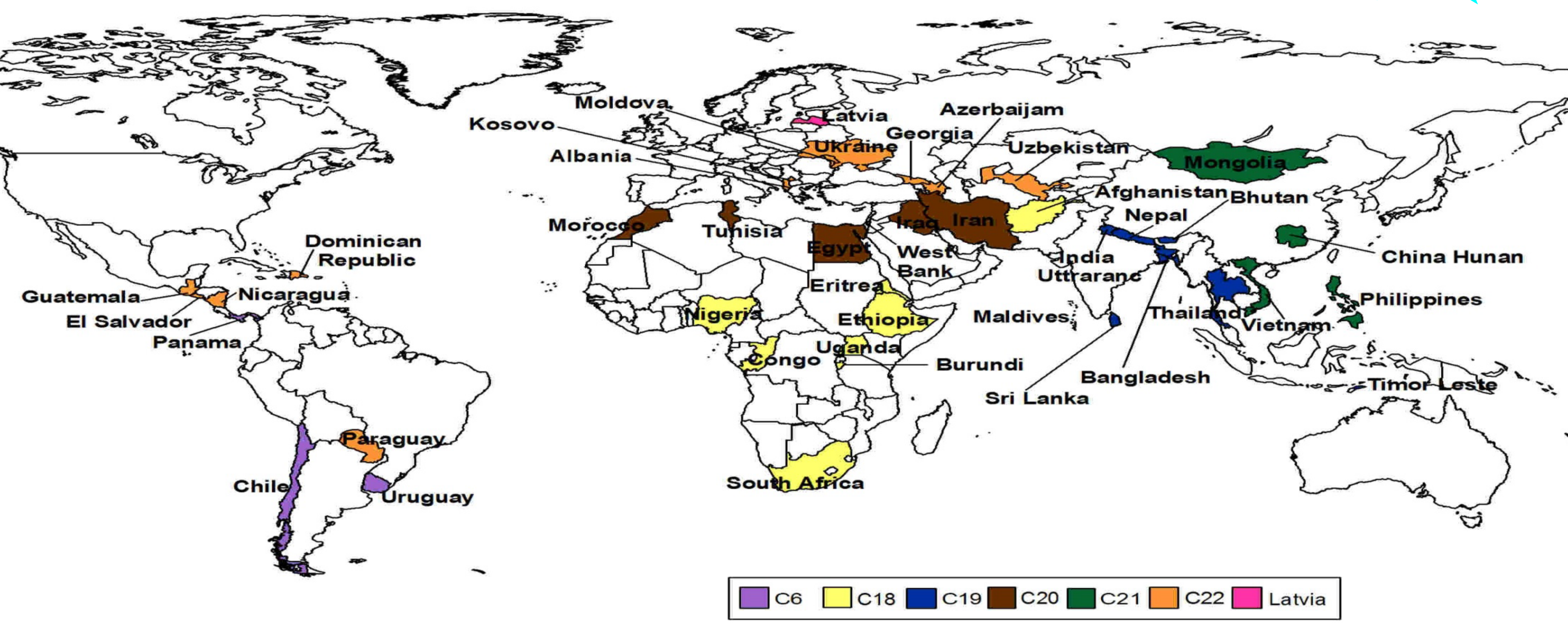
Missing imputation (MIMMI)

Profiling mental health systems in LAMIC

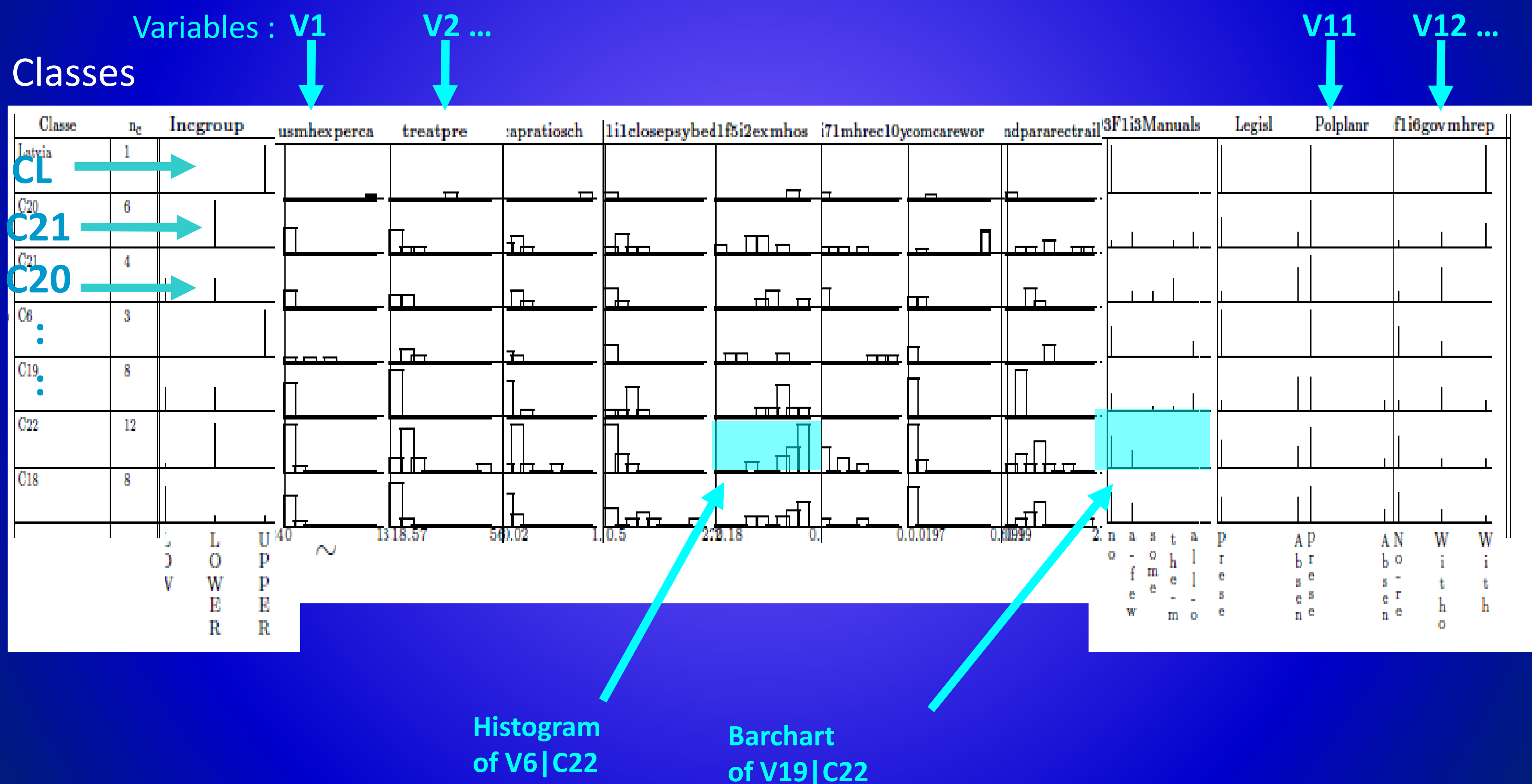
Classe	Objectes
C18	Afghanistan, Burundi, Congo, Eritrea, Ethiopia, Nigeria, South-Africa, Uganda
C22	Albania, Azerbaijan, Dominican-Repu, El-Salvador, Georgia, Guatemala, Kosovo, Moldova, Nicaragua, Paraguay, Ukraine, Uzbekistan
C19	Bangladesh, Bhutan, India-Uttaranc, Maldives, Nepal, Sri-Lanka, Thailand, Timor-Leste
C6	Chile, Panama, Uruguay
C21	China-Hunan, Mongolia, Philippines, Vietnam
C20	Egypt, Iran, Iraq, Morocco, Tunisia, West-Bank
Latvia	Latvia

