La Statistica al CNR al servizio del Paese

Società Italiana di Statistica e Consiglio Nazionale delle Ricerche

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Artificial Intelligence Based on *Statistical Learning*

Ontology, Effectiveness and Limitations

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RESEARCH INSTITUTE on SUSTAINABLE ECONOMIC GROWTH

OUTLINE

Part 1.

AI definition, paradigms, application and limitations

Part 2.

AI research at CNR-IRCRES: Optimal Policy Learning (OPL)

PART 1

AI definition, paradigms, application and limitations

What is Artificial Intelligence?

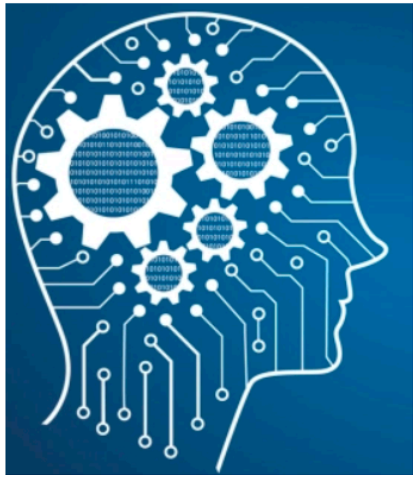
- **Artificial intelligence** (AI) is intelligence demonstrated by artifacts (e.g., machines)

- AI is opposed to **natural intelligence (NI)** displayed by animals, including humans

- AI endows machines of human-like **cognitive** functions, such as **learning** and **problem solving**

What is **intelligence**?

Ability to perceive an environment, elaborates on it, and take actions/decisions that *maximize the chance of achieving a given goal*

Environment →  → Goal

Perception/computation

The ingredients of the *cake*: AI = C + B + A

Computation

+

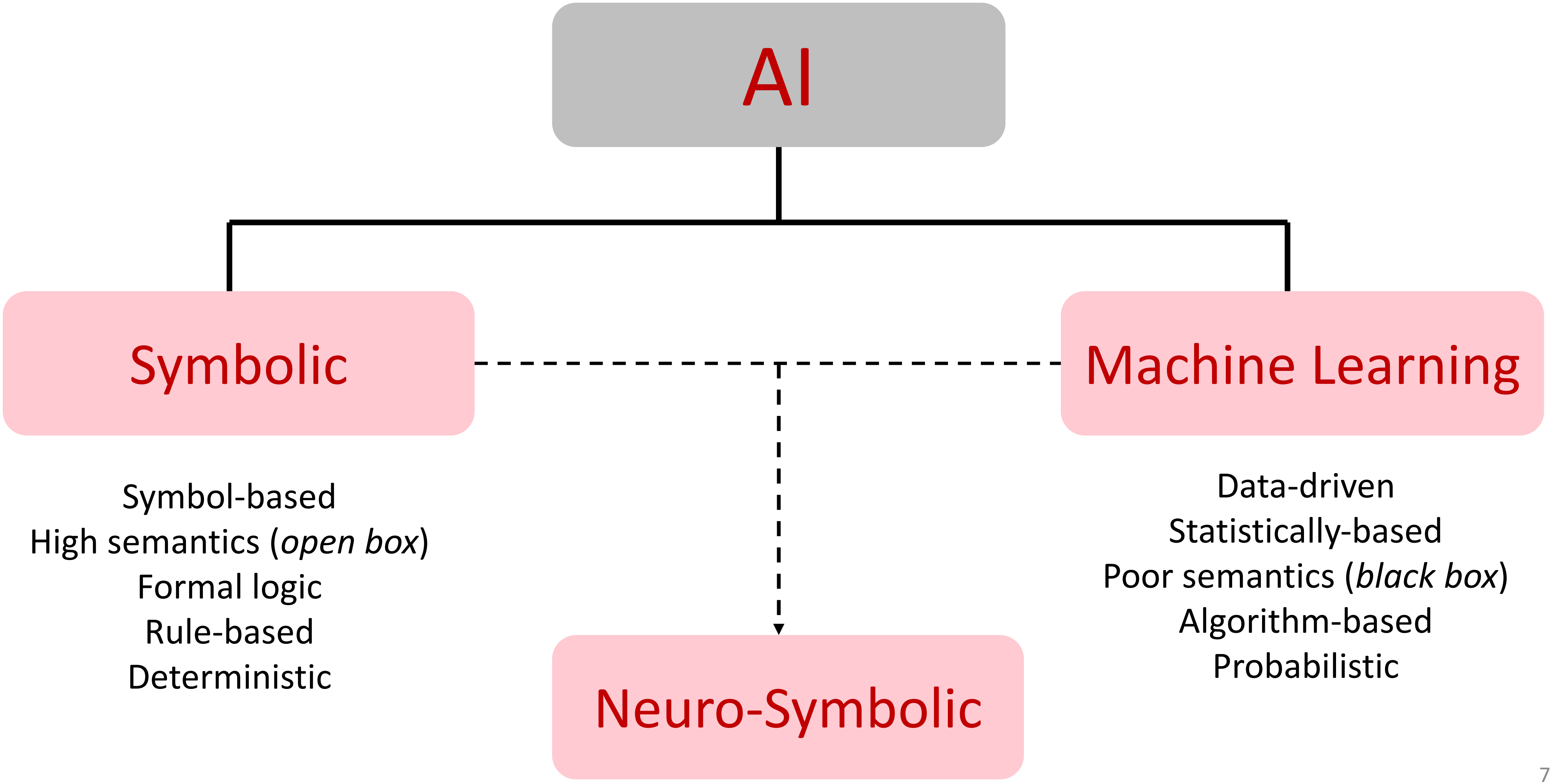
Big data

+

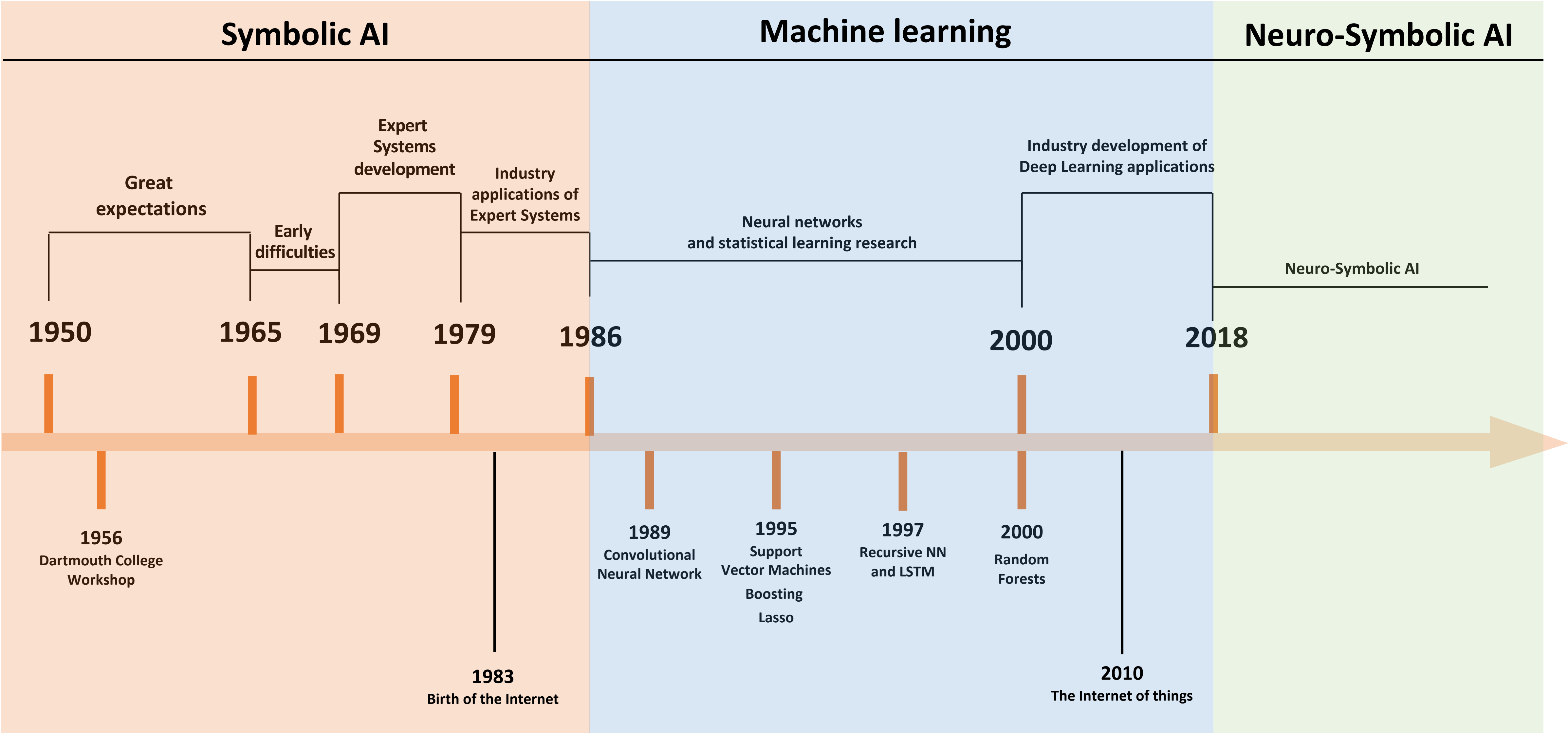
Algorithms

AI is the product of a tremendous increase in C, B, and A

AI paradigms?



Timeline of AI development?



Cerulli, 2022

Symbolic AI

vs.

Statistical learning

Rise and fall of Symbolic AI - 1

What is Symbolic AI ?

Branch of artificial intelligence attempting to explicitly represent **human learning** in a **declarative form** (i.e. **facts** and **rules**)

Based on **Thomas Hobbes** statement:

«Thinking is manipulation of symbols and Reasoning is computation»

Building "General Problem Solvers"

Hard-wired rule-based reasoning systems like Expert Systems became the foundation for almost 40 years of AI research

Allen **Newell**, Herbert A. **Simon**
Pioneers in Symbolic AI

Rise and fall of Symbolic AI - 2

What is a symbol?

