Energy poverty prediction and effective targeting for just transitions with machine learning

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Energy Poverty: defining, measuring and examining recent trends in Ireland
30th November 2022

“The energy transition is ultimately a human transition”

Sallem Berhane,
Rocky Mountain Institute

(Source: World Bank)

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Work in progress and preliminary results

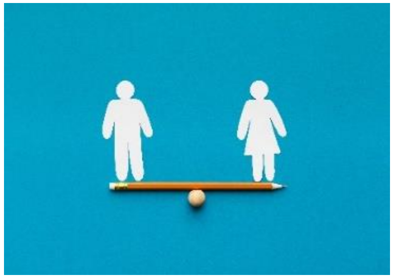
Background

Definition

Energy poverty = The inability of households to meet their energy needs, due to limited supply, affordability, quality, quantity, reliability or a combination of the above (*Cong et al., 2022*)

What is the connection with energy justice?

Energy justice: All individuals should have access to energy that is affordable, safe, sustainable and able to sustain a decent lifestyle, as well as the opportunity to participate in decisions



Energy justice: All individuals should have access to energy that is affordable, safe, sustainable and able to sustain a decent lifestyle, as well as the opportunity to participate in decisions

to alleviate energy poverty

Is energy poverty a serious issue?

2 billion people *(IEA)*

25% of households *(EU EPOV)*

20% of households *(Lin and Wang, 2020)*

30% of middle-aged & older adults *(Li and Yang, 2022)*

30% of households *(US EIA)*

65% of households *(Gupta et. al, 2020)*

(all approximate, "some form of energy poverty")

Policy challenge:

To achieve the clean energy transition while alleviating energy poverty (or, at least, not making it worse…)

(Source: European Parliament)

The problem

Energy poverty is multifaceted, might be hidden or hard to identify

Major targeting challenge: to properly identify who needs energy assistance. No widely-accepted framework to determine it

Many ways to measure it. No metric works for every particular situation. No metric is limitations-free

10% metric: might not be able to distinguish between energy poor and income poor households. E.g., it might classify as energy poor households that have both high income and high energy consumption

Low Income High Cost: Low-income households might be excluded from the energy poor class if their energy expenditure is lower than certain thresholds

The problem

Energy poor households are not necessarily income poor (and vice versa)

Limited recognition of this distinction in EU legislation

Serious shortcoming: protecting the income poor and addressing energy poverty are distinct challenges requiring distinct solutions

Our contribution

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Improve the prediction and targeting mechanisms of energy poverty alleviation schemes. Better identification of energy poor households

Create an EU-wide knowledge base of what are key drivers of energy poverty, beyond income

Our approach

Develop a machine learning modeling framework for improved prediction and targeting of energy poor households in EU + UK

What individual (household-level) and contextual (country-level) characteristics best predict energy poverty?

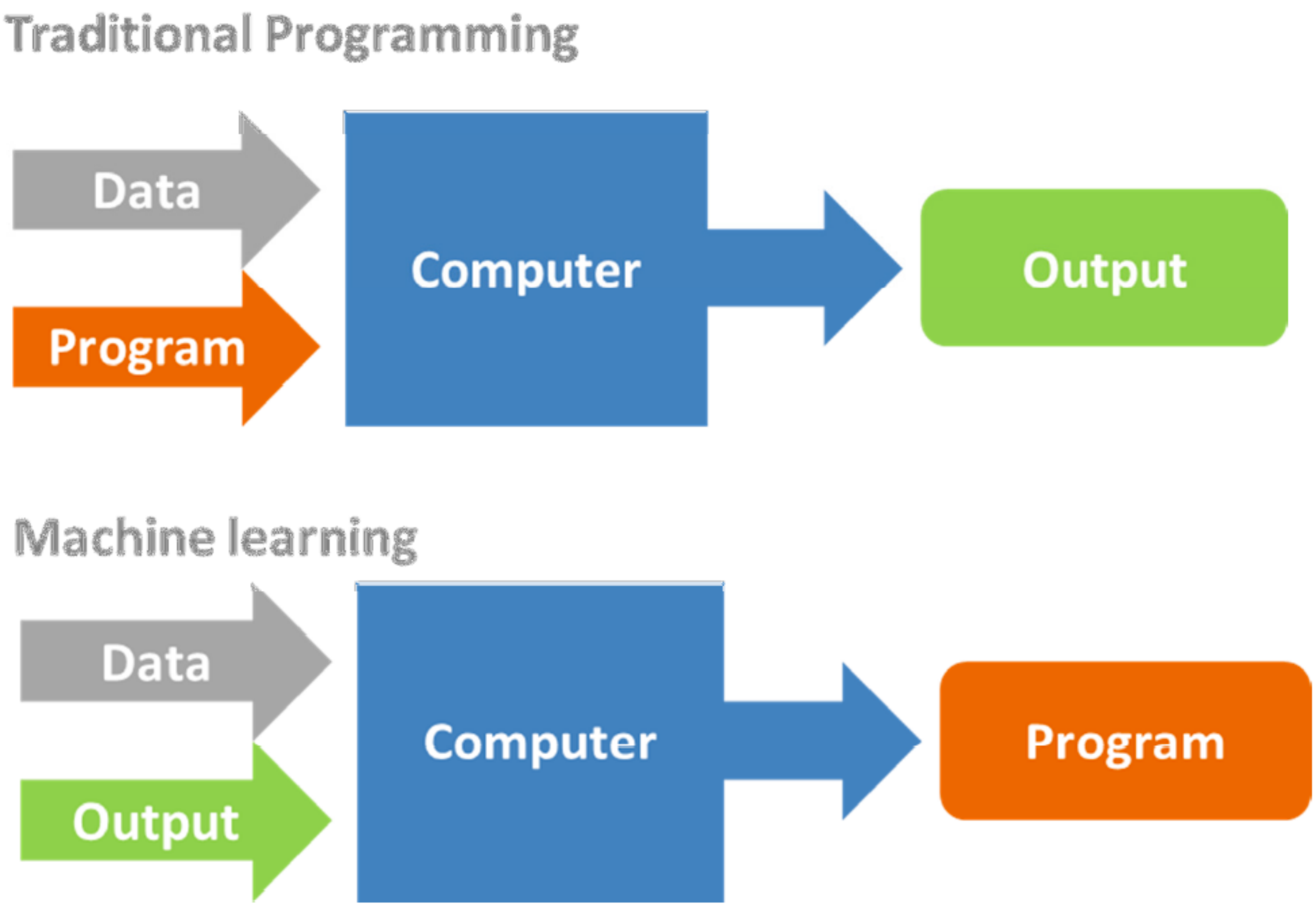
Evaluate the fairness potential of energy poverty alleviation policies

Methods

Why machine learning?

Solve complex problems, work with large data sets in relatively less computational time, identify non-typical relationships between variables

How machine learning works?