Spatial data



Profiling mental health systems in LAMIC

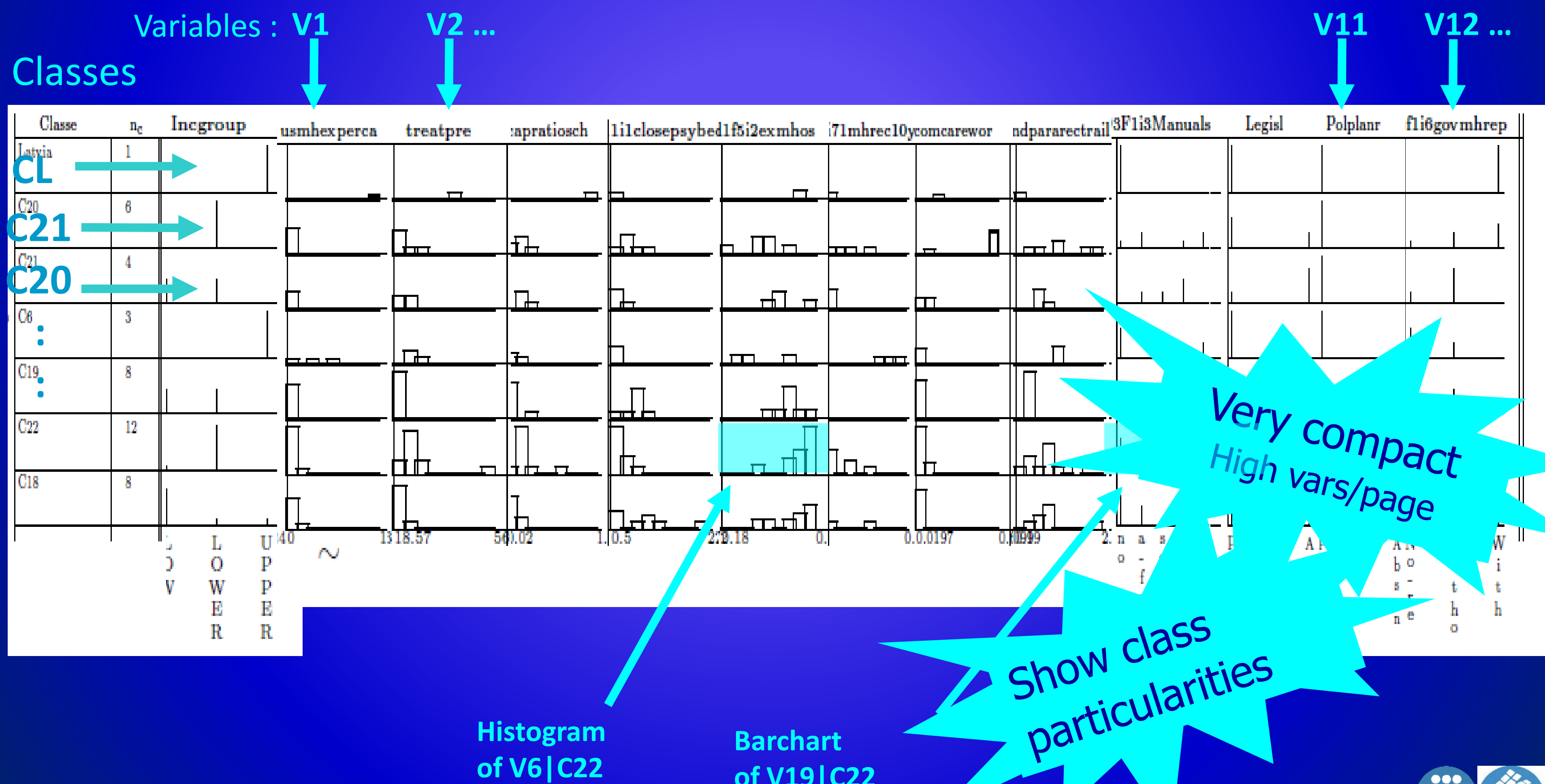
Class Panel Graph *[Gibert 08b]*



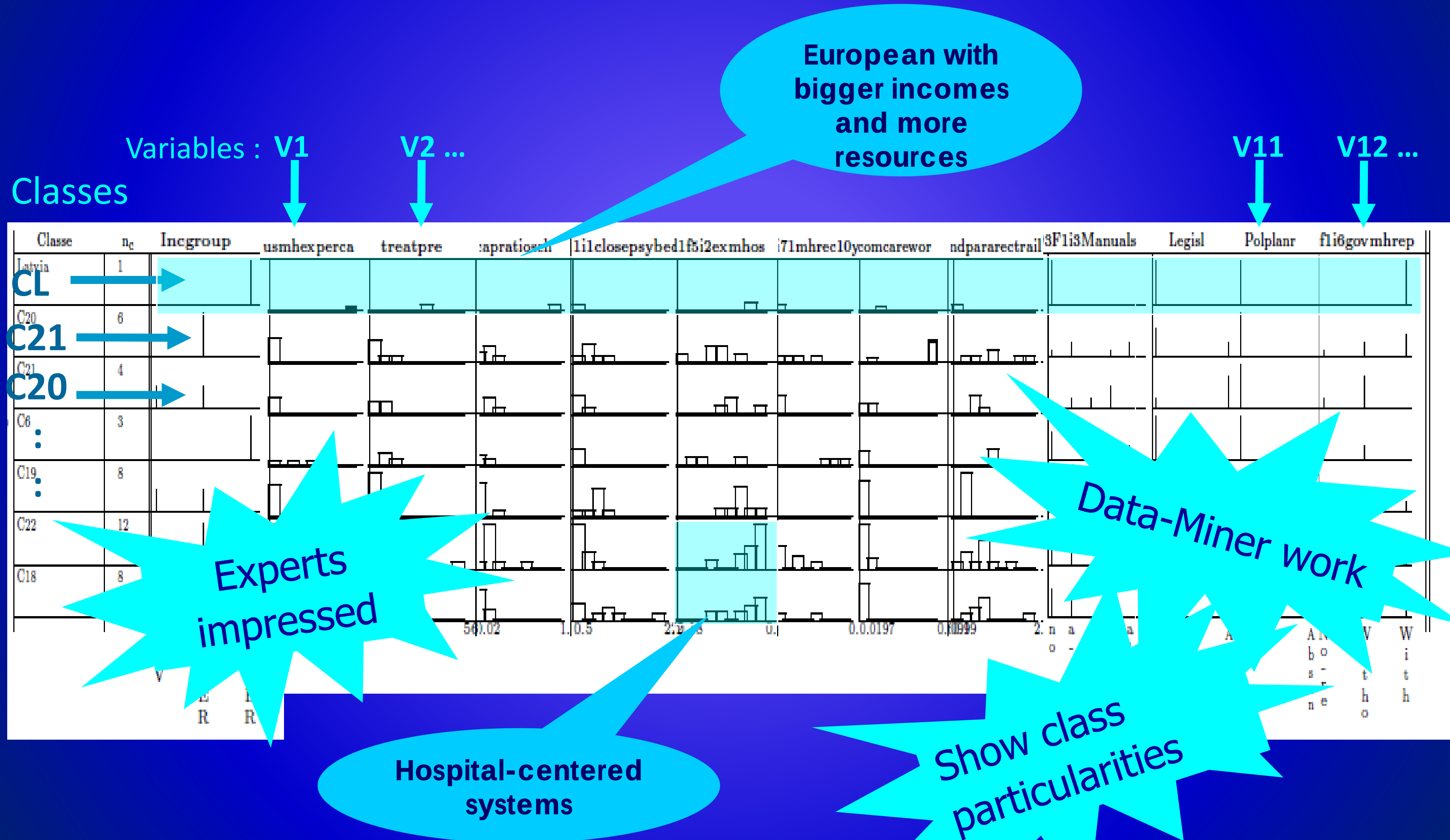
Gibert K, A. García-Rudolph, G. Rodríguez-Silva (2008): The role of KDD Support-Interpretation tools in the conceptualization of medical profiles: An application to neurorehabilitation. Acta Informatica Medica 16(4) 178-182

