becc
behavior, energy & climate change

BEHAVIOR, ENERGY &
CLIMATE CHANGE CONFERENCE

A conference focused on understanding the behavior and decision-making of individuals and organizations and on using that knowledge to accelerate our transition to an energy-efficient and low-carbon future

convened by ACEEE American Council for an Energy-Efficient Economy · ciee University of California · Precourt Energy Efficiency Center Stanford University

OCCUPANT BEHAVIOR OF WINDOW OPENING AND CLOSING IN OFFICE BUILDINGS: **DATA MINING APPROACHES**

Simona D'Oca

December 8th, Washington DC

BERKELEY LAB
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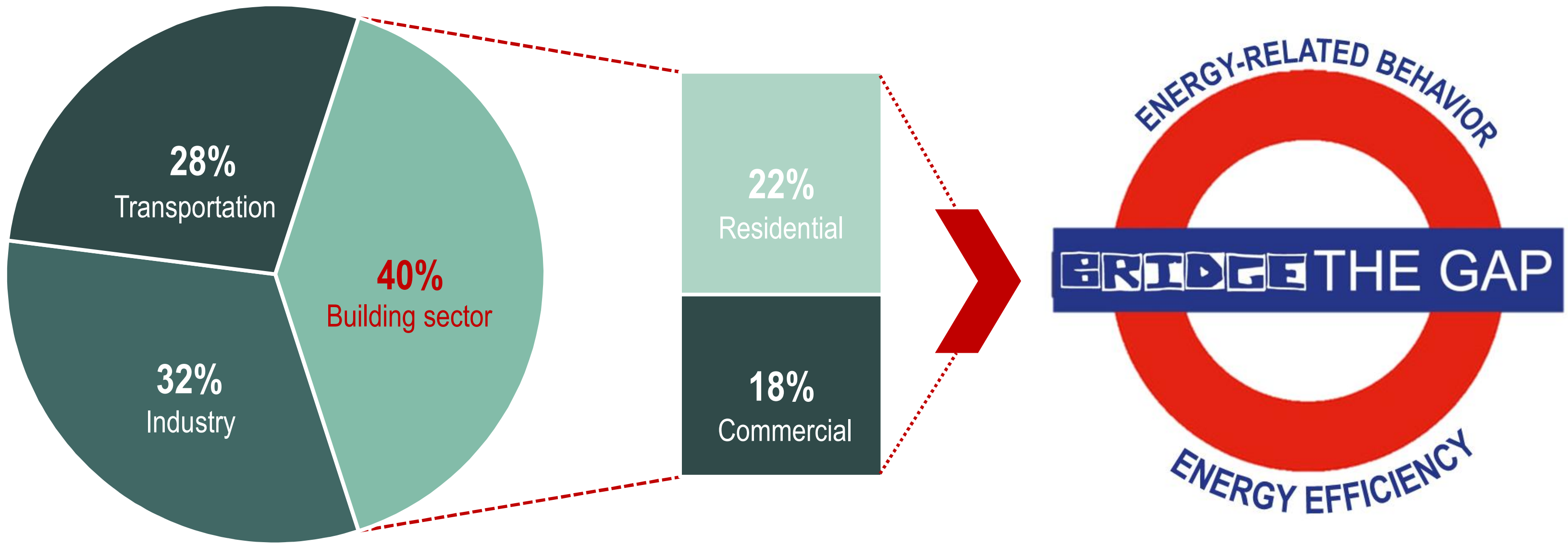
THE CREDIBILITY GAP OF BUILDING ENERGY CONSUMPTION

The US Energy Big Picture



US Energy Information Administration (EIA 2013)

"the loss of credibility when design expectations of **energy efficiency** and **actual building consumption** outcomes differ substantially.

Bordass et al., 2004

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THE CREDIBILITY GAP OF BUILDING ENERGY CONSUMPTION

ENERGY PERFORMANCE

REAL

PREDICTED

STOCHASTIC

Lack of knowledge

[…] credibility gaps arise because the **assumptions** often used are not well enough informed by **what really happens** in practice."