"A perceptible something that stands for something else"

- Alphabet symbols, numerals, road signs, music symbols, etc.
- A symbol such as 'apple' it symbolizes something which is edible, red in color. In some other language, we might have some other symbol which symbolizes the same edible object

New knowledge comes up from manipulating symbols via ***logical rules***

Symbols → Manipulation by hard-wired *Rules* → New Knowledge

Rise and fall of Symbolic AI - 3

The fall of Symbolic AI

The main problem with Symbolic AI was that it aimed at

TEACHING A MACHINE LOGICAL RULES

instead of

LETTING THE MACHINE TO LEARN FROM EXPERIENCE

Complex intelligence tasks, general patterns' recognition and unspecialized procedural tasks cannot successfully carried out using the Symbolic AI paradigm

Rise and fall of Symbolic AI - 4

The **Symbolic AI** cannot solve the ***"learning-by-experience paradox"***

Emma was here a six year old girl. She spoke a fluent Italian. She was able to understand it and make herself understood by other Italian people

Emma was ***never taught a single Italian grammar rule***. She did not even know about the existence of grammar rules

But she was able to recognize words, understand their meaning, and process them accordingly

She has learnt Italian ***by experience***

The rise of *Statistical Learning* - 1

In 1959, **Arthur Samuel**, pioneered the field of Machine Learning (ML), by defining it as the *"field of study that gives computers the ability to learn without being explicitly programmed"*

ML can be understood as a set of computational methods that use "***experience***" (i.e. ***past event frequencies***) to improve performance by generating **accurate predictions**

IF HUMANS LEARN FROM EXPERIENCE

↓

LET MACHINES LEARN FROM DATA

The rise of *Statistical Learning* - 2

Data (y , X)

Collection of many single events occurred in the past
(frequencies = experiences) linking an event y and many events X

↓

Learning algorithm: a mapping of X into y

↓

Learning = higher predictive power

The rise of *Statistical Learning* - 3

$$
\begin{tikzcd}
{[X_1, X_2, \dots, X_p]} \arrow[r, "\overset{\textbf{MAPPING}}{f}"] & Y \arrow[d] \\
& \textbf{PREDICTION}
\end{tikzcd}
$$

The rise of *Statistical Learning* - 4

The fundamental **statistical object** designing the **mapping** is the **conditional expectation** of y given $\mathbf{X} = [X_1, X_2, \dots, X_p]$:

$$E(Y \mid X_1, X_2, \dots, X_p) = f(\mathbf{X})$$

NOTE: we do not focus on $P(y|\mathbf{X})$ as it is too demanding

EXAMPLE

Numeral recognition

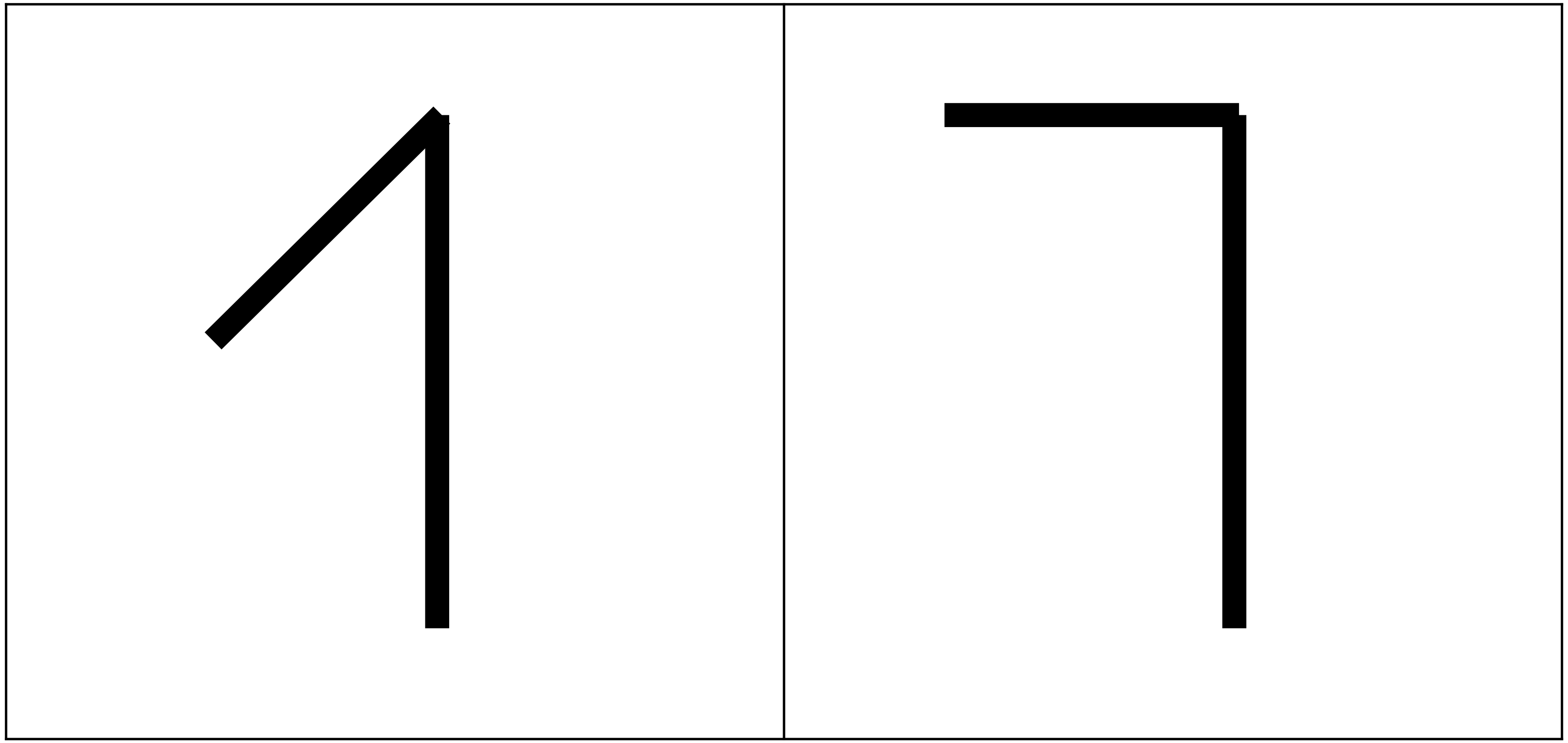
Symbolic AI

vs.

Machine Learning

Numeral recognition

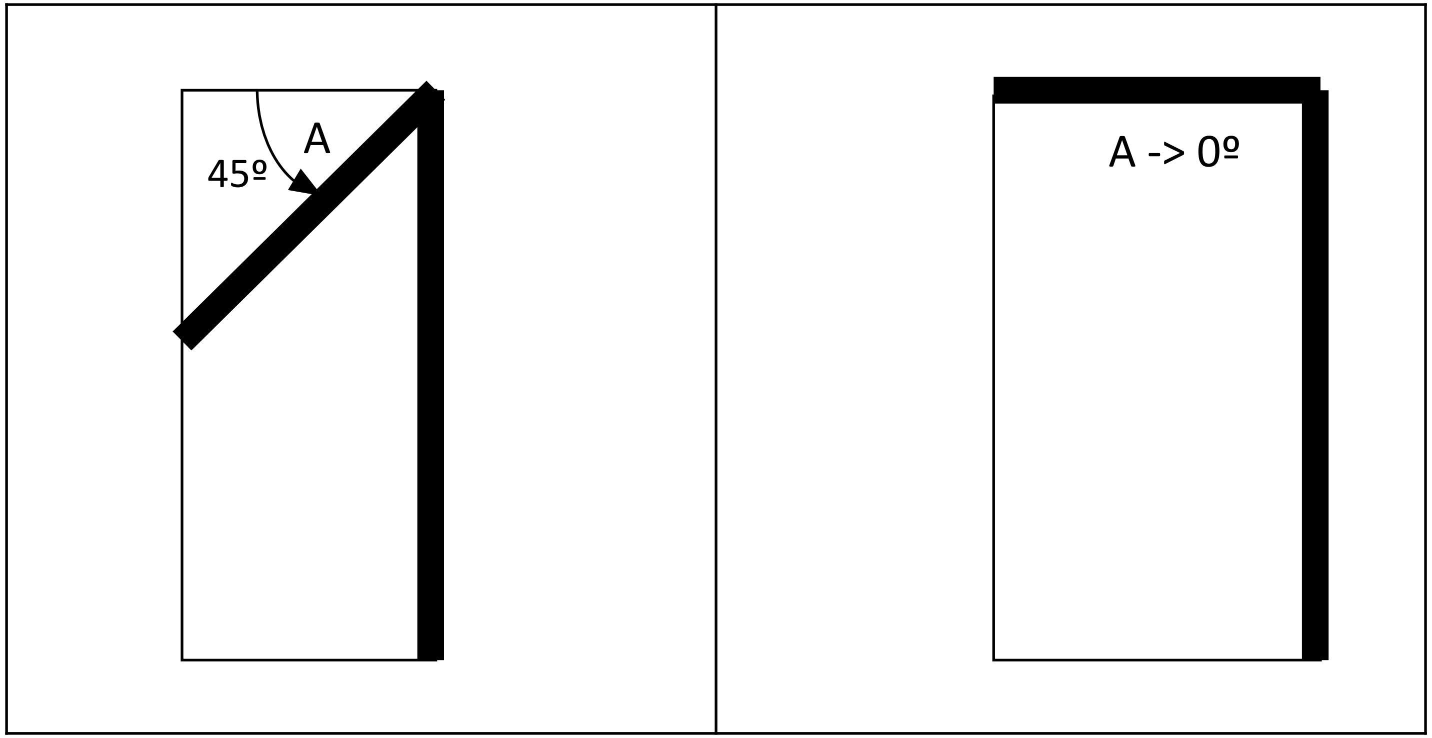
Task: Making a machine able to recognize whether this numeral is a 1 or a 7



This number is a 1 | This number is a 7

Numeral recognition: Symbolic AI - 1

Possible strategy. Put the numbers into a rectangle. Then, consider the angle A as follows:

