Data processing possibilities for large-scale IAQ prediction

A GLM Case Study in natural ventilated dwellings

46th AIVC - 14th TightVent - 12th venticool Conference
Sonia García Ortega

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The problem

Growing interest in integrating IAQ into the EU Renovation Wave -> need to know current situation.

How can we target renovation support at large scale to the worst-performing cases if we cannot identify them?

Monitoring is expensive, invasive, and non-scalable. Simulations are complex.

Can we develop **IAQ estimates** for the existing housing stock?

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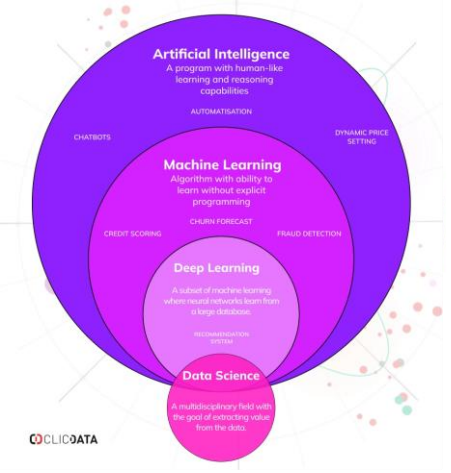
The way forward



Machine Learning is a subset of artificial intelligence that enables systems to **identify complex patterns** and make **data-driven predictions** by learning from experience rather than following rigid, pre-defined instructions.

what happened?
→ what is likely to happen?

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The way forward

Goal: Estimate IAQ using simple, available input data

Many interacting factors (climate, occupancy, volume, infiltration…) **not always intuitive** e.g. is occupancy really negative?

Can ML help identify hidden drivers and predict IAQ at large-scale?

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Most important thing: Data

Data availability is the current limitation

Expected to become more available in the medium term thanks to:

- Monitoring campaigns
- IOT
- Initiatives of data-base like Pandora

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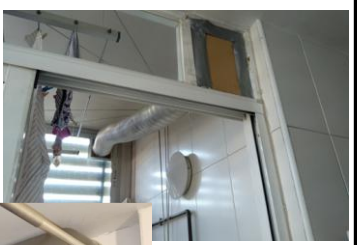
Prospective study

Generalized Linear Model

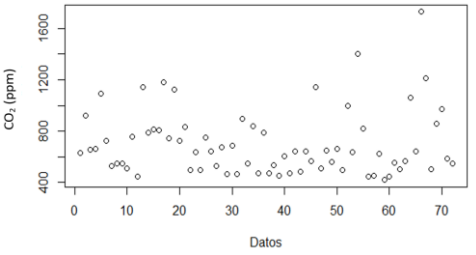
Approach: Generalized Linear Model (GLM) with Gamma distribution and inverse link.
Sample: 72 monitoring campaigns across 12 real dwellings in Madrid, riche contextual data
Objective: Predict CO_2 concentration as an IAQ indicator without direct measurements.

Prospective study



Prospective study

Objetive variable: CO_2 average



Possible predictor variables:

Construction year	Number of dry rooms
Occupied floor level	Facade orientation
Year of whole renovation	Occupancy habits / patterns
Total number of building storeys	Building use
Dwelling compactness	Number of occupants
Building / Construction typology	Ventilation system
Urban environment compactness / Urban density	Occupants' age
Opaque building envelope / Opaque elements	Domestic Hot Water (DHW) system
Location	Airing habits / Window opening habits
Glazed openings / Fenestration	Cooking system
Monitoring season	Occupants' subjective IAQ assessment
Envelope permeability / Airtightness	General ventilation system
Monitoring month	Indoor laundry drying
Number of ventilation shafts (shunts)	Complementary ventilation system
Room use / Room function	Indoor smoking / smokers
Net floor area / Usable floor area	Additional kitchen ventilation system
Number of wet rooms	Occupancy density
Number of facades	