Bordass et al., 2004

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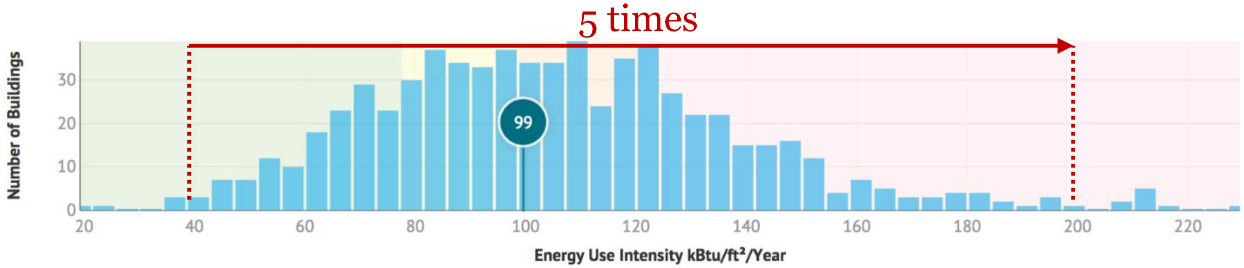
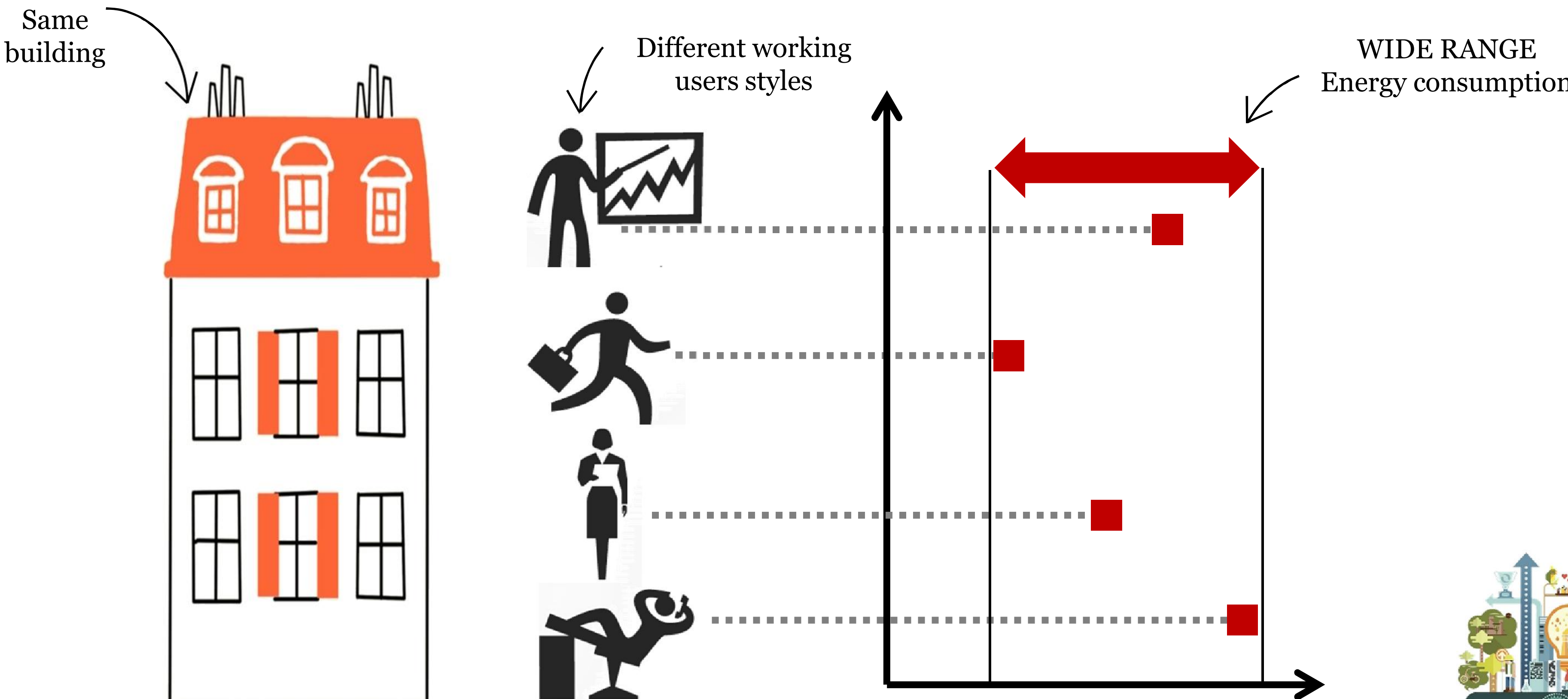
THE CREDIBILITY GAP OF BUILDING ENERGY CONSUMPTION