(Source: UK Department of Business, Energy & Industrial Strategy)

Going beyond income

- Income+ household, dwelling characteristics
  - Single parent? How many children?
  - Damaged dwelling? (leaking roof, damp walls/floor, etc.)
  - Dwelling too dark?
  - How many rooms?
  - Receiving benefits?

Going beyond income

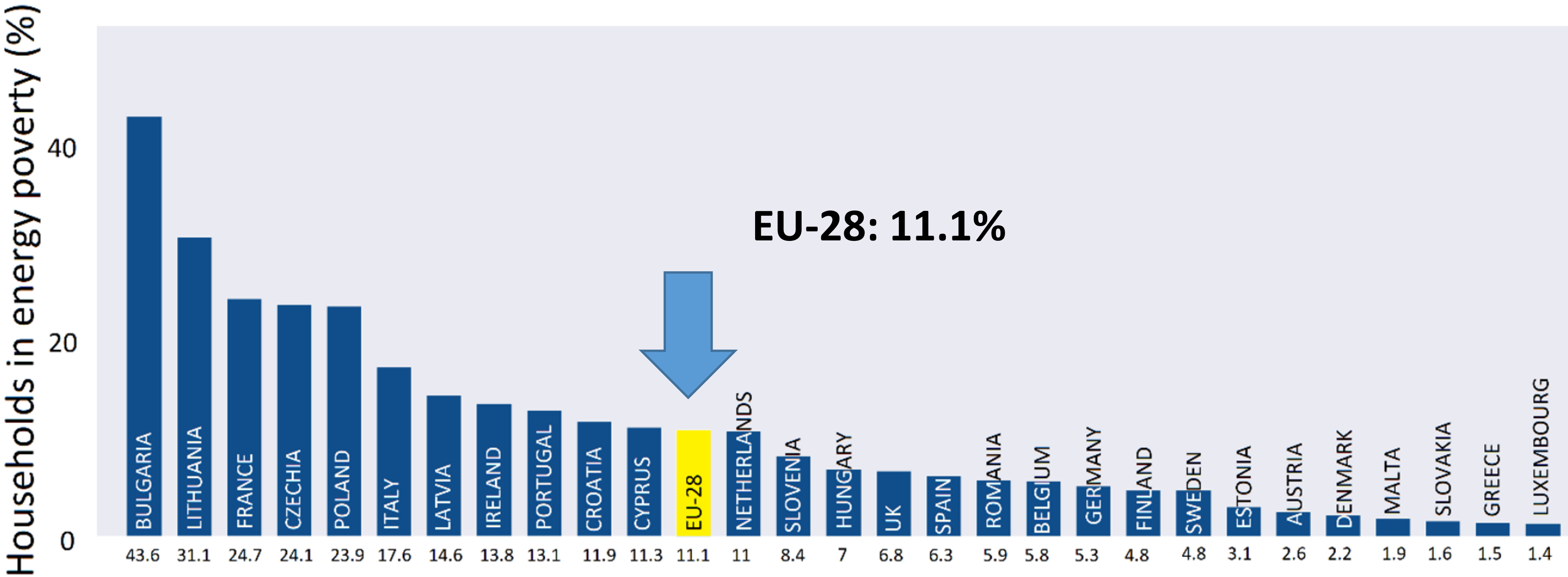
- Income+ household, dwelling characteristics
    - Single parent? How many children?
    - Damaged dwelling? (leaking roof, damp walls/floor, etc.)
    - Dwelling too dark?
    - How many rooms?
    - Receiving benefits?

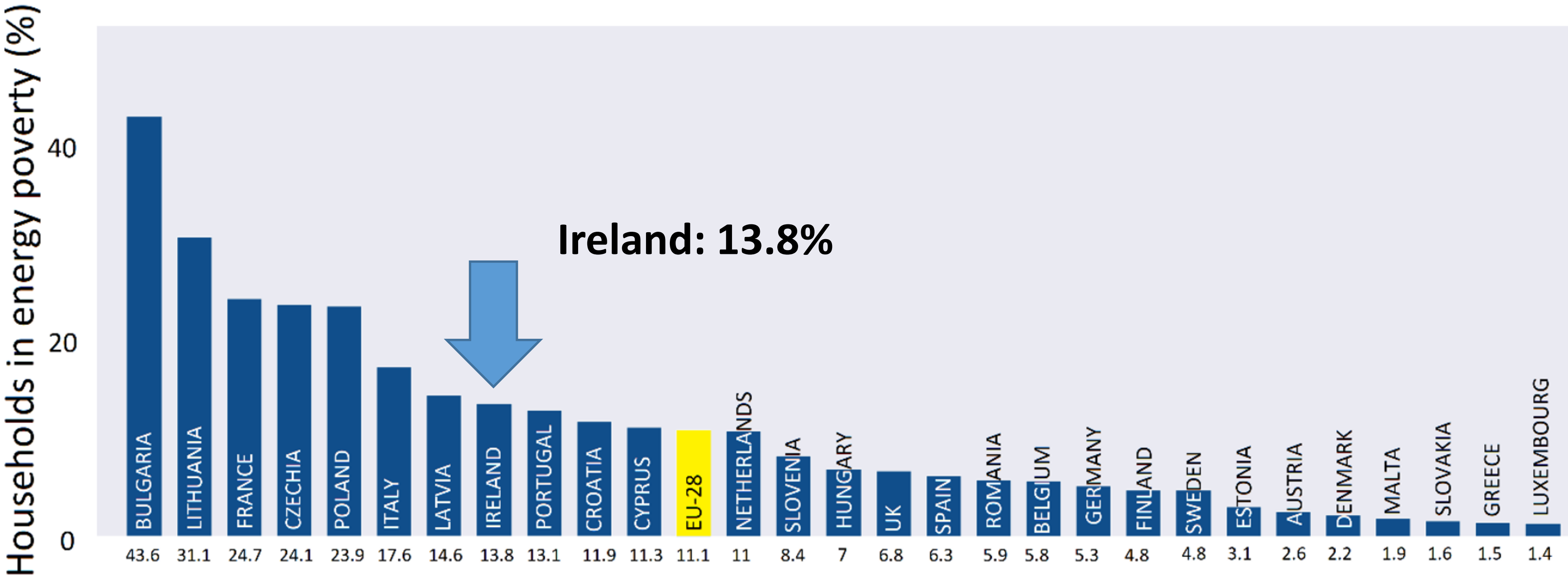
- Country-level characteristics
    - Social protection policies
    - Efficiency level for household heating
    - Gas market features (prices, switching supplier trends)

- EU Statistics on Income and Living Conditions, 2010-2020
- Energy poverty = inability to keep home adequately warm