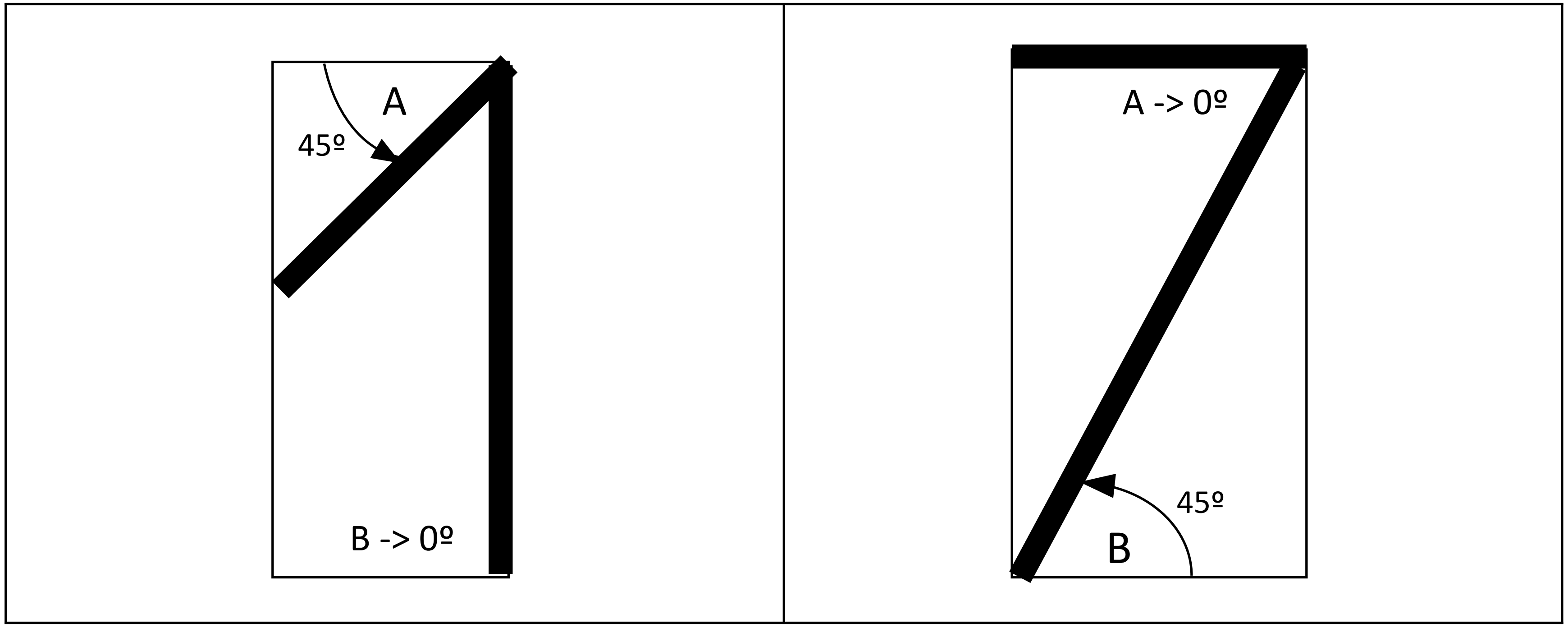


Come up with this possible **rule**:

- If (A <= 45º): it is a 7
- Else if (A > 45º): it is a 1

Numeral recognition: Symbolic AI - 2

Complication. Number 7 is commonly written using a steeper bar (we can then exploit angle B):

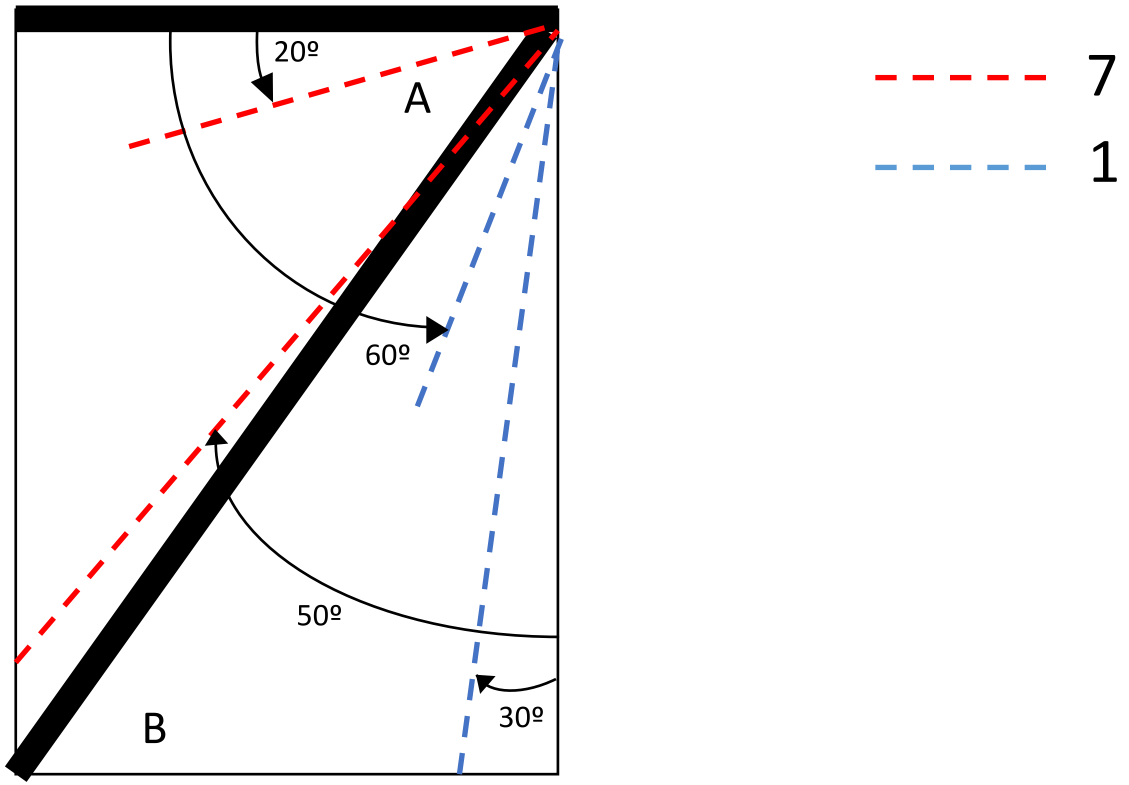


Come up with this possible **rule**:

If (A <= 45º) & (B > 45º): it is a 7
If (A > 45º) & (B <= 45º): it is a 1

Numeral recognition: Symbolic AI - 3

Complication. Number 7 is commonly written using a steeper bar (we can then exploit angle B):



Come up with this possible **rule**:

If (A <= 45º) & (B > 45º): it is a 7

If (A > 45º) & (B <= 45º): it is a 1

Numeral recognition: limits of Symbolic AI - 1

Can we design **rule-based symbolic algorithms** able to let a machine recognize "hand-written" numerals?

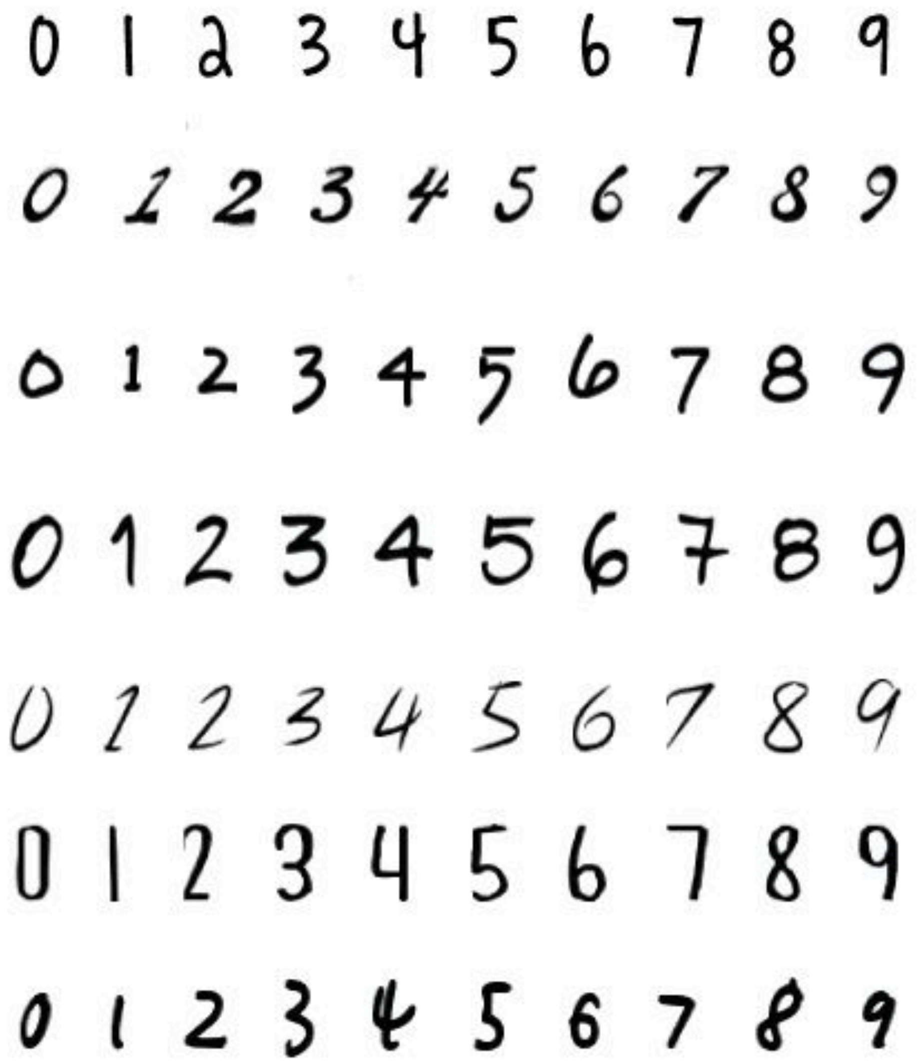


Image recognition: Limits of Symbolic AI - 2

Can we design **rule-based symbolic algorithms** able to let a machine recognize patterns like these ones?

Puppy

or

Muffin ?