Delivered energy intensities distribution
Commercial buildings, USA

(LBNL 2014)



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DATA MINING APPROACHES

Techniques that take advantage of large-scale data sets to detect **patterns of behavior**

- **Information** extraction from data (***classification techniques***)
- Provide **knowledge** about structure and interrelation among data (***association techiques***)
- Create **models** predicting future events (***decision trees***)

Some applications:

Market sales: actionable associations between buying diapers and beer on thursdays (product placement)
Witten and Frank (2005)

Telecomunication companies: identify clients needs and trends relater to household characterics
McCarty (1997)

Political campaign operatives: identify potential supporters by datamining of database of existing voters
Esdall (2006)

Patterns of energy related behavior?

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DATA SET

Bank office building
(Frankfurt, Germany)

16 offices (W, E oriented)
Single/double occupancy

Monitoring aspects	Parameters	Interval
Climate	Outdoor air temperature, outdoor humidity, wind speed, solar radiance	10 min
Operation & Maintenance	Monitoring of heating, cooling, lighting and ventilation system, and related energy flows	10 min
Indoor environmental quality	Indoor (operative) temperature, humidity, (CO_2)	10 min
Occupants' activities and behavior	**Window state (open/closed)** **Presence**	10 min

2 years data

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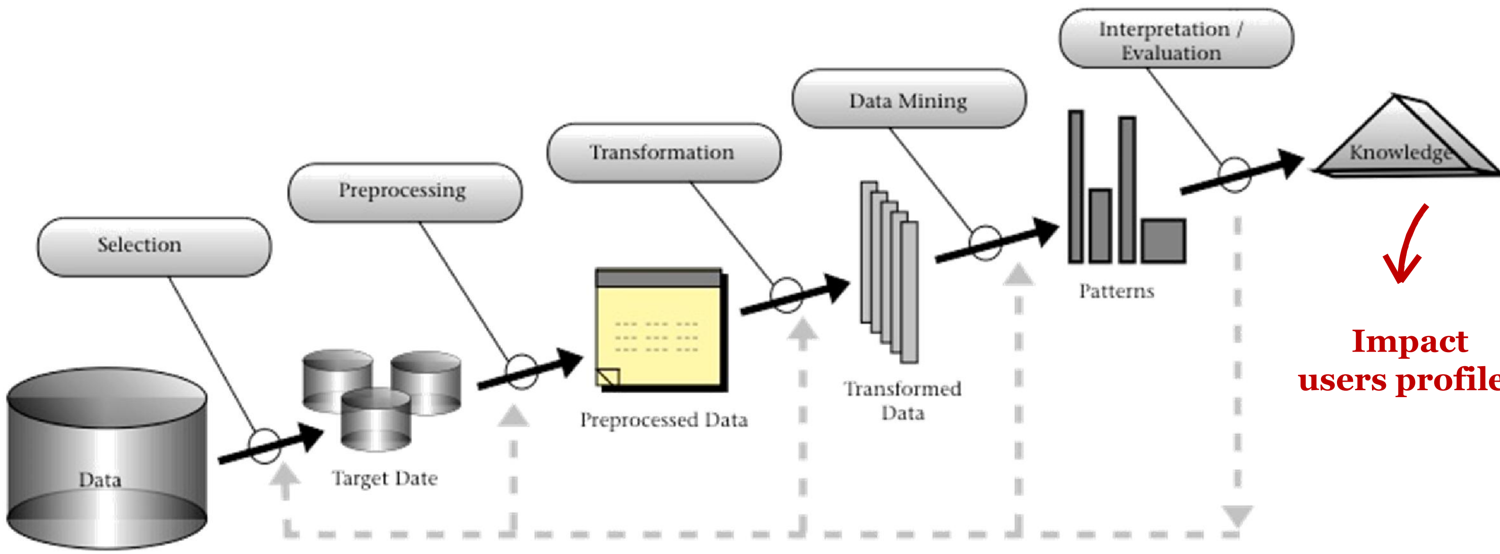
KNOWLEDGE DISCOVERY IN DATABASE (KDD)