Profiling mental health systems in LAMIC

From CPG to Traffic Ligth Panel



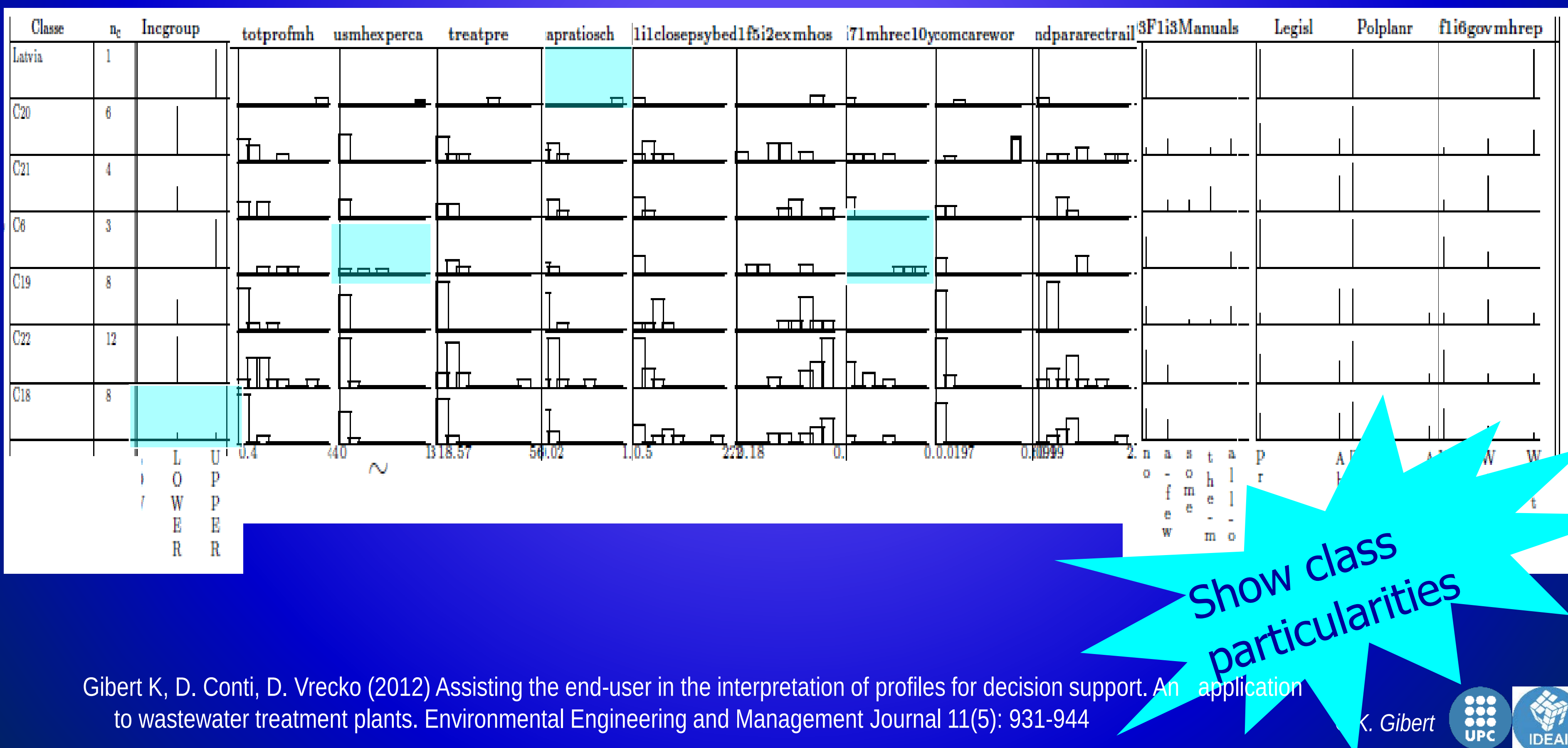
Profiling mental health systems in LAMIC



Profiling mental health systems in LAMIC

From CPG to Traffic Ligth Panel *[Gibert 2012b]*

Detect particularities



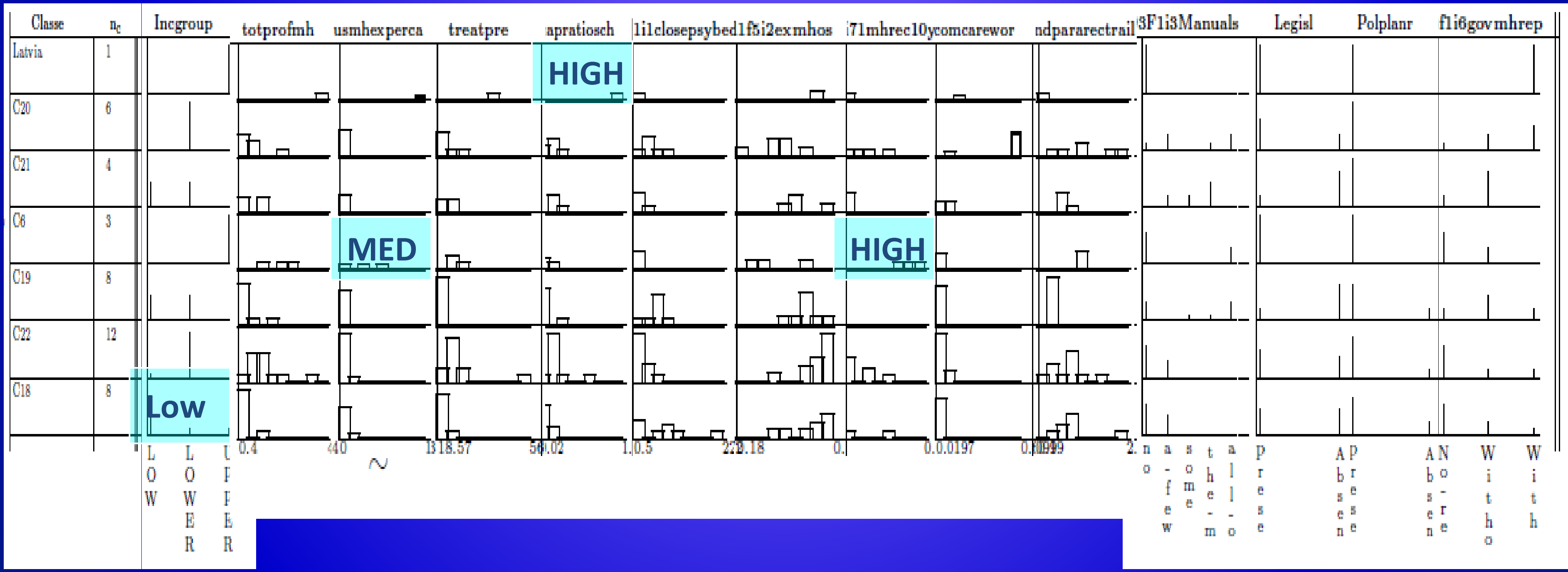
Gibert K, D. Conti, D. Vrecko (2012) Assisting the end-user in the interpretation of profiles for decision support. An application to wastewater treatment plants. Environmental Engineering and Management Journal 11(5): 931-944