- Eurostat, Odyssee-Mure, 2010-2020

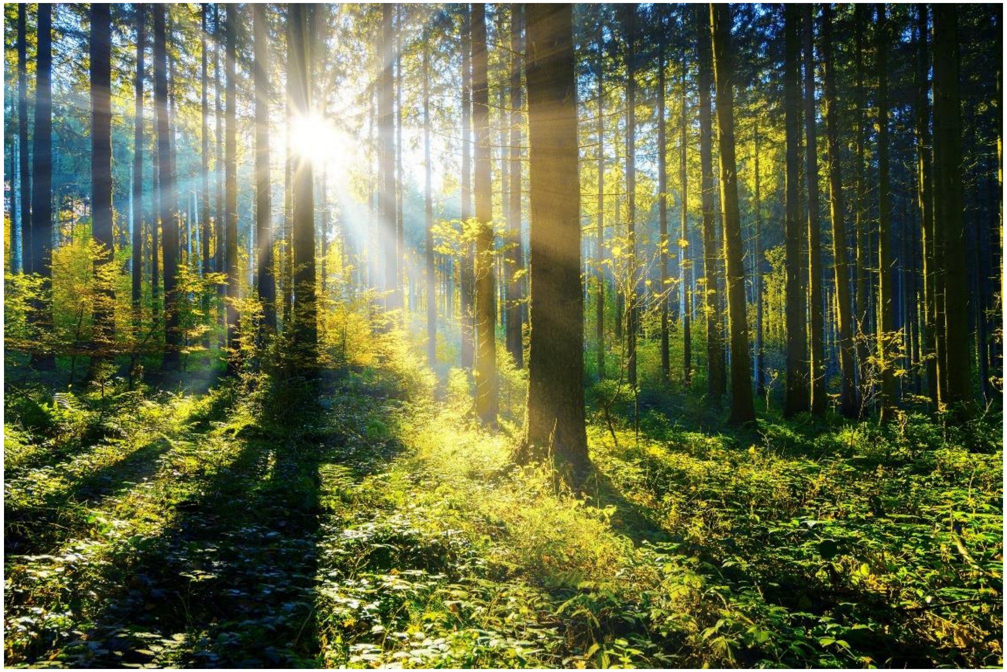
Total: +2 million observations, 28 countries


Households in energy poverty (%)
0
20
40
EU-28: 11.1%
BULGARIA 43.6
LITHUANIA 31.1
FRANCE 24.7
CZECHIA 24.1
POLAND 23.9
ITALY 17.6
LATVIA 14.6
IRELAND 13.8
PORTUGAL 13.1
CROATIA 11.9
CYPRUS 11.3
EU-28 11.1
NETHERLANDS 11
SLOVENIA 8.4
HUNGARY 7
UK 6.8
SPAIN 6.3
ROMANIA 5.9
BELGIUM 5.8
GERMANY 5.3
FINLAND 4.8
SWEDEN 4.8
ESTONIA 3.1
AUSTRIA 2.6
DENMARK 2.2
MALTA 1.9
SLOVAKIA 1.6
GREECE 1.5
LUXEMBOURG 1.4


Households in energy poverty (%)
40
20
0
Ireland: 13.8%
BULGARIA
LITHUANIA
FRANCE
CZECHIA
POLAND
ITALY
LATVIA
IRELAND
PORTUGAL
CROATIA
CYPRUS
EU-28
NETHERLANDS
SLOVENIA
HUNGARY
UK
SPAIN
ROMANIA
BELGIUM
GERMANY
FINLAND
SWEDEN
ESTONIA
AUSTRIA
DENMARK
MALTA
SLOVAKIA
GREECE
LUXEMBOURG
43.6 31.1 24.7 24.1 23.9 17.6 14.6 13.8 13.1 11.9 11.3 11.1 11 8.4 7 6.8 6.3 5.9 5.8 5.3 4.8 4.8 3.1 2.6 2.2 1.9 1.6 1.5 1.4