Impact users profiles

More than 1 million data points for each office

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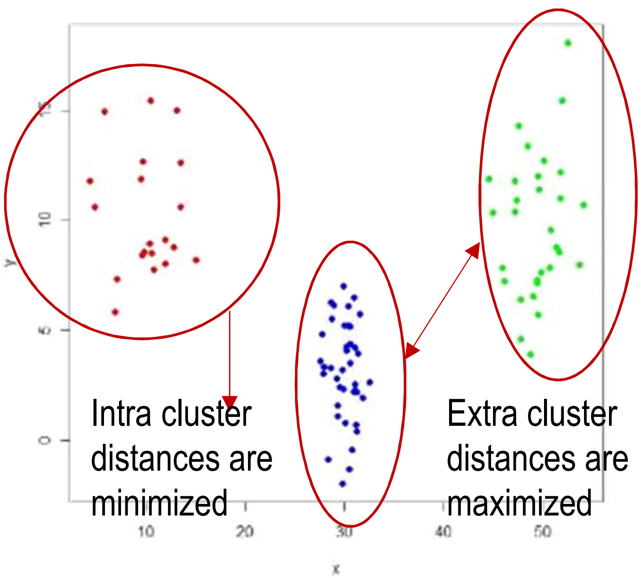
DATA MINING APPROACHES

STEP 1
CLUSTER ANALYSIS
K-MEANS ALGORITHM

Grouping data objects into **clusters**

objects in the same cluster have high similarity,

objects in different clusters have low similarity.



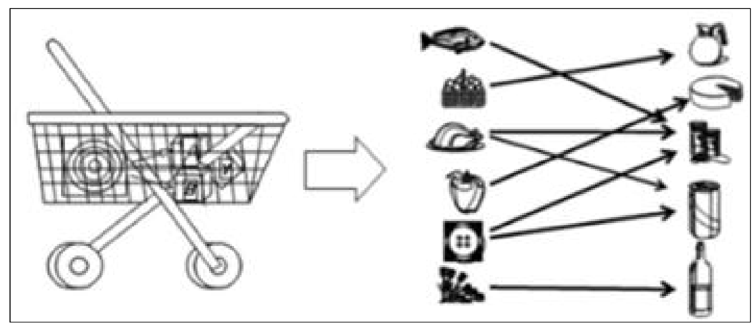
PATTERNS OF BEHAVIOR

STEP 2
ASSOCIATION RULE MINING
FP-GROWTH ALGORITHM

Associations and **correlations** *(rules)*

between attributes of the same dataset

based on information obtained from cluster analysis



THE MARKET BASKET ANALYSIS

WORKING USER PROFILES

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STEP 1
CLUSTER ANALYSIS
k-means algorithm

PATTERNS OF BEHAVIOR

Improvement of the notion of behavioral patterns not only as statistical relevant clusters

Incorporating the motivational dimension with typical window opening habits, preferences and attitudes.