Profiling mental health systems in LAMIC

From CPG to Traffic Ligth Panel

Detect particularities

Get semantics and polarity of variables (termometers)



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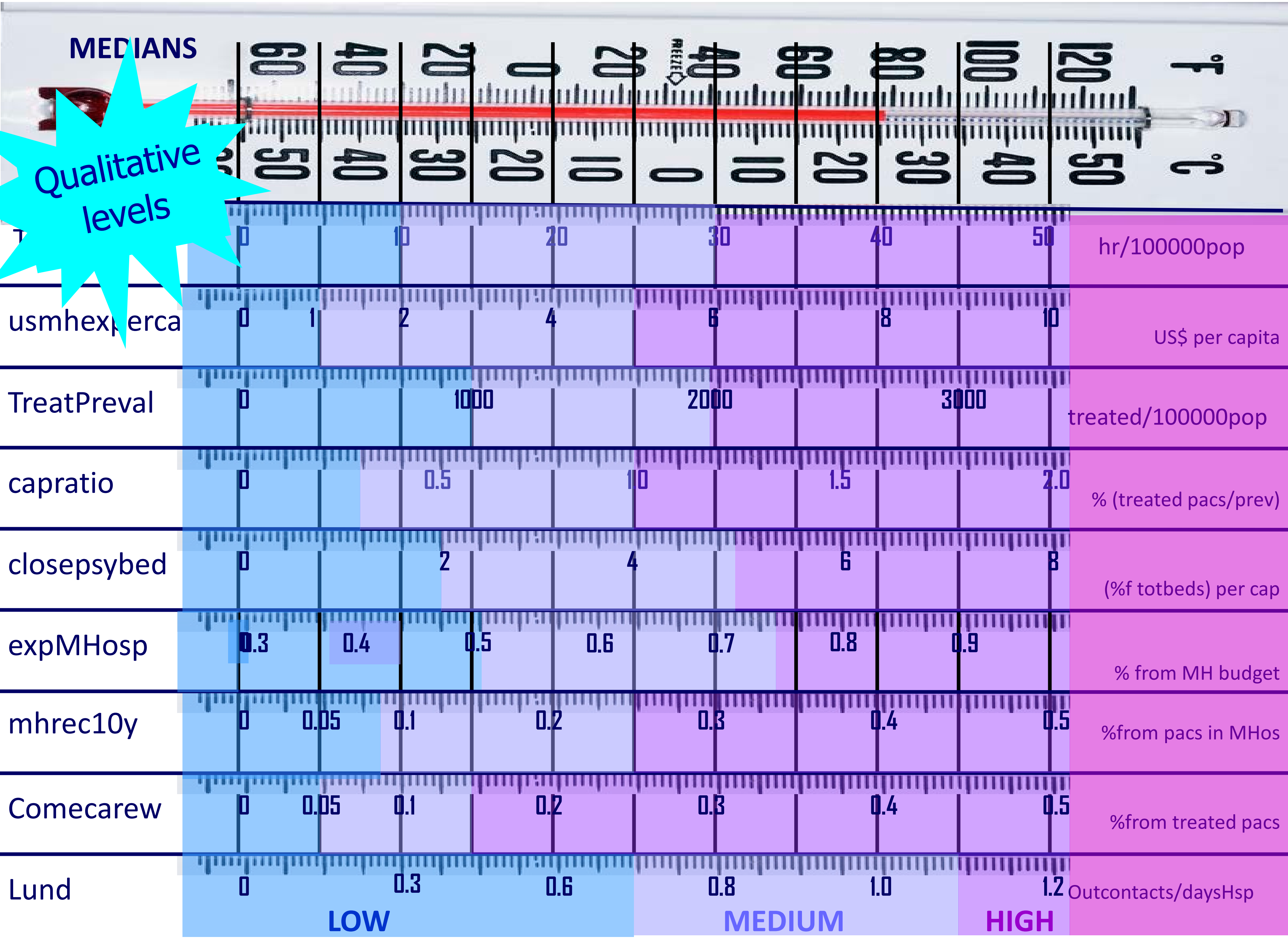
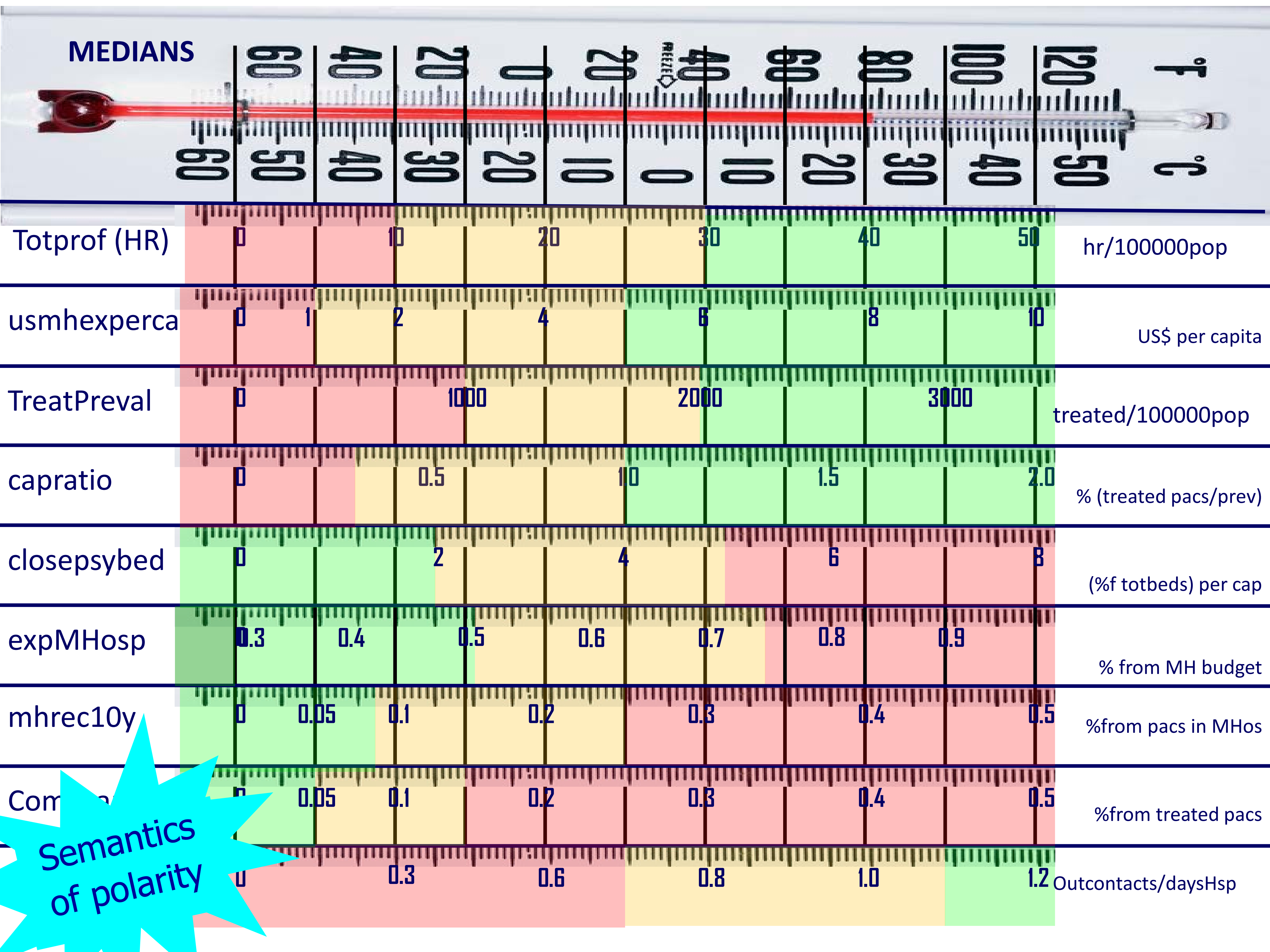