Numeral recognition: limits of Symbolic AI - 3

- The previous **rule-based recognition algorithm** is simple, and it is likely to assure a recognition accuracy around 90% or even more

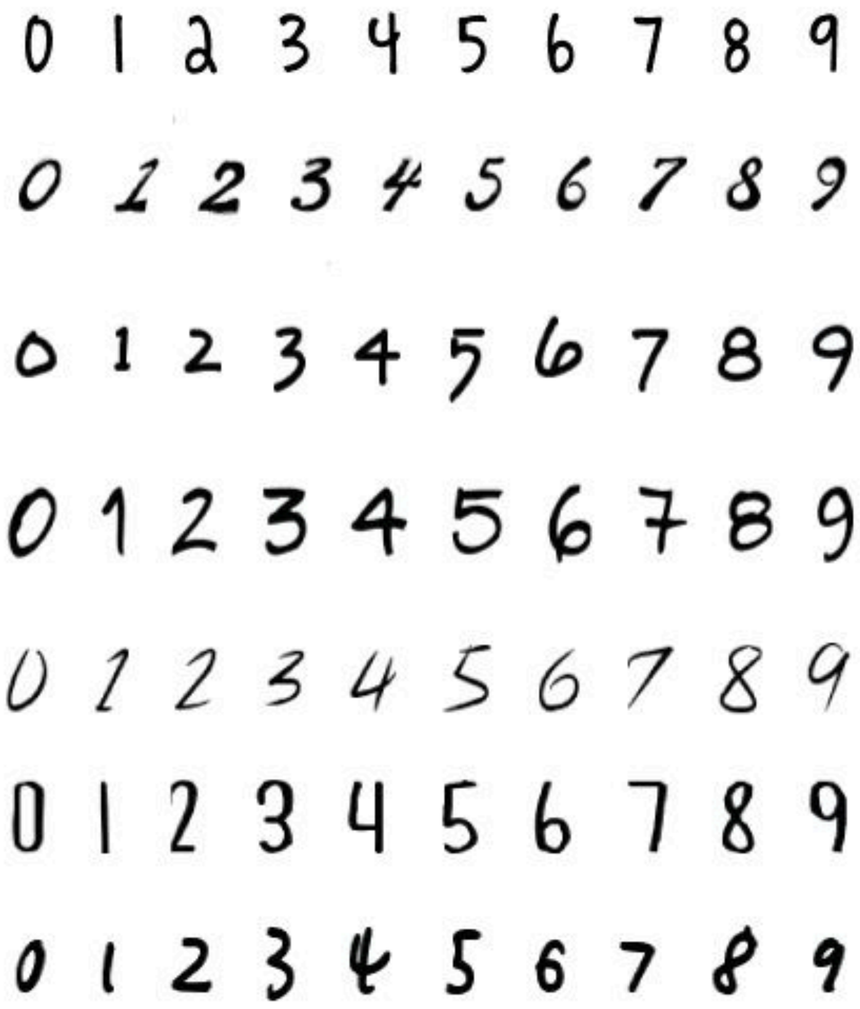
- However, when considering other numerals, the problem gets more complicated, and we need a larger set of rules to come up with a good recognition accuracy

- But what about recognition of fuzzier images, as ”hand-written” numerals? In this case things get much more complicated and rule-based recognition may dramatically fail or require extravagant ruling patterns, that most of the times are ”local rules” not generalizable to other recognition settings

- **Machine Learning** – i.e. learning from experience – is a workable more effective solution

Numeral recognition: Machine Learning

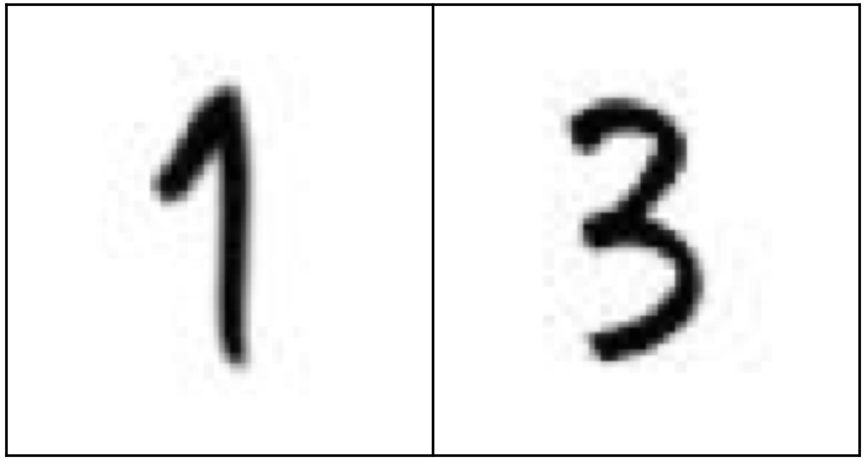
ML uses past recorded experience on how people connected specific numerals to specific configurations (patterns) of hand-written numerals



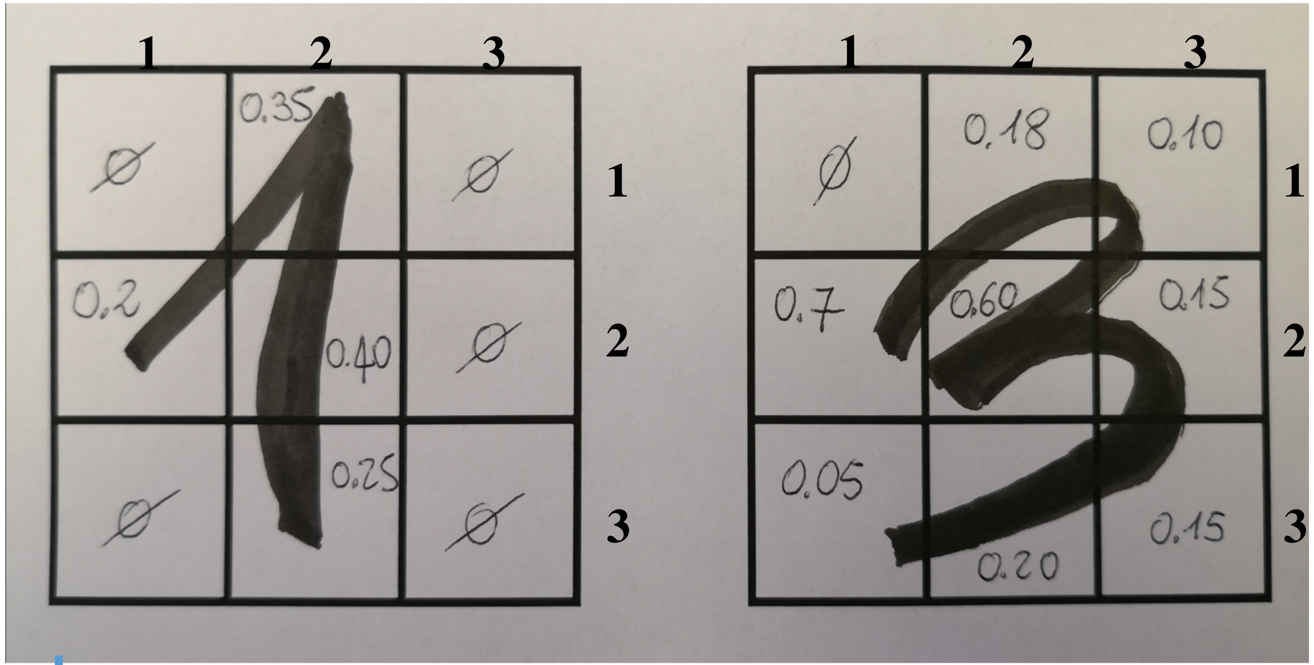
Numeral recognition: Machine learning

Task: Making a machine able to recognize whether the numeral is a 1 or a 3

- ML re-organizes the problem as a (y,X) **mapping** problem where (y,X) is a ***(training) dataset***
- So, ML needs to generate a dataset able to map y (the true numeral) into X (the usual ways people write numerals 1 and 3 by-hand)
- The trick is to decompose the numeral into adjacent equally spaced pieces (pixels) and use them as predictors (X)



next slide



- Each single square is one **pixel**
- The **number inside each pixel** is the **percentage** of the pixel area covered by the **ink**

Data representation of the two images

	Y	x1	x2	x3	x4	x5	x6	x7	x8	x9
Image of "1"	1	0	0.35	0	0.2	0.4	0	0	0.25	0
Image of "3"	3	0	0.18	0.1	0.7	0.6	0.15	0.05	0.2	0.15

Based on many images we aim to predict new images

	Y	x1	x2	x3	x4	x5	x6	x7	x8	x9
Image of "1"	1	0	0.35	0	0.2	0.4	0	0	0.25	0
Image of "3"	3	0	0.18	0.1	0.7	0.6	0.15	0.05	0.2	0.15
Image of "1"	1	0	0.30	0	0.1	0.4	0	0.01	0.22	0
Image of "1"	1	0	0.35	0.01	0.3	0.4	0	0	0.23	0
Image of "3"	3	0	0.16	0.1	0.65	0.6	0.16	0.09	0.3	0.14
Image of "3"	3	0	0.15	0.1	0.75	0.7	0.14	0.06	0.2	0.15
Image to predict	?	0	0.30	0	0.1	0.4	0	0.01	0.22	0
Image to predict	?	0	0.35	0	0.2	0.4	0	0	0.25	0