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Prospective study

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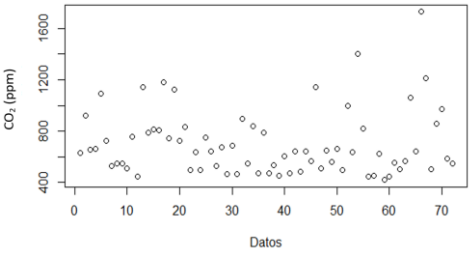

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Looking for the smart predictiors:

- Ease of data collection
- Experimental relevance
- Inter-variable correlation
- % of variance explained

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Prospective study

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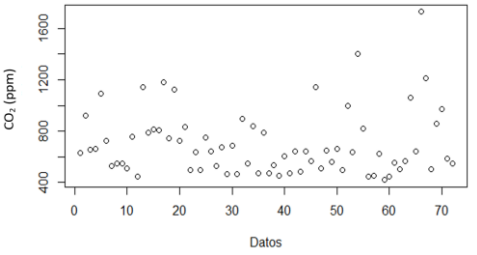

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Prospective study

$$[CO_2] = \frac{1}{2.430 \cdot 10^{-3} + \mathbf{R} + \mathbf{S} - 4.90 \cdot 10^{-4}\mathbf{F} - 2.14 \cdot 10^{-4}\mathbf{O} + 8 \cdot 10^{-6}\mathbf{A}}$$

Where:

$[CO_2]$– Average to be expected [ppm].

R – Type of room (Living/dining room: $-1.12 \cdot 10^{-4}$; Master bedroom: $-1.86 \cdot 10^{-4}$; 2nd bedroom: $-2.94 \cdot 10^{-4}$; 3rd Bedroom: $-1.39 \cdot 10^{-5}$; Kitchen: $2.63 \cdot 10^{-5}$; Bathroom/toilet: $1.48 \cdot 10^{-4}$; Other room: 0).

S – Season (Summer: $2.68 \cdot 10^{-4}$; Winter: 0).

F – Number of façades of the dwelling: 1 to 3.

O – Number of usual occupants of the dwelling: 1 to 4.

A – Total living area of the dwelling: 29 to 150 [m^2].

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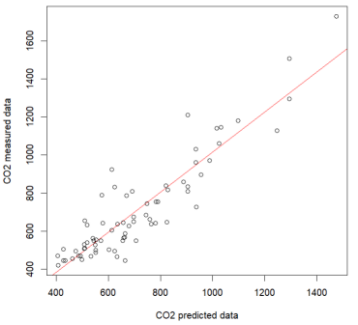
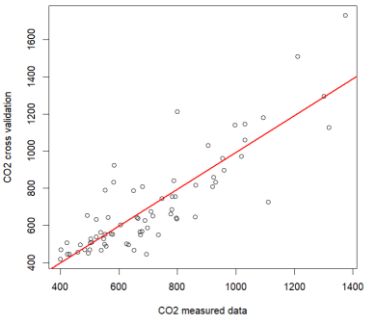
How good this result is??

	% var
Model	80.7%
Season	29.8%
Living area	23.5%
Number of occupants	17.5%
Number of façades	15.8%
Room type	15.4%

Measured vs. predicted
McFadden Pseudo-R^2 = 0.79



Cross- validation
McFadden Pseudo-R^2 = 0.73



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Conclusions

- Predicting IAQ using simple parameters and statistical data processing is a **promising approach to enable large-scale assessments**.
- This methodology could support **decision-making in large-scale EU renovation strategies** within the Renovation Wave.
- It does **not replace measurement**—it **extends it** to cases where measurement is not feasible.
- It does **not replace simulation**; rather, it can **support it** by identifying new relevant variables or factors.
- The foundation is **large amounts of labelled data for training**, which is costly and not always feasible. **Initiatives like Pandora** will help make this possible.
- **If the training data is of low quality and contain bias**, the model will amplify it.

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