MEDIANS
Qualitative levels
hr/100000pop
usmhexpercap
US$ per capita
TreatPreval
treated/100000pop
capratio
% (treated pacs/prev)
closepsybed
(%f totbeds) per cap
expMHosp
% from MH budget
mhrec10y
%from pacs in MHos
Comecarew
%from treated pacs
Lund
Outcontacts/daysHsp
LOW
MEDIUM
HIGH


MEDIANS
°F
°C
Totprof (HR)
hr/100000pop
usmhexperca
US$ per capita
TreatPreval
treated/100000pop
capratio
% (treated pacs/prev)
closepsybed
(%f totbeds) per cap
expMHosp
% from MH budget
mhrec10y
%from pacs in MHos
%from treated pacs
Outcontacts/daysHsp
Semantics of polarity

The KLASS thermometer-tool

hr/100000pop

US$ per capita

treated/100000pop

% (treated pacs/prev)

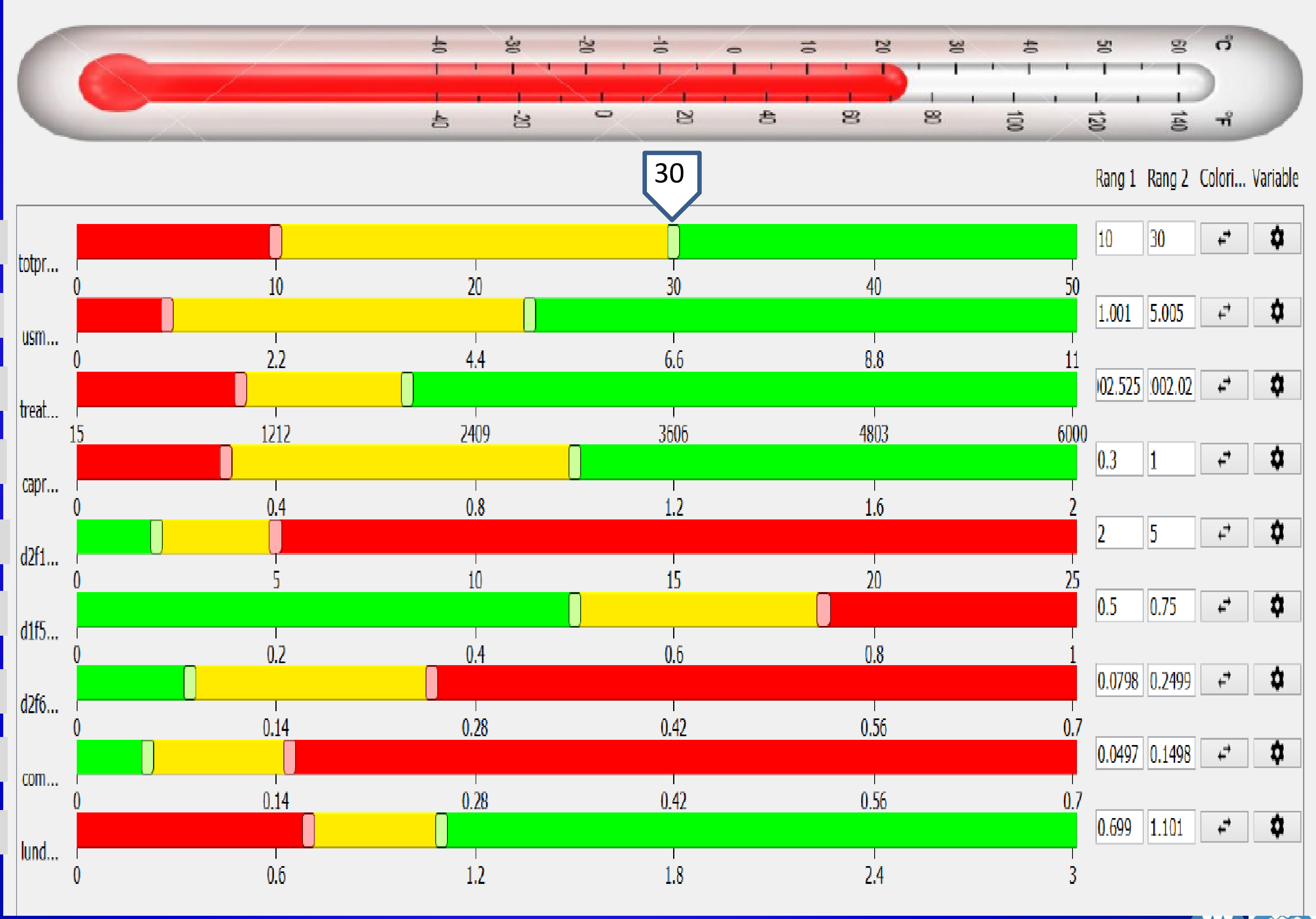
(%f totbeds) per cap

% from MH budget

%from pacs in MHos

%from treated pacs

Outcontacts/daysHsp



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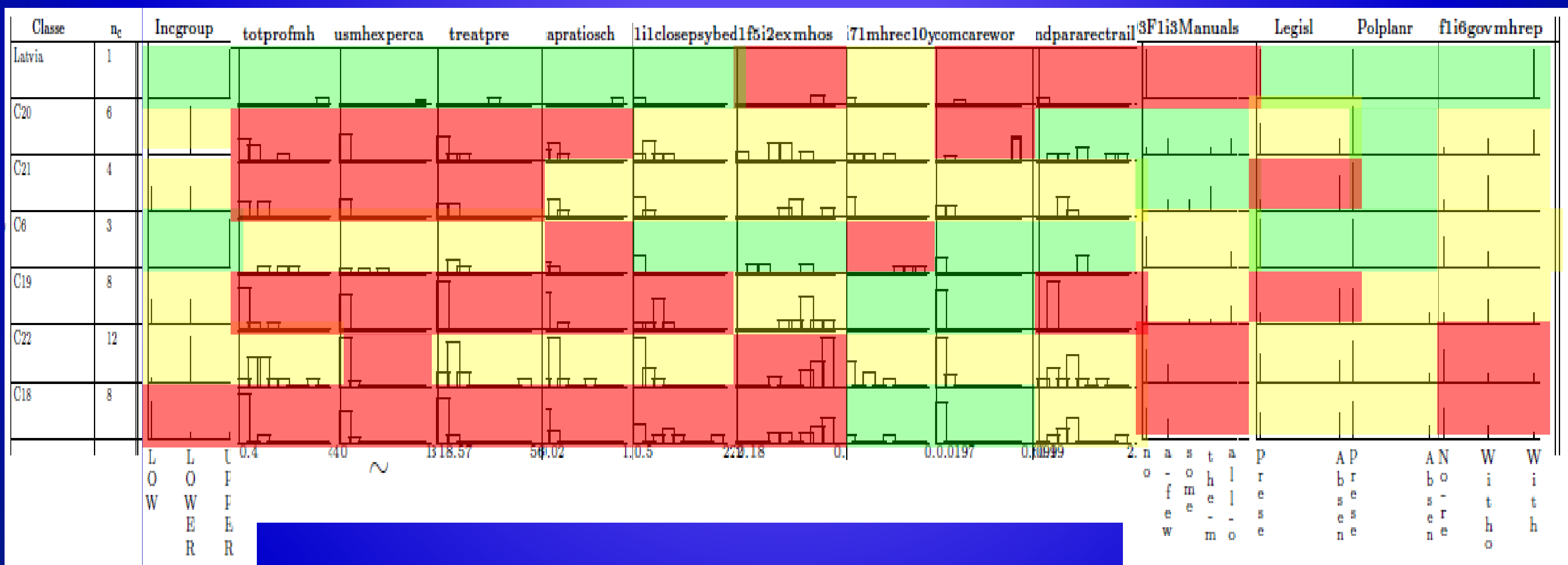
Profiling mental health systems in LAMIC