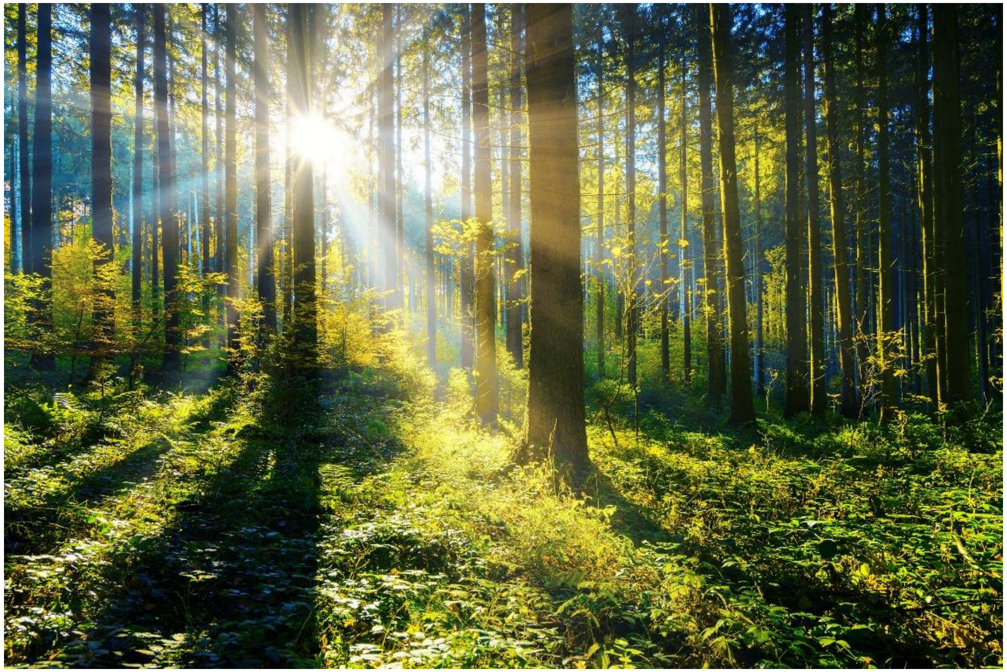
Results

“Random forest” algorithm



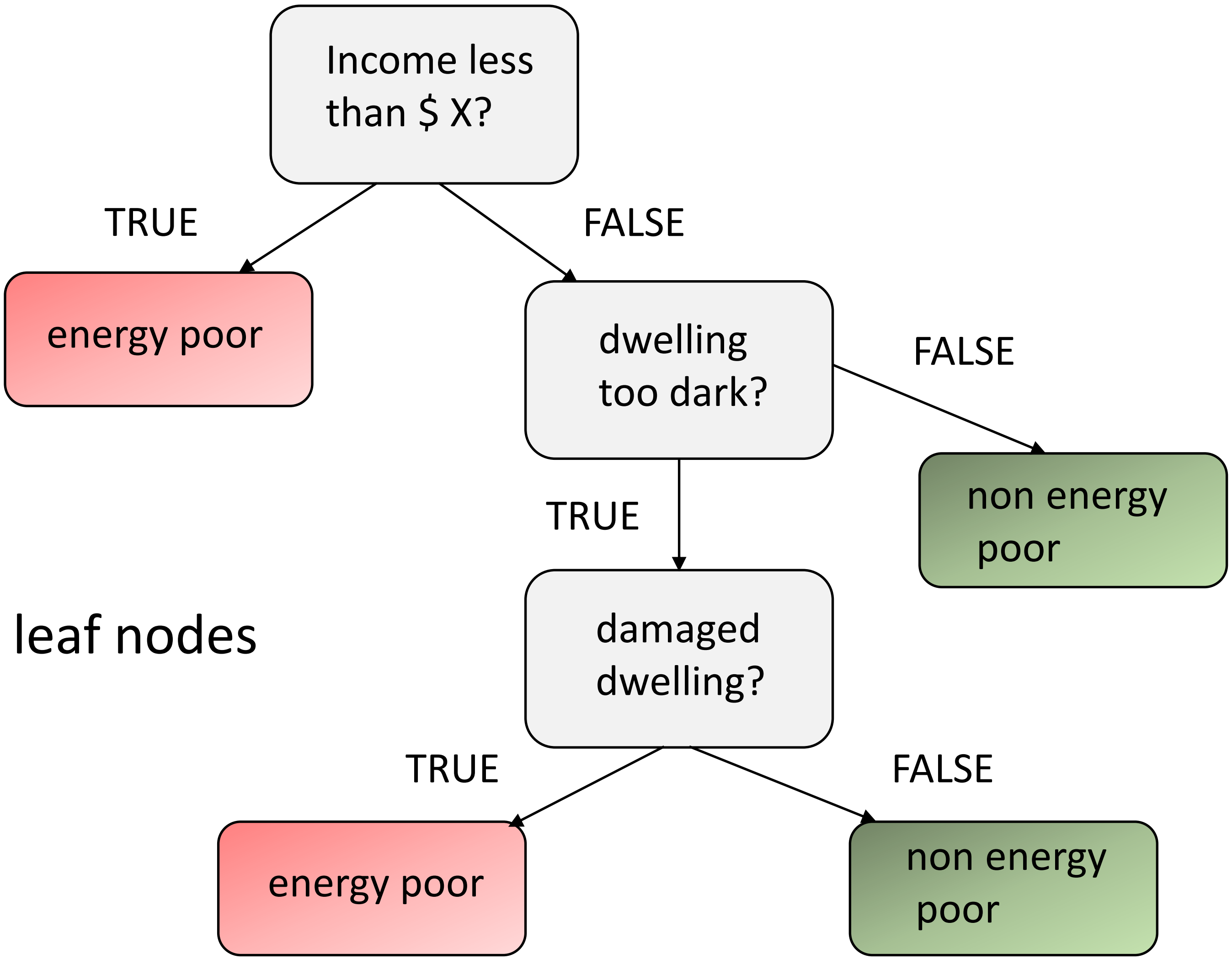
Prediction accuracy: the ratio of correct predictions over the total number of predictions made

"Random forest" algorithm



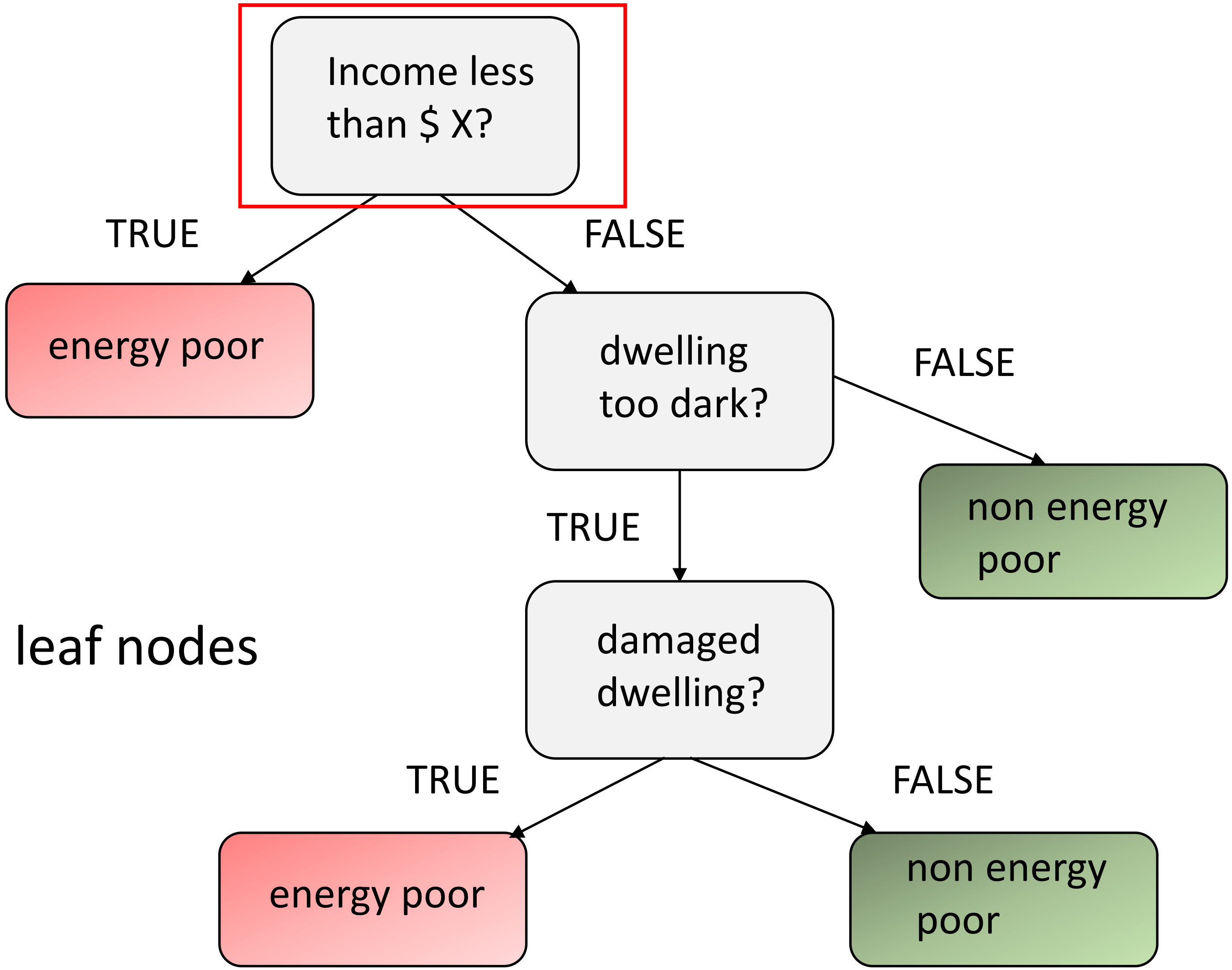
80% prediction accuracy for energy poor class, different time periods