Patterns of behavior	Mined parameters	Subset data
Motivational	Window opening/closing drivers	Influencing variables
Opening duration	Window state	h window open or close/day
Interactivity	Window changes	n changes/day
Position	Window degree of opening	tilting angle (from 0 to 1)

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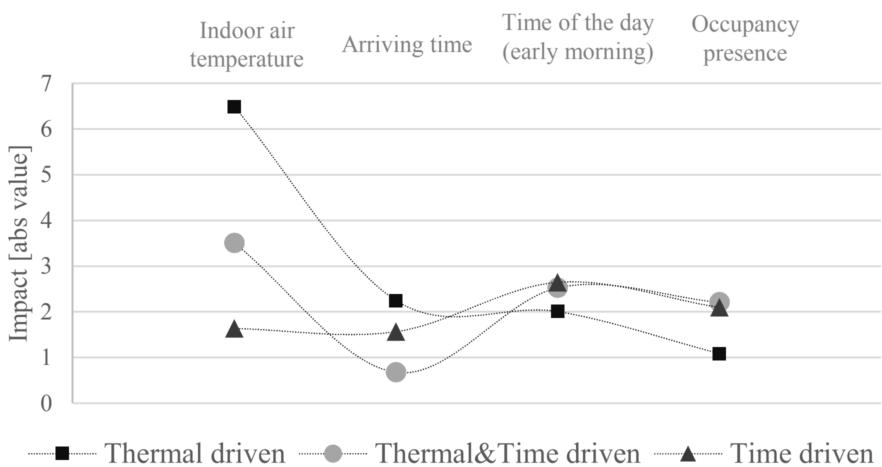
DATA MINING FRAMEWORK

STEP 1
CLUSTER ANALYSIS
k-means algorithm

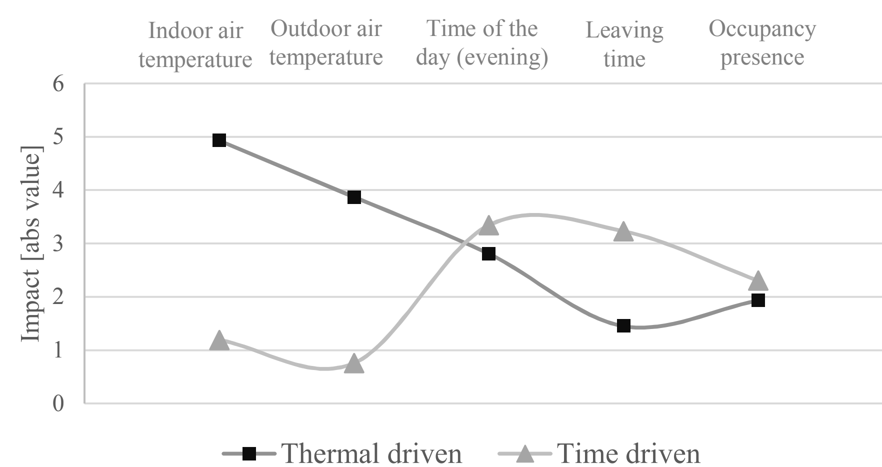
PATTERNS OF BEHAVIOR

Patterns of behavior	Mined parameters	Subset data
Motivational	Window opening/closing drivers	Influencing variables