Protocol of imaging recognition

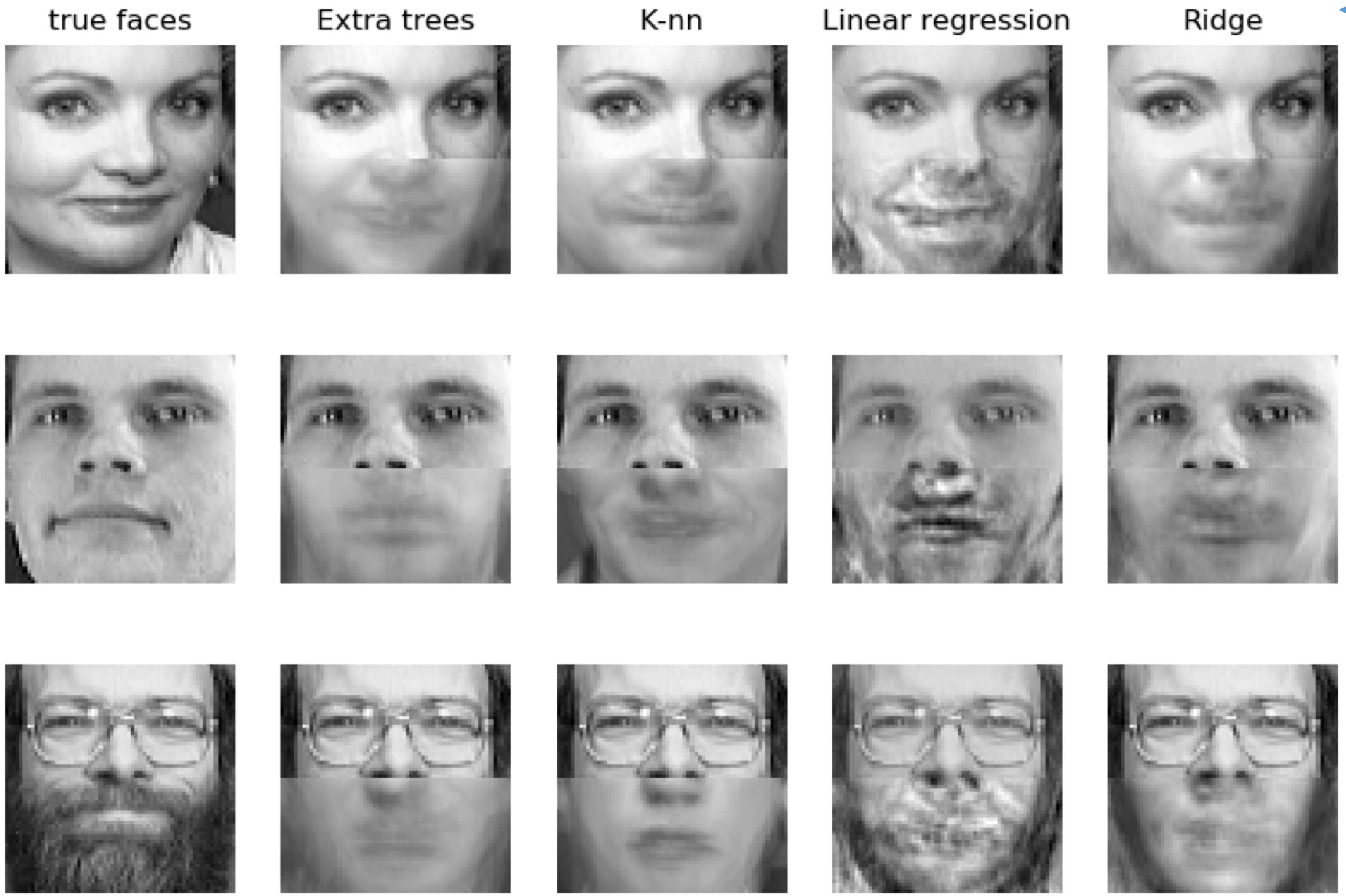
1. Build a **training dataset** made of all the images

2. Use a **learner**, i.e. a mapping between {Y} and X={x1, … ,x9}

3. As long as certain **configurations** of X are likelier to be associated to a specific Y, a proper learner **can learn how to link** a **new configuration** (i.e., a new image) to a **specific numeral**

More complex images recognition (faces, objects) follow a similar logic

Face completion: predict the lower half of a face by knowing the upper half



Learners

Olivetti faces dataset

Limitations and failure of statistical learning

ML limitations

- **Ethics**

  When decisions are taken by a machine, who is **responsible** for their effect?

- **Causality**

  The mapping found out by a ML algorithm is based on **correlation**, **not on causality**

- **Scope**

  Should we use ML in whatever analytical context? Even when the aim is pure prediction, ML algorithms can skip **fundamental theory**: *“should we make weather forecasts without relying on Newton's laws of motion”*?

- **Interpretability**

  There exists a fundamental **trade-off between predictability and interpretability**. In some research contexts interpretability is more important that predictability

ML failure

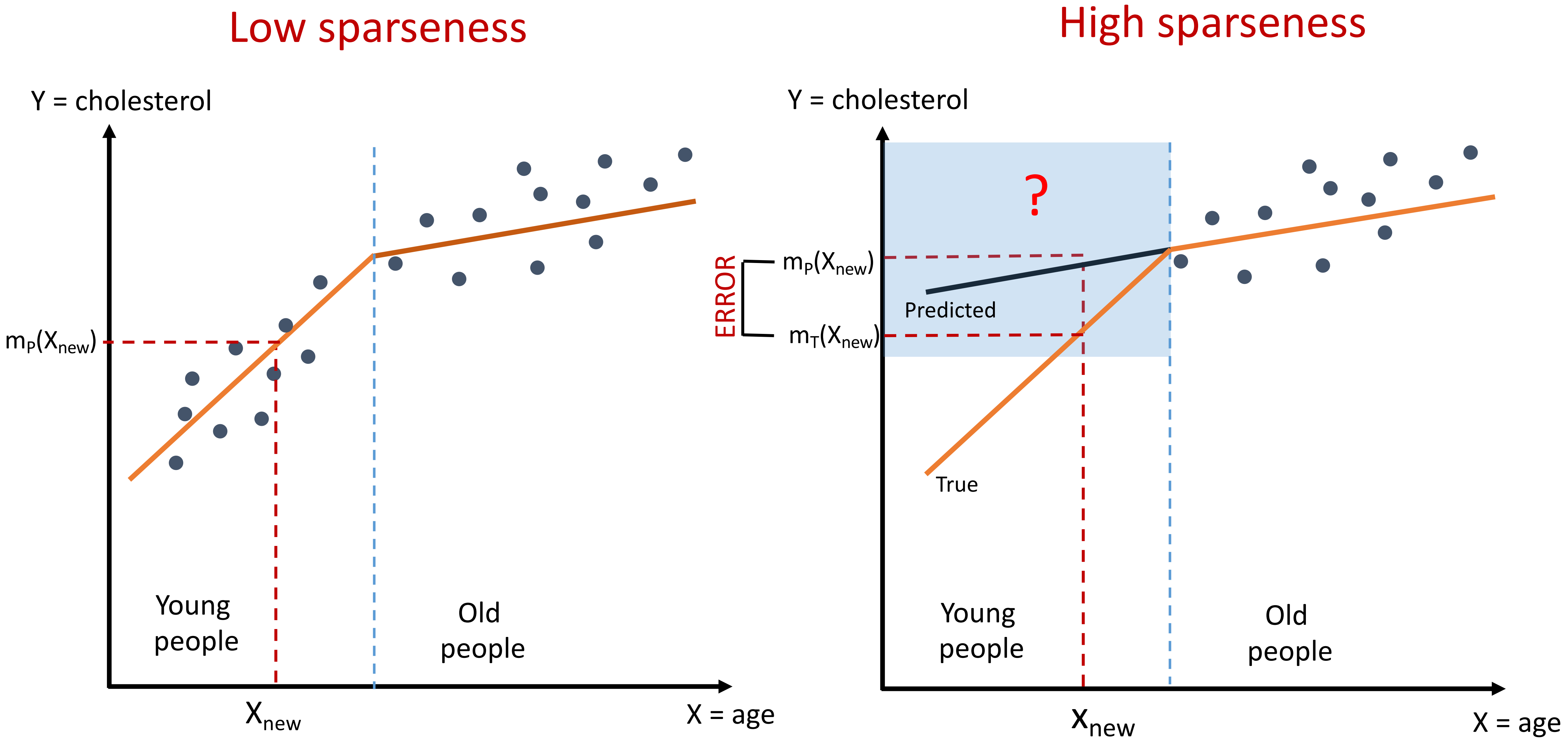
Can ML prediction fail? Yes! == > It may depend on **data constrains**

Data constrains

- **Availability**
  Poor information about y and X
- **Quality**
  Poor data quality and measurement errors
- **Ordering**
  Spatial/temporal ordering of features and observations
- **Sparseness**
  Information about y and X is *sparse*

The consequences of **data sparseness**

Data sparseness weakens prediction

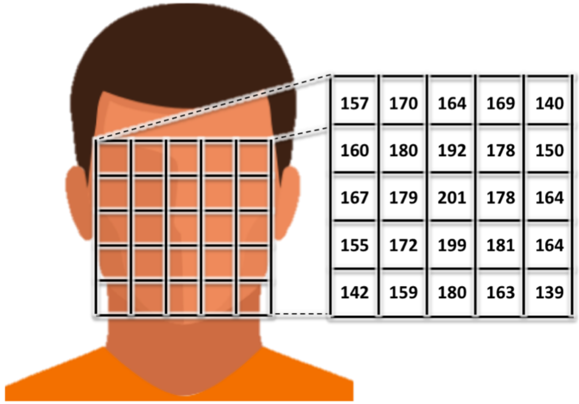


The consequences of **data unordering**

Higher data **ordering** implies **higher prediction**

Imaging recognition

Face recognition



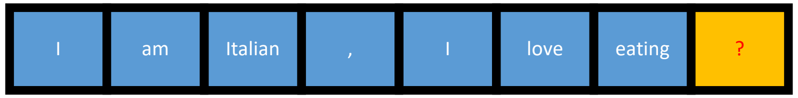
1. Each pixel is a variable in the dataset
2. Adjacent pixels are highly correlated

This depends on the fact that, by nature, the nose is at the center of the face, with eyes on the left and right and forehead at the top, ….

Similar to **spatial correlation** in statistics

Natural Language processing

One-token-ahead prediction



1. Find the more likely word after a **sequence of words**
2. Train over a frequency-context (e.g., *whatsup chats*)

This depends on human beings
conventionality / Homophily

Similar to **serial correlation** in statistics

Lower data **ordering** implies **lower prediction**

- In the **social-sciences**, information is strongly **unordered**
- This explains why **deep learning** prediction is **poorly successful** for micro socio-economic data (data on workers, businesses, farms, etc.)
- Generally, **other ML methods** than neural networks do better with socio-economic data (*Random forests*, *Boosting*, *SVM*)

Conclusions

- **AI matters:** revolutionizing human activities and society
- **Machine Learning:** today's **leading AI paradigm**
- **ML limits**: ethics, interpretability, and scope
- **ML failure**: *sparseness, poor ordering*

Can **symbolic AI** help ML in **failing** situations?
The **neuro-symbolic** approach seems a promising way to go
(TBA in a next seminar …. ☺)

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PART 2

AI research at CNR-IRCRES: Optimal Policy Learning (OPL)

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What AI research at CNR-IRCRES?