From CPG to Traffic Ligth Panel

Detect particularities
Get semmantics and polatity of variables (termometers)



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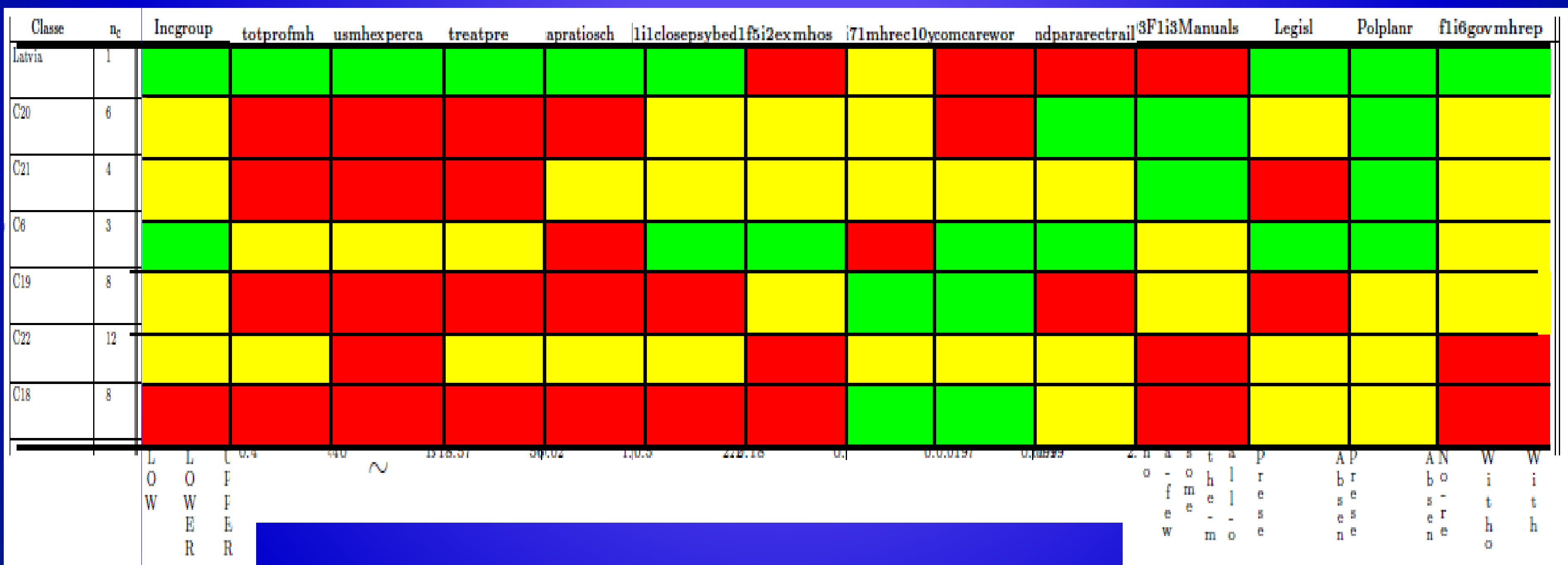


Symbolic abstraction
Includes semantics

Profiling mental health systems in LAMIC

Traffic Ligth Panel

Color-guided permutation of rows

CLASS	Incom	HR	$MHe	Treat pre	Cap-ratio	close beds	%$m-hosp	LTC-pacs	comc arew	Lund	Manua	Legis	Pol-plan	Gov-Rep
CI	UpMid	Highst	Highst	Highst	Highst	Lowest	High++	High	High	Lowest	No	yes	yes	yes
C6	UpMid	Mod	Mod	Mod	Low	Low	Mod	Highest	Low	High	Some	yes	yes	Some
C22	LMid	Mod	Low	Mod	Mod	Mod	Highest	High	Mod	Mod	No	Some	Some	No
C21	LMid	Low	Low	Low	Mod	Mod	High	High	Mod	Mod	yes	No	yes	Some
C20	LMid	Low	Low	Low	Low	Mod	High	High	Highest	Highest	yes	Some	yes	Some
C19	LMid	Low	Low	Lowest	Lowest	High	High	Low	Low	High	Some	No	Most	Most
C18	Low	Low	Low	Low	Low	Highst	High++	Low	Low	Mod	No	Few	Most	No

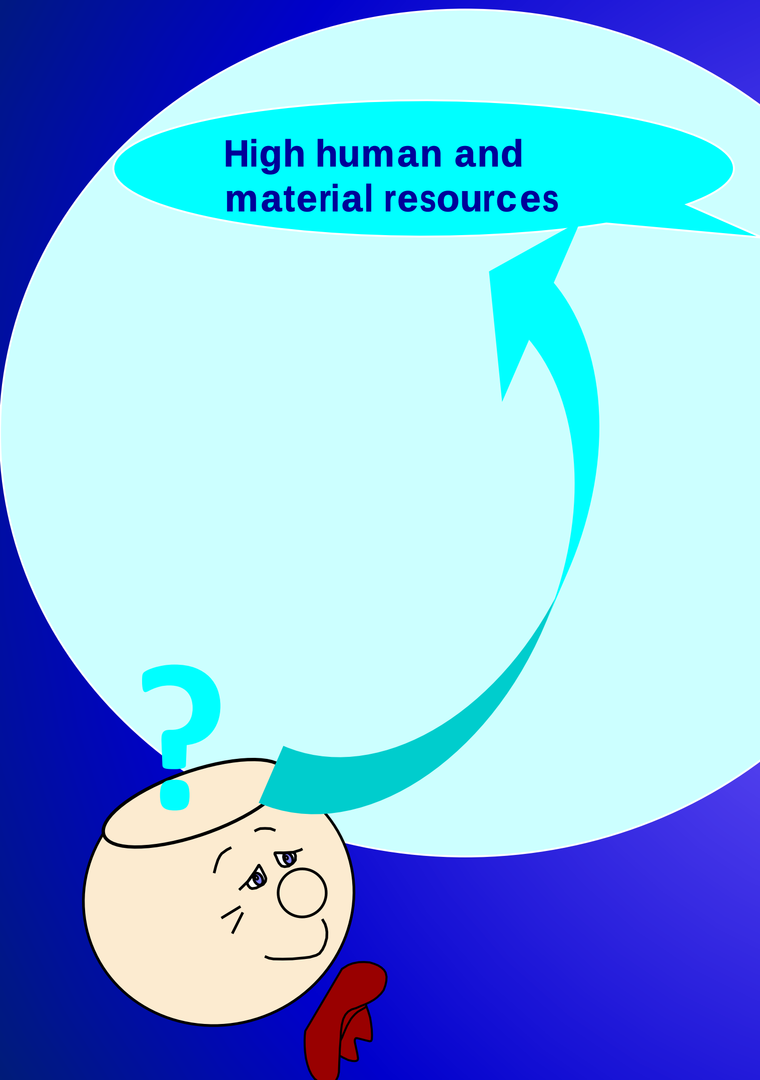
Adequate

Moderate

Basic

Gibert K, D. Conti (2015) aTLP: A color-based model of uncertainty to evaluate the risk of decisions based on prototypes. Artificial Intelligence Communications 28:113-126, IOSPress