"Random forest" algorithm



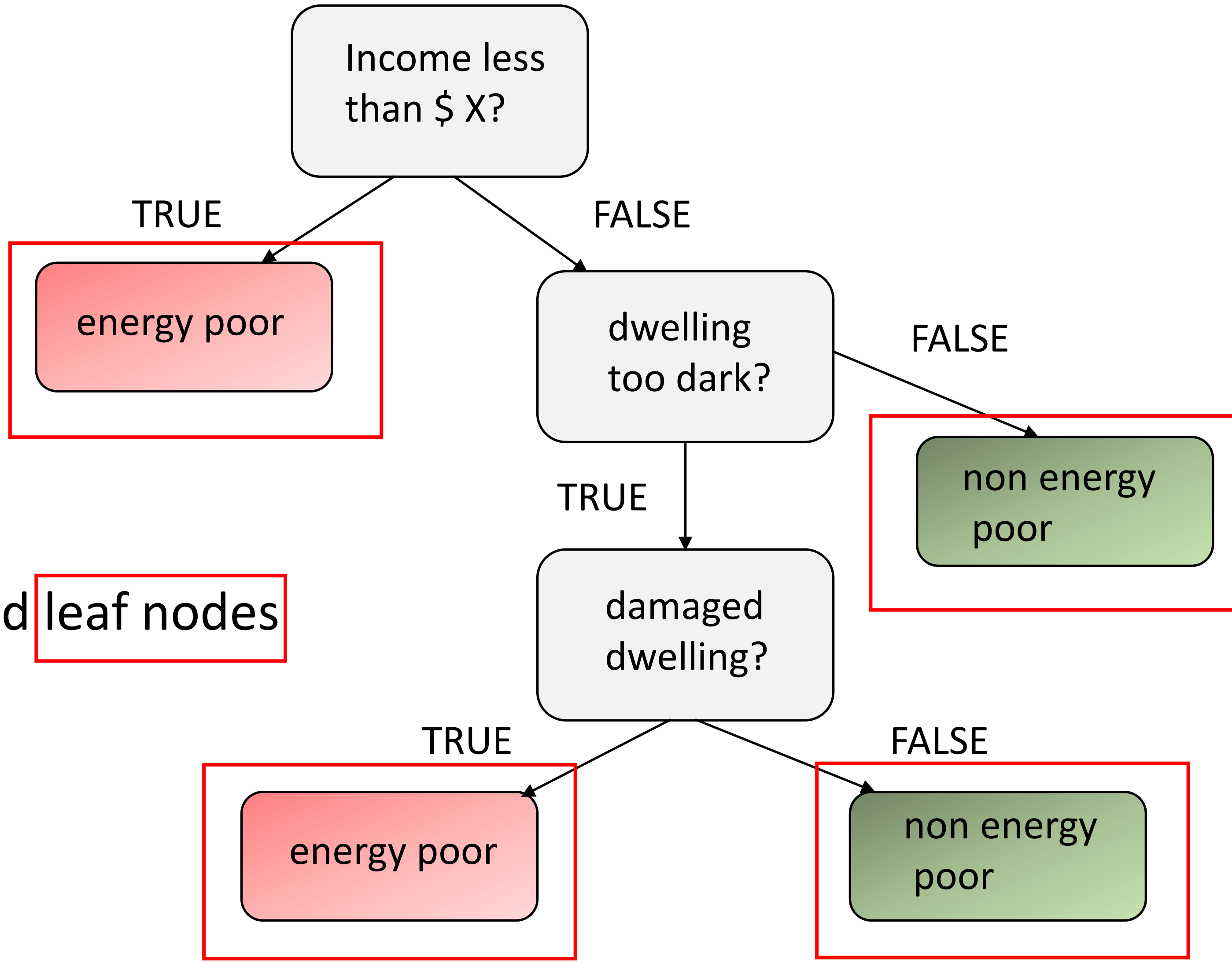
A root note and leaf nodes

“Random forest” algorithm



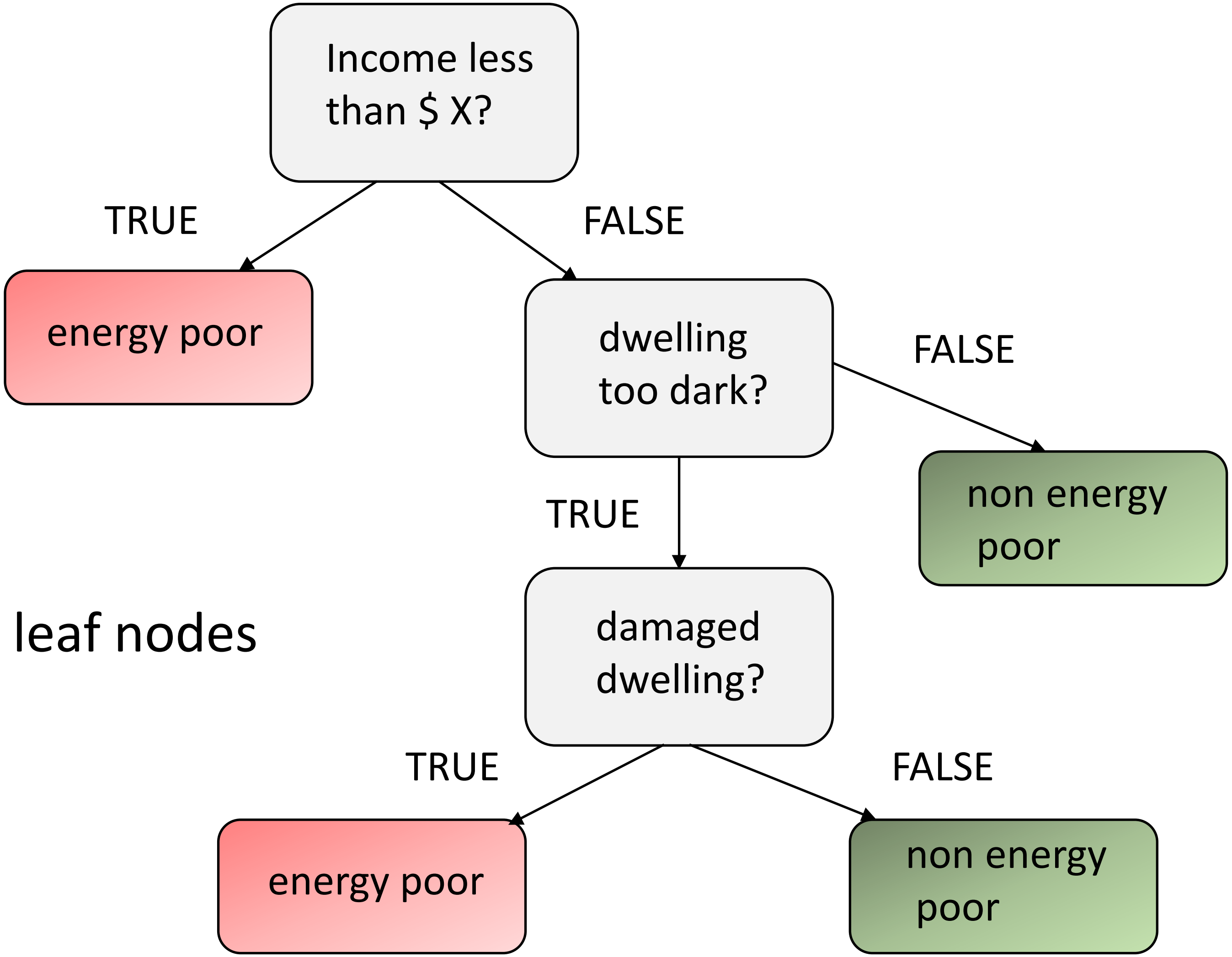
A root note and leaf nodes