Statistical learning for optimal socio-economic policy design

↓

Optimal Policy Learning (OPL)

OPL definition

- **What is policy learning?**

  Process of improving program **welfare** achievements by re-iterating similar policies over time

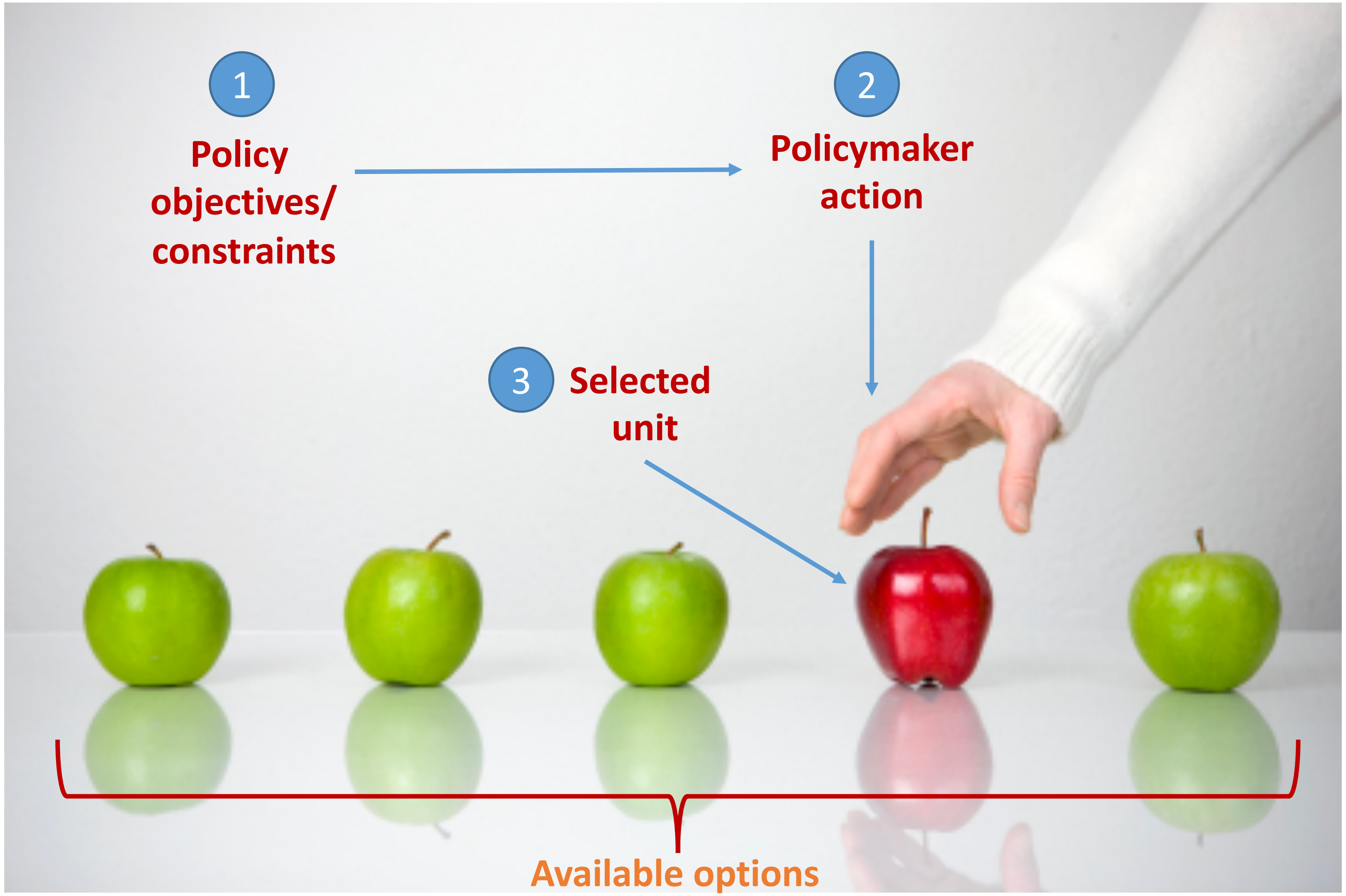
- **Optimal treatment assignment**

  Policymakers can **optimally fine-tune the treatment assignment** of a prospective policy using the results from an RCT or observational study. Assignment rules depends on the **class of policies** considered (here we focus on **threshold-based** and **linear-combination** policies)

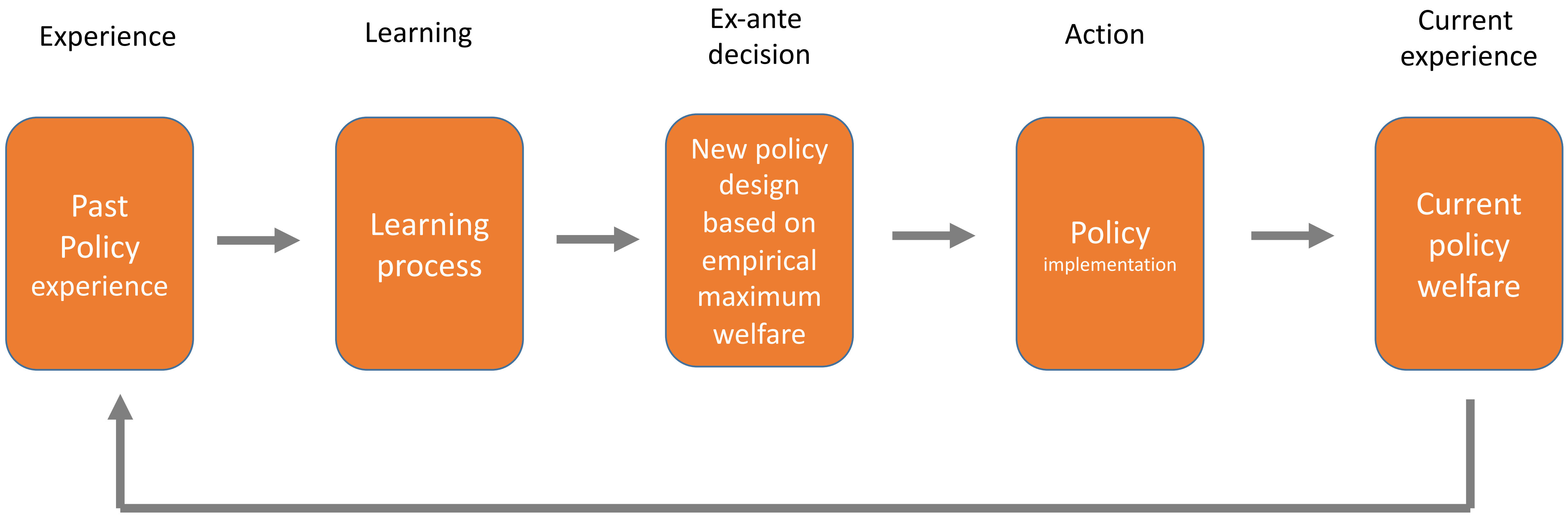
- **Maximizing constrained welfare**

  The policymaker hardly manage to reach the best solution (**unconstrained maximum welfare**) because of institutional/economic contains of various sort

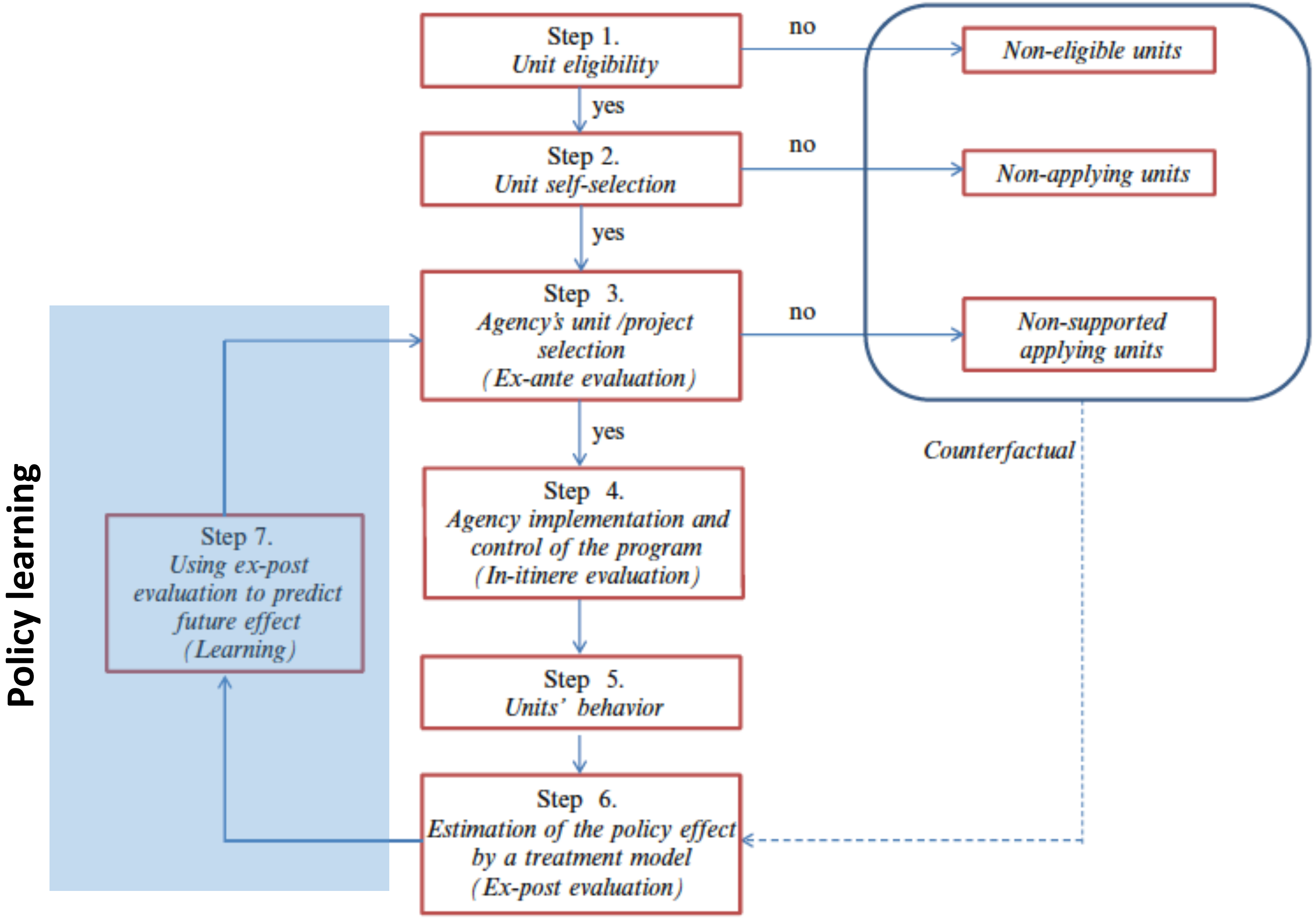
Policy as selection problem



Learning policy from experience



Policy learning within policy EVALUATION cycle



Policy direct and indirect effect

Total
Policy effect

$$\underbrace{\gamma(S)}_{\text{Total Policy effect}} = \underbrace{\alpha}_{\text{Direct effect}} + \underbrace{\beta(S)}_{\text{Indirect effect}}$$

Direct
effect

Indirect
effect

S = Selection process operated by a specific **treatment rule**

Empirical Welfare Maximization aims at maximizing the **indirect effect** via *optimal assignment to treatment* within specific *classes of policies*

This is the effect obtained if the "assignment to treatment" was run at **random**

Optimal treatment assignment

Let X be an individual's vector of characteristics, Y an outcome of interest, $T = \{0, 1\}$ a binary treatment. A policy assignment rule $\mathcal{G}$ is a function mapping X to T, specifying which individuals are or are not to be treated:

$$\mathcal{G} : X \rightarrow T$$

Define the (population) policy conditional average treatment effect as:

$$\tau(X) = E(Y_1|X) - E(Y_0|X)$$

where Y_1 and Y_0 represent the two potential outcomes of the policy, and $E_X[\tau(X)] = \tau$ the average treatment effect.