TLP supports expert conceptualization



Resources variables

CLASS	Incom	HR	$MHe	Treatpre	Cap-ratio	closebeds
CI	UpMid	Highst	Highst	Highst	Highst	Lowest
C6	UpMid	Mod	Mod	Mod	Low	Low
C22	LMid	Mod	Low	Mod	Mod	Mod
C21	LMid	Low	Low	Low	Mod	Mod
C20	LMid	Low	Low	Low	Low	Mod
C19	LMid	Low	Low	Lowest	Lowest	High
C18	Low	Low	Low	Low	Low	Highst

TLP supports expert conceptualization

Higher human and material resources

High res., low coverage

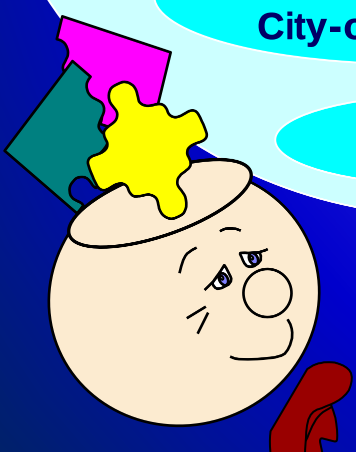
Moderate resources

Low res., moderate coverage

Very Low res. Semi-distributed

Very Low res. City-oncentrated

Scarcity



Resources variables

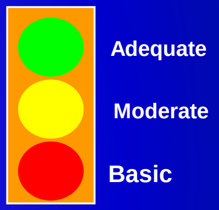
CLASS	Incom	HR	$MHe	Treatpre	Cap-ratio	closebeds
Cl	UpMid	Highst	Highst	Highst	Highst	Lowest
C6	UpMid	Mod	Mod	Mod	Low	Low
C22	LMid	Mod	Low	Mod	Mod	Mod
C21	LMid	Low	Low	Low	Mod	Mod
C20	LMid	Low	Low	Low	Low	Mod
C19	LMid	Low	Low	Lowest	Lowest	High
C18	[illegible]	Low	[illegible]	[illegible]	Low	[illegible]

KNOWLEDGE DISCOVERY:
New Domain Model

TLP elicits clustering criteria

Powerful perspective of ALL relevant variables

CLASS	Incom	HR	$MHe	Treat pre	Cap-ratio	close beds	%$m-hosp	LTC-pacs	comc arew	Lund	Manua	Legis	Pol-plan	Gov-Rep
CI	UpMid	Highst	Highst	Highst	Highst	Lowest	High++	High	High	Lowest	No	yes	yes	yes
C6	UpMid	Mod	Mod	Mod	Low	Low	Mod	Highest	Low	High	Some	yes	yes	Some
C22	LMid	Mod	Low	Mod	Mod	Mod	Highest	High	Mod	Mod	No	Some	Some	No
C21	LMid	Low	Low	Low	Mod	Mod	High	High	Mod	Mod	yes	No	yes	Some
C20	LMid	Low	Low	Low	Low	Mod	High	High	Highest	Highest	yes	Some	yes	Some
C19	LMid	Low	Low	Lowest	Lowest	High	High	Low	Low	High	Some	No	Most	Most
C18	Low	Low	Low	Low	Low	Highst	High++	Low	Low	Mod	No	Few	Most	No