Top 4 factors influencing window opening



Top 5 factors influencing window closing



OPENING CLUSTER 1 | **OPENING CLUSTER 2** | **OPENING CLUSTER 3** | **CLOSING CLUSTER 1** | **CLOSING CLUSTER 2**

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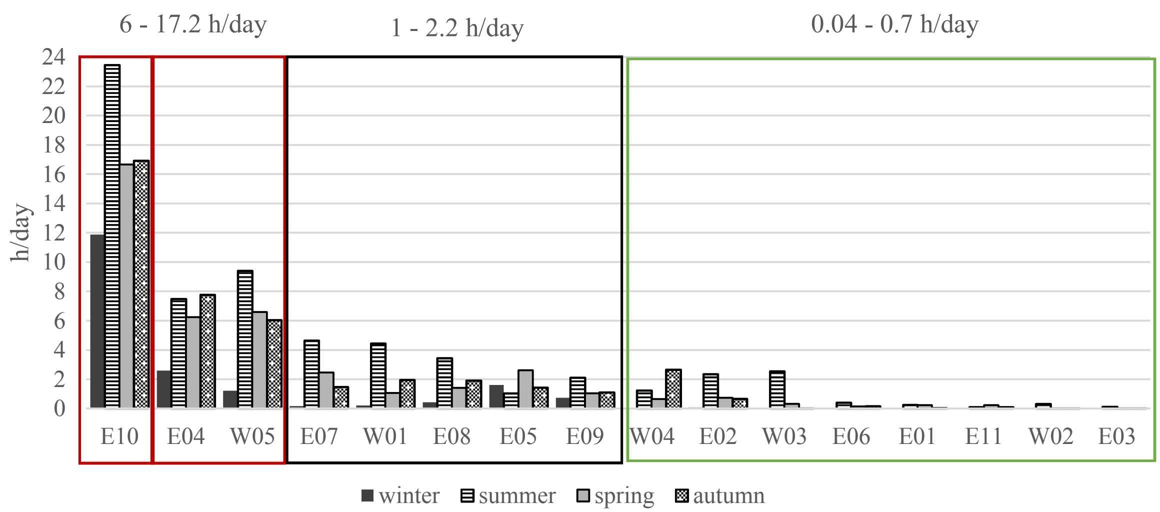
DATA MINING FRAMEWORK

STEP 1
CLUSTER ANALYSIS
k-means algorithm

PATTERNS OF BEHAVIOR

Patterns of behavior	Mined parameters	Subset data
Opening duration	Window state	h window open or close/day



LONG OPENING **MEDIUM OPENING** **SHORT OPENING**

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DATA MINING FRAMEWORK

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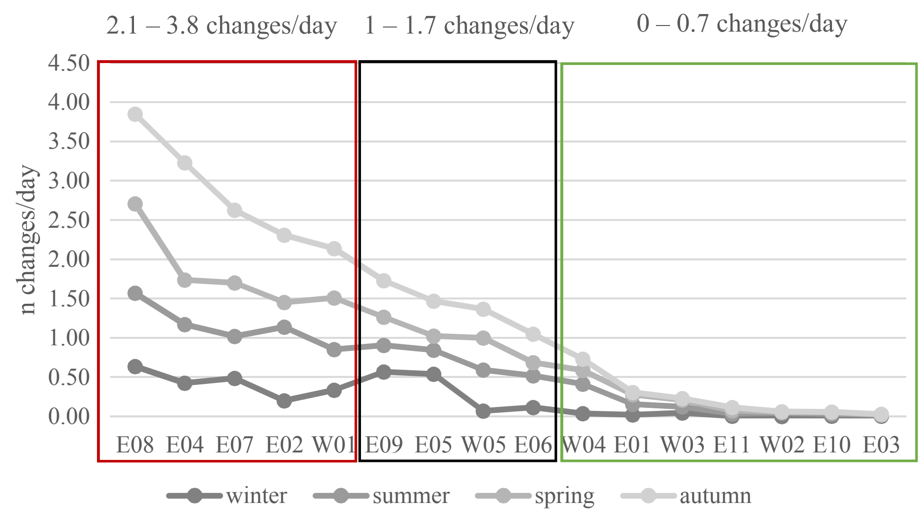
k-means algorithm

PATTERNS OF BEHAVIOR

Patterns of behavior	Mined parameters	Subset data
Interactivity	Window changes	n changes/day