Optimal treatment assignment

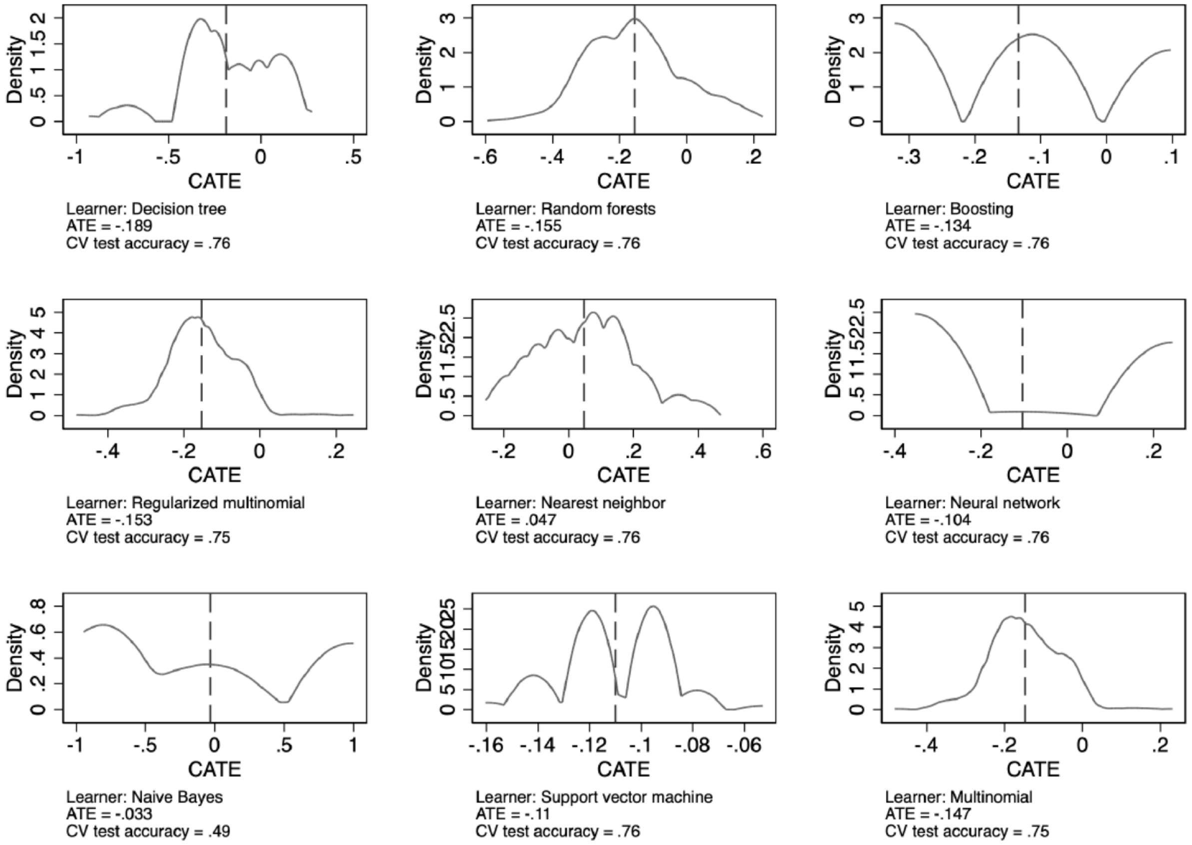
Under **selection-on-observables**, we know that:

$$\tau(X) = E(Y|X, T=1) - E(Y|X, T=0)$$

These two **conditional expectations** are **identified** by data. Whatever **ML algorithm** can be used for estimation (Boosting, Random forests, Neural networks, Nearest neighbor, etc.)

Extension to **selection-on-unobservables** straightforward

ML estimation of $\tau(X)$



Estimation of the **distribution** of the **conditional average treatment effects** (**CATE**) using the ML methods implemented via **`c_ml_stata_cv`** (Cerulli, 2022). Note: dashed vertical line indicates the **average treatment effect** (**ATE**).

Optimal unconditional welfare

The estimated policy actual total effect (or *welfare*)

$$\widehat{W} = \sum_{i=1}^{N} T_i \cdot \hat{\tau}(X_i)$$

and the estimated policy *unconstrained* optimal total effect (or *unconstrained maximum welfare*) as:

$$\widehat{W}^* = \sum_{i=1}^{N} \hat{T}_i^* \cdot \hat{\tau}(X_i)$$

where:

$$\hat{T}_i^* = \mathbf{1}[\hat{\tau}(X_i) > 0]$$

is the estimated optimal unconstrained policy assignment.

The difference between the estimated (unconstrained) maximum achievable welfare and the estimated welfare associated to the policy actually run is called *regret*, and it is defined as:

$$\widehat{regret} = \widehat{W}^* - \widehat{W}$$

NAÏVE OPTIMAL SELECTION

1. Given {X,Y,T} from an already-implemented policy: estimate the **idiosyncratic effect** $\boldsymbol{\tau(X)}$. This means we have learnt the mapping:

$$X \to \tau(X) \quad \text{(\textit{learning from experience})}$$

2. Consider a prospective second policy round with a new eligible set {X'}, and compute the learnt $\{\tau(X')\}$ over X'.

3. Rank individuals so that: $\tau({X_1}') > \tau({X_2}') > \tau({X_3}') > \ \ldots > 0$.

4. Given a monetary budget C and a unit cost c_i, find N_1^*:

$$\sum_{i=1}^{N_1^*} c_i = C$$

Constrained welfare maximization - 1

- Eligibility, budget, ethical, or institutional constrains make policymakers unable to implement the *optimal unconstrained policy assignment*

- They are obliged to rely on a constrained assignment rule selecting treated units according to their characteristics

- The welfare thus obtained may drop down

- Policymakers can however produce the largest feasible constrained welfare

Constrained welfare maximization - 2

- The policymaker wants to treat only “young” people

- In theory, he can continue to use the naïve approach, by excluding from treatment all the individuals with age smaller than a certain age A^*

- The problem is that different A^* can induce different level of welfare

- The problem becomes that of **choosing A^* to maximize the effect/welfare**

Example: constrained univariate threshold-based policy

- The policymaker wants to treat only “young” people

- In theory, he can continue to use the naïve approach, by excluding from treatment all the individuals with age smaller than a certain age $A*$

- The problem is that different $A*$ can induce different level of welfare

- The problem becomes that of **choosing $A*$ to maximize the effect/welfare**

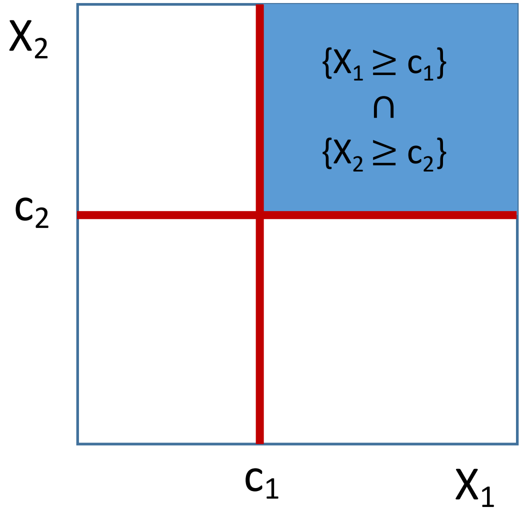
Policy classes

There exist however several **classes of policies** used by policymakers to select in a constrained decision context. The most popular are:

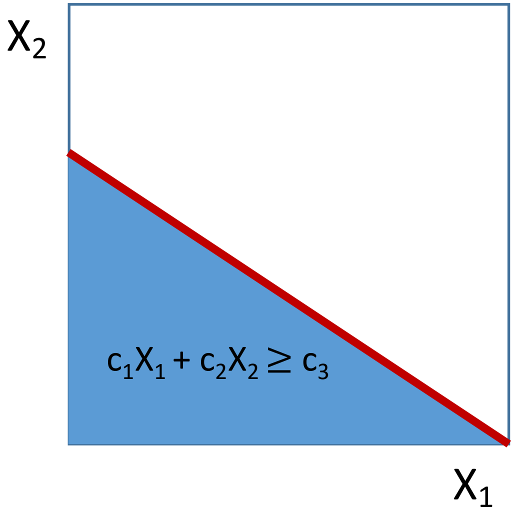
- ❑ Threshold-based
- ❑ Linear combination
- ❑ **Fixed-depth decision trees**