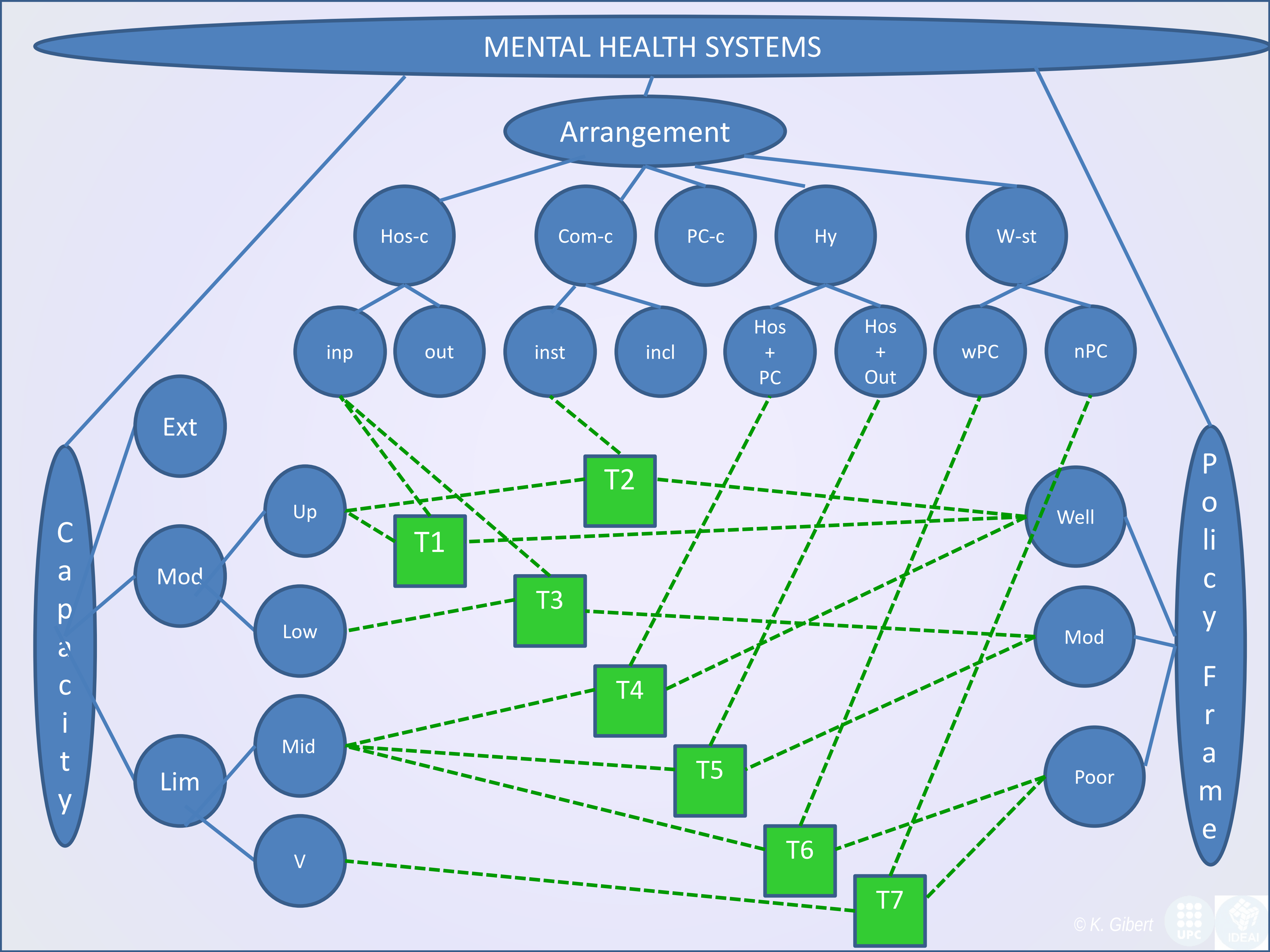
TLP elicits clustering criteria

Induces categories of variables and classes

BLOCK		CLASS	CARE CAPACITY						CARE ARRANGEMENT					POLICY FRAMEW		
			Incom	HR	$MHe	Treat pre	Cap-ratio	close beds	%$m-hosp	LTC-pacs	comc arew	Lund	Manua	Legis	Pol-plan	Gov-Rep
I	*Upper-Moderate*	CI	UpMid	Highst	Highst	Highst	Highst	Lowest	High++	High	High	Lowest	No	yes	yes	yes
		C6	UpMid	Mod	Mod	Mod	Low	Low	Mod	Highest	Low	High	Some	yes	yes	Some
	Low-Mod	C22	LMid	Mod	Low	Mod	Mod	Mod	Highest	High	Mod	Mod	No	Some	Some	No
II	*Mid-Limited*	C21	LMid	Low	Low	Low	Mod	Mod	High	High	Mod	Mod	yes	No	yes	Some
		C20	LMid	Low	Low	Low	Low	Mod	High	High	Highest	Highest	yes	Some	yes	Some
		C19	LMid	Low	Low	Lowest	Lowest	High	High	Low	Low	High	Some	No	Most	Most
	Very Lim	C18	Low	Low	Low	Low	Low	Highst	High++	Low	Low	Mod	No	Few	Most	No

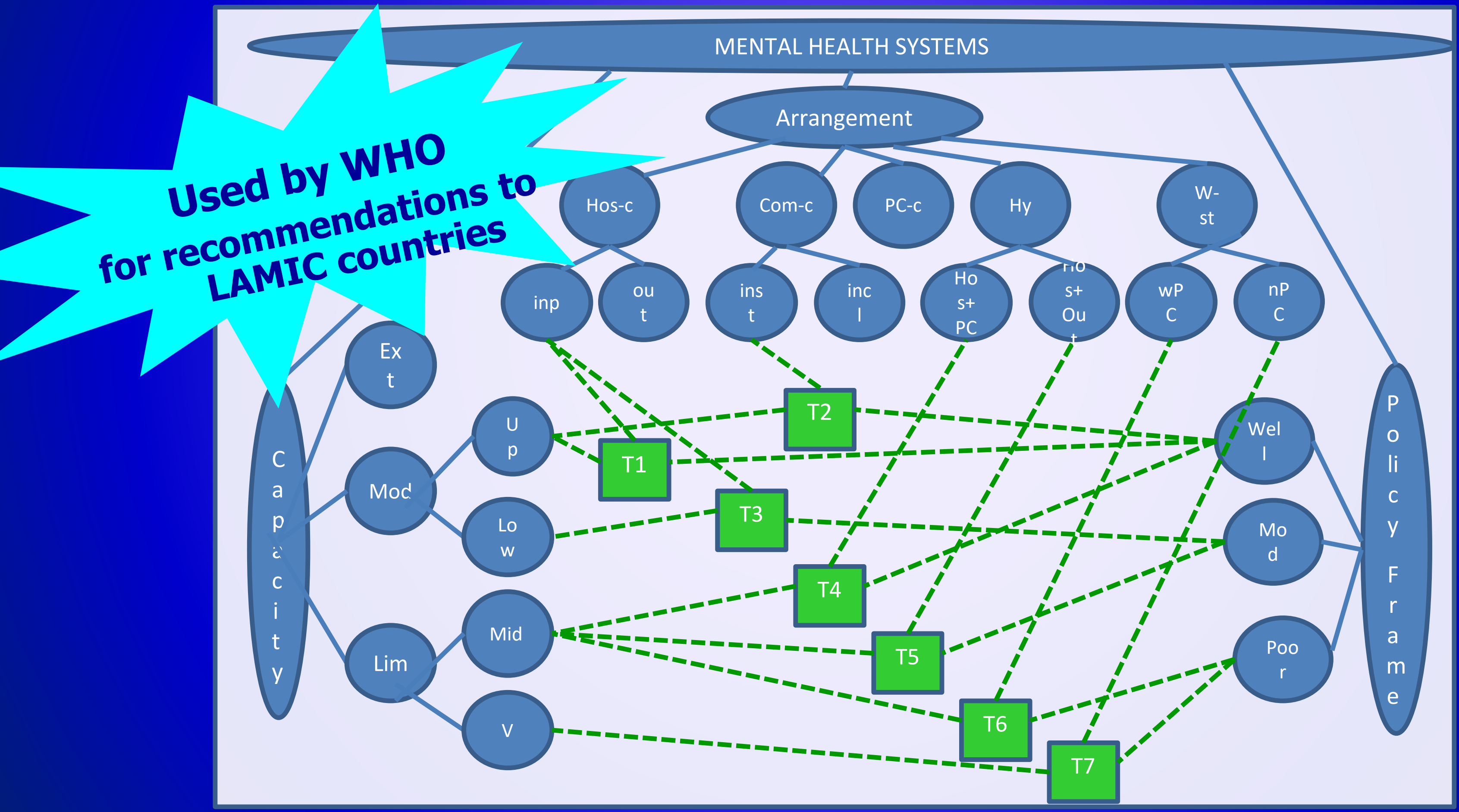
Adequate
Moderate
Basic

Supports data-driven Ontologies


MENTAL HEALTH SYSTEMS
Arrangement
Hos-c
Com-c
PC-c
Hy
W-st
inp
out
inst
incl
Hos + PC
Hos + Out
wPC
nPC
Capacity
Ext
Mod
Lim
Up
Low
Mid
V
T1
T2
T3
T4
T5
T6
T7
Policy Frame
Well
Mod
Poor
© K. Gibert
UPC
IDEAI

Knowledge Production

MHS for LAMIC ontology



Intervention plans designed for each type

Conclusions and future work

- Integral data science approach supporting health policy making
- Preprocessing crucial to clean and impute data
- MIMMI missing imputation method
  - Combines expert knowledge with conditional distributions
  - Good trade-off between precision and simplicity
  - Quicker than EM-based or Monte Carlo estimation methods
- Clustering based on rules gives understandable clusters
  - Combines expert knowledge with hierarchical clustering
  - Clusters consistent with well-known issues in the domain
- Post-processing crucial to produce actionable knowledge
  - Combines expert knowledge with conditional distributions
  - TLP is a easy to understand symbolic abstraction to support conceptualization
  - (a-TLP in progress to visualize also variances)
- Typology of MHS in LAMIC used at WHO to assess interventions

A mixt data/knowledge driven data science approach for complex decision making

Mental Health policy-making in LAMIC at WHO

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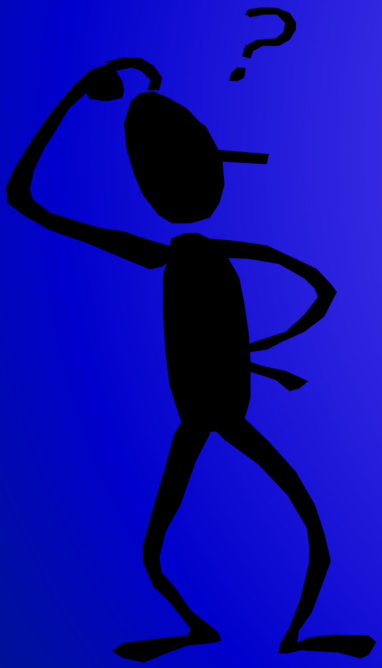
Universitat Politècnica de Catalunya, Barcelona



Are there any questions?...