“Random forest” algorithm



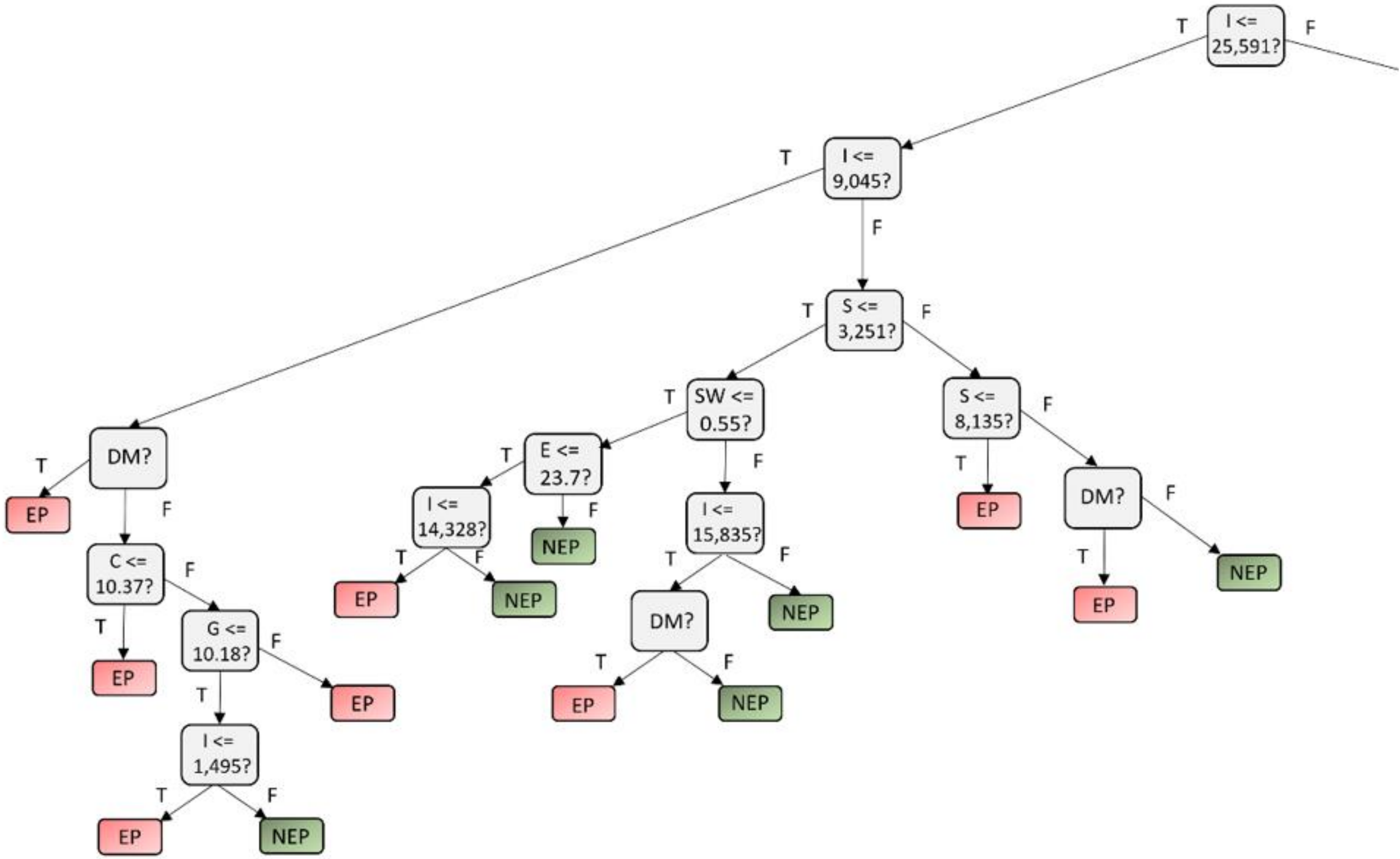
A root note and leaf nodes

“Random forest” algorithm

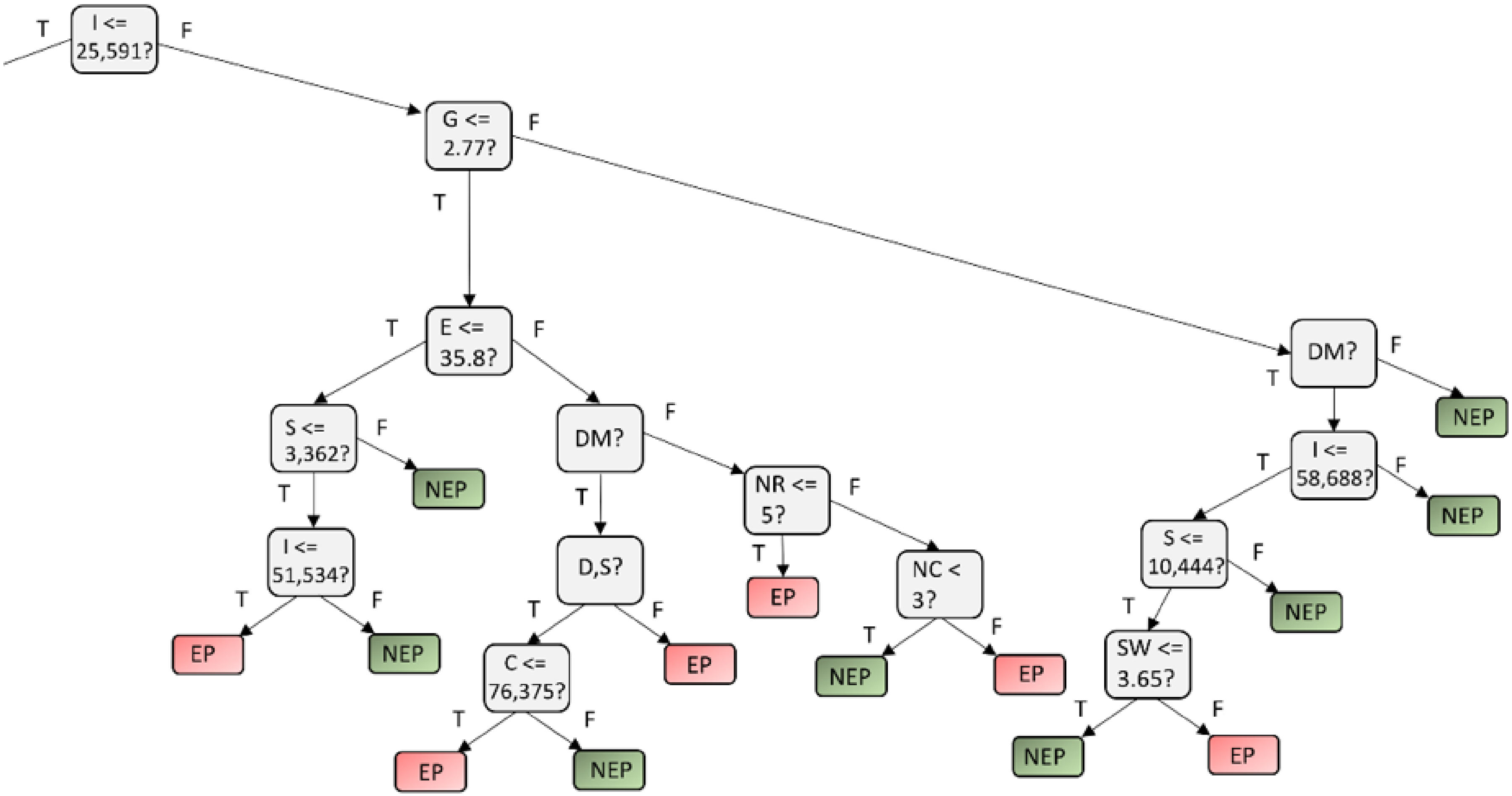


A root note and leaf nodes