ACTIVE OPERATOR **NEUTRAL OPERATOR** **PASSIVE OPERATOR**

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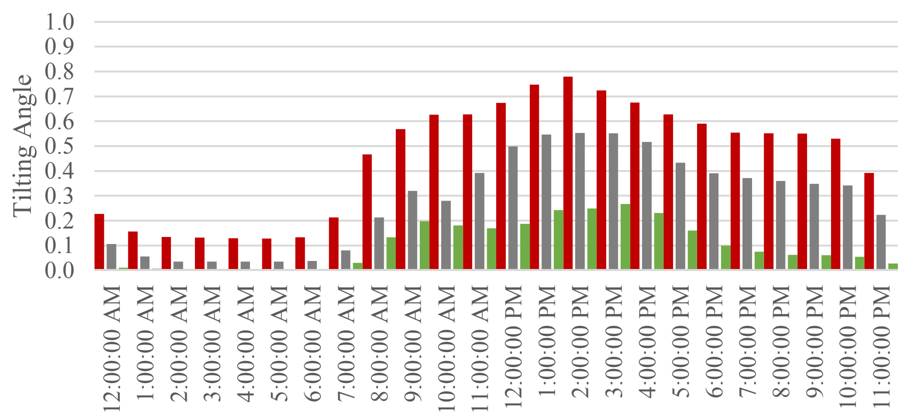
DATA MINING FRAMEWORK

STEP 1
CLUSTER ANALYSIS
k-means algorithm

PATTERNS OF BEHAVIOR



BIG OPENING **INTERMEDIATE OPENING** **SMALL OPENING**

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STEP 2
ASSOCIATION RULES MINING

WORKING USER PROFILES

Find unsuspected relationships and summarize the data in novel ways

Extract frequent correlations from patterns of behavior

	Motivational		Duration	Interactivity	Position
Office	**window opening**	**window closing**	**window state**	**window change**	**window tilting angle**
E01	thermal driven	thermal driven	short openings	passive operation	small openings
E02	thermal/time driven	thermal driven	short openings	active operation	small openings
E03	thermal driven	thermal driven	short openings	passive operation	small openings
E04	thermal driven	thermal driven	long openings	active operation	big openings
E05	thermal/time driven	time driven	medium openings	neutral operation	intermediate openings
E06	time driven	time driven	short openings	neutral operation	small openings
E07	time driven	time driven	medium openings	active operation	intermediate openings
E08	time driven	time driven	medium openings	active operation	intermediate openings
E09	thermal/time driven	thermal driven	medium openings	neutral operation	small openings
E10	time driven	time driven	long openings*	passive operation	big openings*
E11	thermal driven	thermal driven	short openings	passive operation	small openings
W01	time driven	time driven	medium openings	active operation	intermediate openings
W02	thermal driven	thermal driven	short openings	passive operation	small openings
W03	time driven	time driven	short openings	passive operation	small openings
W04	thermal/time driven	time driven	short openings	passive operation	intermediate openings
W05	thermal/time driven	time driven	long openings	neutral operation	big openings

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DATA MINING FRAMEWORK

ASSOCIATION RULES MINING

STEP 2
ASSOCIATION RULES MINING

WORKING USER PROFILES

Find unsuspected relationships and summarize the data in novel ways

Extract frequent correlations from patterns of behavior

	80%	**20%**
Patterns of behavior	**User α**	**User β**
Motivational	physical environmental driven	contextual driven
Opening duration	short periods (0.04 - 0.7 hours/day)	long periods (1.0 - 2.2 hours per day)
Interactivity	infrequently (0 - 0.7 times per day)	frequently (1 - 1.7 times per day)
Position	small openings (< 0.3 degree of tilting angle)	intermediate openings (< 0.6 degree of tilting angle)

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CONCLUSIONS

1. automatically extrapolate **fast legible, valid, novel** occupancy patterns from big data streams
2. key intermediate to visualize **behavioral patterns** in (big) energy data
3. provide accurate assumption of actual **natural ventilation scenarios** in office buildings
4. quantify the **energy/economic impacts** of diverse ventilation scenarios on energy use in a building
5. quantify **motivational drivers, habits, preferences and attitudes** on office building
6. deliver a set of **behavioral rules** at the office level to direct specific **energy saving strategies**
7. allow building designers, operator, manager to **tailor efficient** and **robust** system and building envelope **control strategies** and **design**