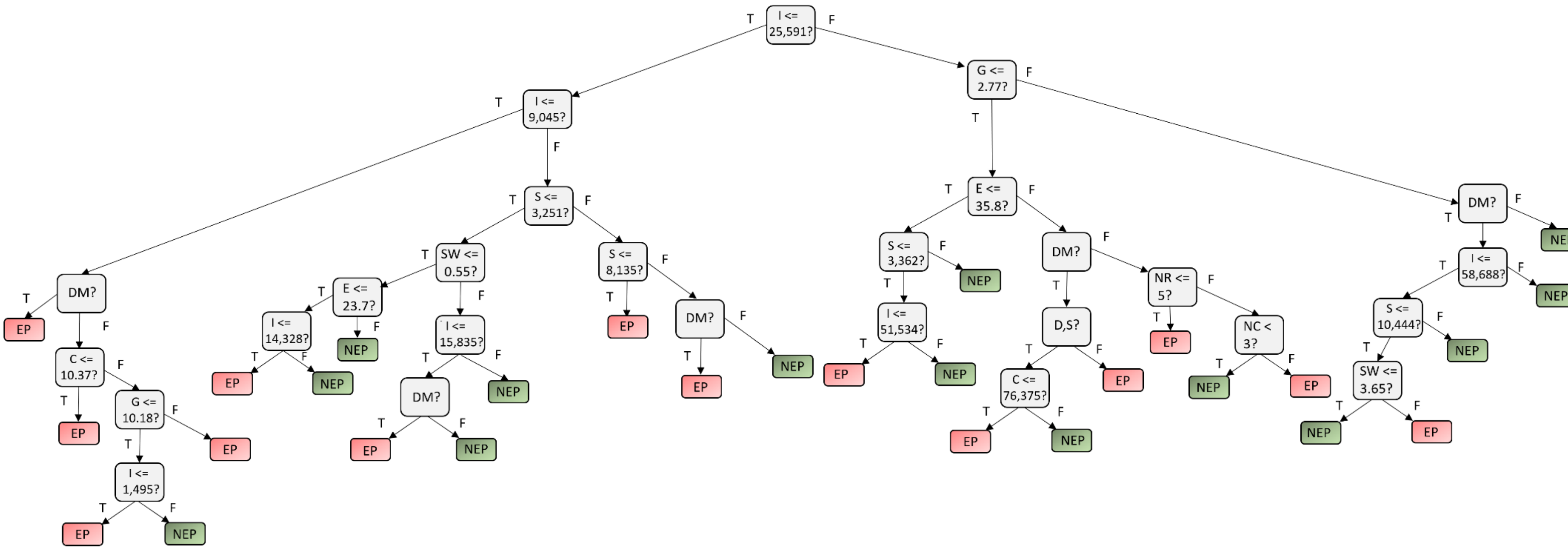
Random Forest model (1 of 10 trees)



Random Forest model (1 of 10 trees)

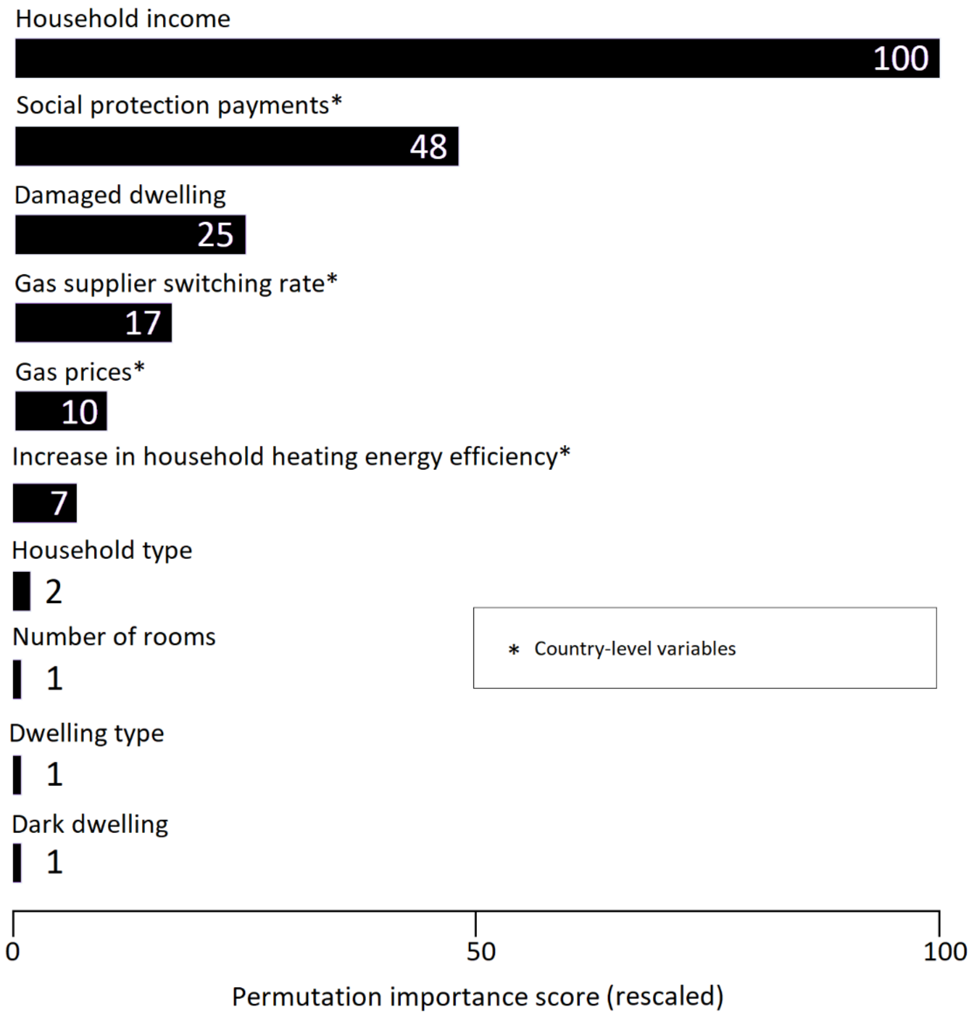


Random Forest model (1 of 10 trees)