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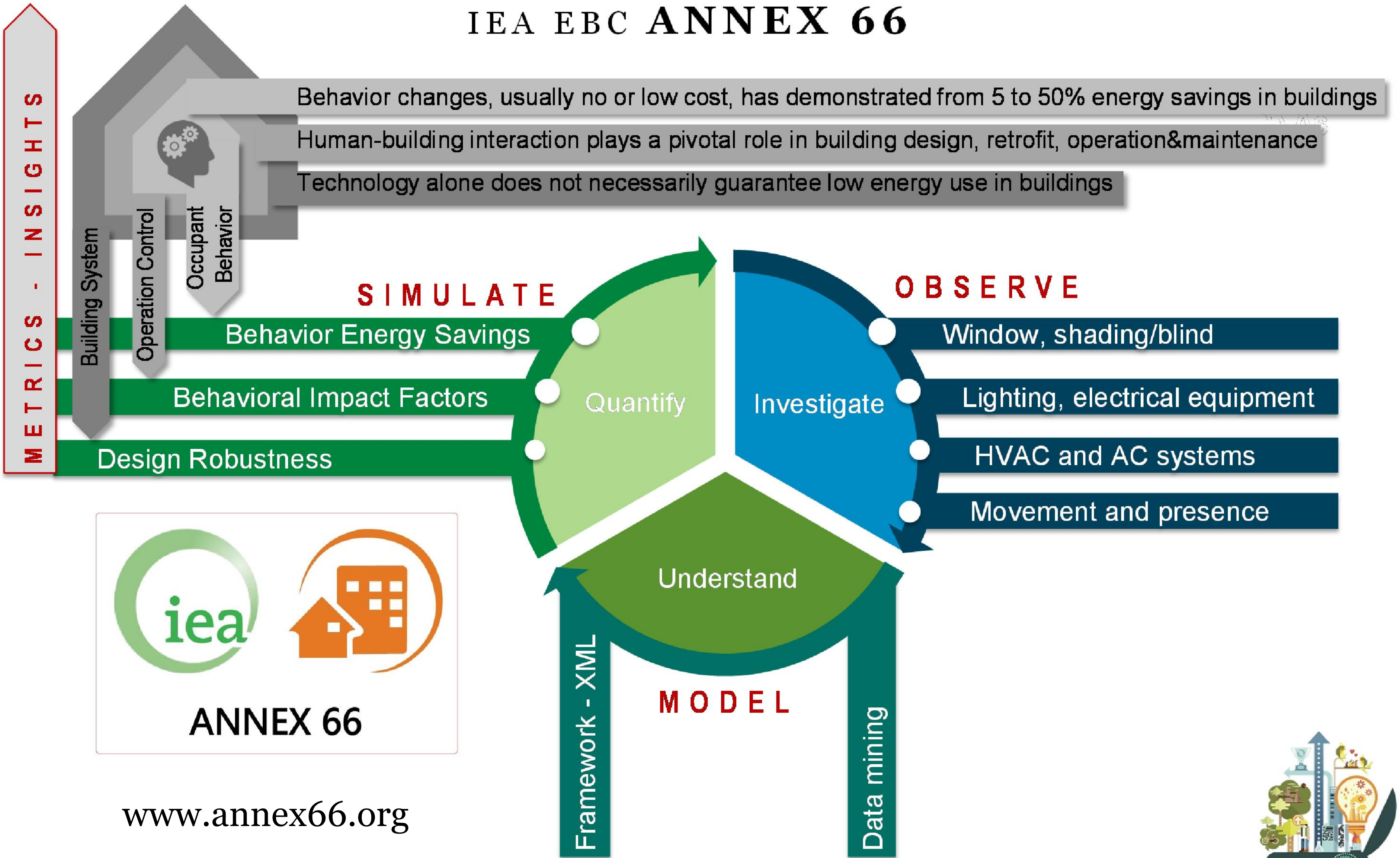
IEA EBC ANNEX 66



www.annex66.org

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