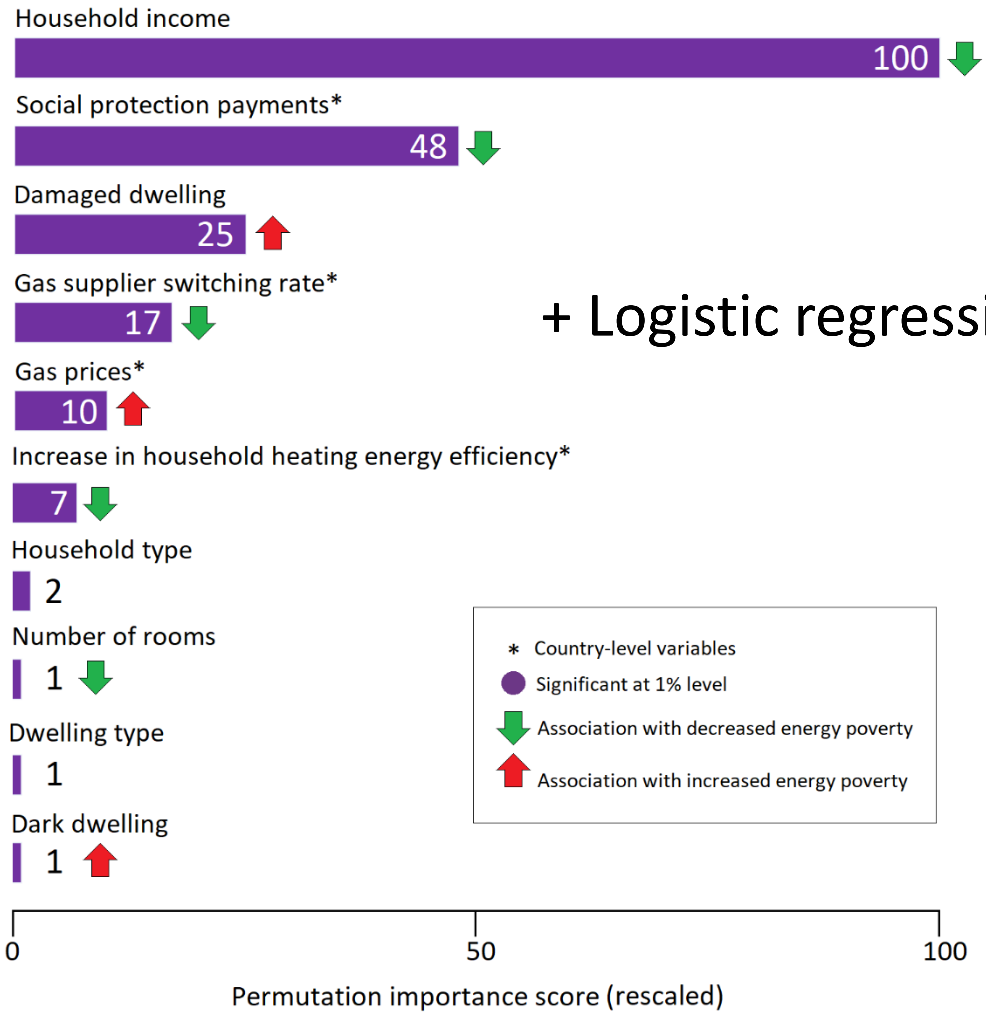


Trade-off between straightforward visualization and accuracy

Most important characteristics



Most important characteristics

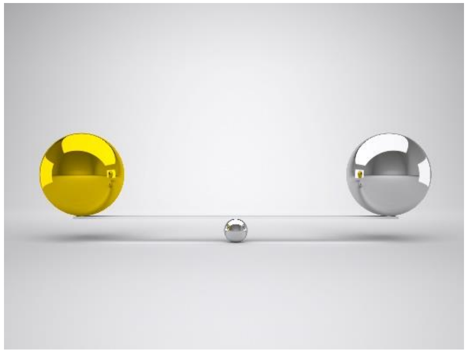


+ Logistic regression model

Evaluating the fairness of energy poverty alleviation policies

No energy poor households are excluded from assistance due to poorly set criteria

EU: income-based criteria, other social welfare-based criteria



Criterion for providing energy assistance

-income below a threshold

-old age

-unemployment status

The non-recipients

(do not meet the criterion)

How many (%) of them are energy poor?

(incorrectly excluded)

Criterion for receiving energy assistance
Income less than €15,000

Criterion for receiving energy assistance	% of non-recipient households that ARE in energy poverty
Income less than €15,000	33.2

Criterion for receiving energy assistance	% of non-recipient households that ARE in energy poverty
Income less than €15,000	33.2
Income less than €20,000	25.8
Income less than €25,000	21.3
Income less than €35,000	17.9
Income less than €50,000	15.8

Criterion for receiving energy assistance	% of non-recipient households that ARE in energy poverty
Old age	50.8
Unemployment	56.1

Implications

Implications

Machine learning can be a practical and useful tool in improving the prediction and targeting of alleviation policies

Merging household-level and country-level data: important in the absence of a standardized framework to compare energy poverty across countries

Model worked equally well for different time periods, 2010-2019 and 2020: important ability to make predictions with new batches of data, without the need to re-train

Implications

2 pillars of EU's alleviation schemes: social protection payments and supporting household energy efficiency

Continuous efforts are necessary, but we need additional ways

Need to facilitate fuel supplier switching. Right now, it depends mostly on the willingness and ability of consumers to do so

Implications

Social welfare systems and their criteria should not be the only channels for identifying recipients of energy assistance

If that happens, significant numbers of households in need of the assistance might be incorrectly excluded from it

Enrich the criteria-defining process

E.g., dwelling condition. Incorporating information about the building stock (e.g. EU building stock observatory)

Future perspectives

Future perspectives

1) Keeping one's home adequately warm is only one dimension. What about keeping it cool?

(Source: IEA)

Future perspectives

2) Incorporate data on supplementary factors: e.g., have the households negotiated with their supplier for better terms?

3) Incorporate data on energy limiting behaviors *(Cong et al., 2022).*

E.g., At what temperature users turn on their heating/cooling devices?

Future perspectives

The availability of big sets of relevant data will be essential

Machine learning can handle them and turn them into meaningful insights

Thank you for the data

THANK YOU

Q&A

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