Policy *classes*

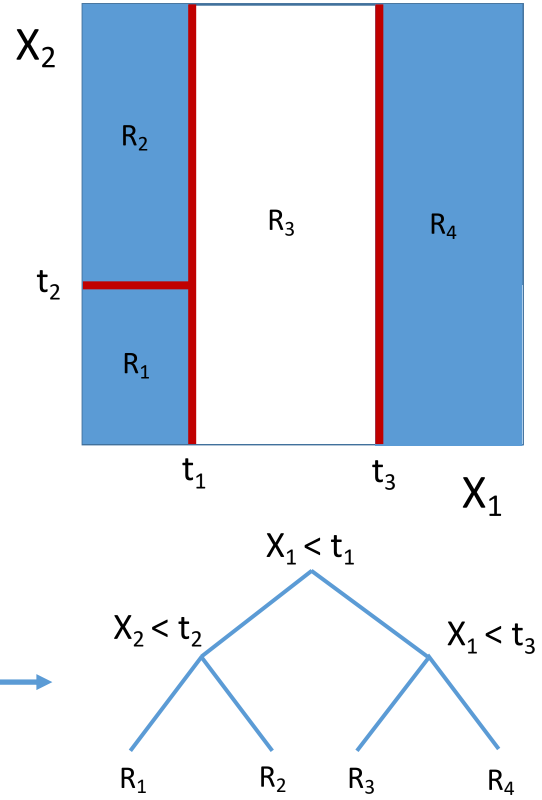
Threshold-based



Linear combination



Fixed-depth tree



2-depth tree →

Legend:

Decision boundary

Selection area

Optimal constrained welfare

The corresponding welfare is a function of c_x:

$$\widehat{W}(x, c_x) = \sum_{i=1}^{N} \hat{T}_i(x, c_x) \cdot \tau(X_i)$$

We define the optimal choice of the threshold c_x as the one maximizing $\widehat{W}(x, c_x)$ over c_x:

$$c_x^* = \mathtt{argmax}_{c_x} [\widehat{W}(x, c_x)]$$

If c_x^* exists, the estimated optimal constrained welfare will thus be equal to $\widehat{W}(c_x^*)$.

Threshold-based policy

Optimal constrained treatment rule

Splitting feature

Unit selection function

$$\hat{T}_i(x, c_x) = \hat{T}_i^* \cdot \mathbf{1}[x >= c_x]$$

Optimal unconstrained policy

Threshold value

$$\hat{T}_i^* = \mathbf{1}[\hat{\tau}(X_i) > 0]$$

Optimal constrained treatment rule (*multivariate case*)

Policymakers rely on two or more selection indicators

Splitting feature *x*

Splitting feature *z*

$$\hat{T}_i(c_x, c_z) = \hat{T}_i^* \cdot \mathbf{1}[x >= c_x] \cdot \mathbf{1}[z >= c_z]$$

Optimal unconstrained policy

Threshold Value for *x*

Threshold Value for *z*

Implementation algorithm

Procedure. Threshold–based optimal policy assignment

1. Suppose to have data from an RCT or from an observational study consisting of the information triple (Y, X, T) available for every unit involved in the program.

2. Run a quasi–experimental method with observable heterogeneity, estimate $\tau(X)$, and compute the (estimated) actual total welfare of the policy $\widehat{W}$.

3. Identify the estimated optimal unconstrained policy $\hat{T}^*$, and compute $\widehat{W}^*$, i.e. the estimated maximum total welfare achievable by the policy, and estimate the regret as $\widehat{W}^* - \widehat{W}$.

4. Consider an estimated constrained selection rule $\hat{T}(x, c)$ based on a given set of selection variables, x, and related thresholds, c, and define the estimated maximum constrained welfare as $\widehat{W}(x, c)$.

5. Build a greed of K possible values for $c \in \{c_1, ..., c_K\}$, compute the optimal vector of thresholds c_{k^*} and the corresponding maximum estimated welfare $\widehat{W}(x, c_{k^*})$ thus achieved.

Linear combination policy (bivariate case)

Generates a **score** to compare with a threshold

$$\hat{T}_i(c_1, c_2, c_3) = \hat{T}_i^* \cdot \mathbf{1}[\underbrace{c_1 x_1 + c_2 x_2}_{\text{score}} \geq \underbrace{c_3}_{\text{threshold}}]$$

Optimal
unconstrained
policy

Application

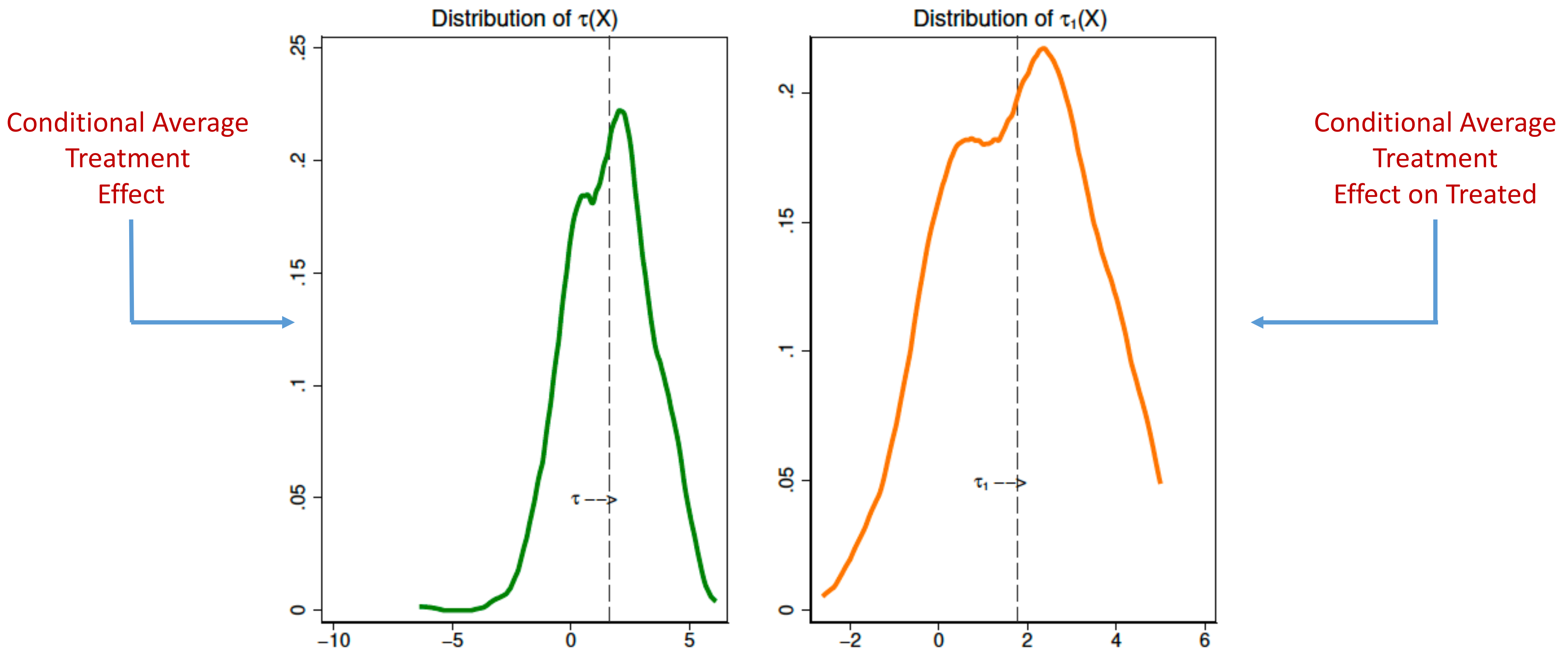
DATA: National Supported Work Demonstration (NSWD), an RCT by LaLonde (1986).

TARGET: Effect of a 1976 job training program on people real earnings in 1978

CONTROLS: age, race, educational attainment, previous employment condition, real earnings in 74 and 75

Estimation of ATE(x) and ATET(X)

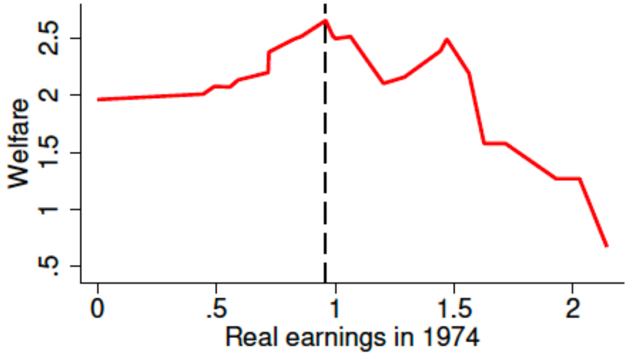
Figure 1: Distribution of $\hat{\tau}(X)$ and $\hat{\tau}_1(X)$. Program: National Supported Work Demonstration (NSWD). Data: LaLonde (1986). Target variable: Real earnings in 1978. Estimation technique: Regression–adjustment (with observable heterogeneity).



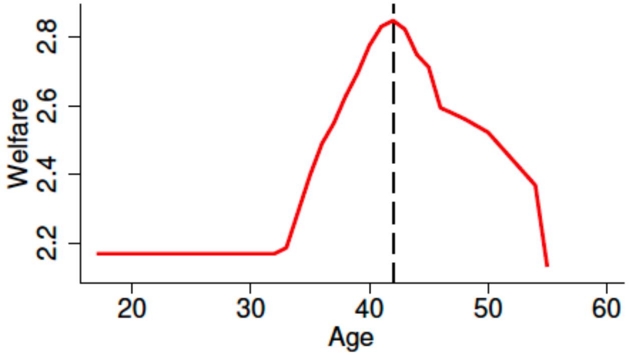
Constrained welfare maximization (univariate)

Figure 2: Computation of the policy optimal selection threshold in univariate cases. Program: National Supported Work Demonstration (NSWD). Data: LaLonde (1986). Target variable: real earnings in 1978. Univariate selection variables: real earnings in 1974, age, and educational attainment.

AWG =
2.65 - 1.76 =
0.89



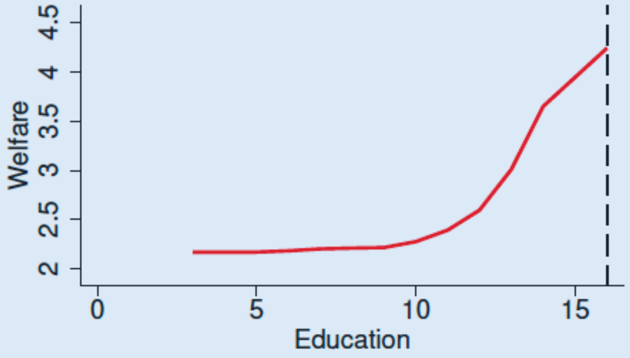
Optimal threshold = .96
Optimal average welfare = 2.65
Number of treated units = 108 out of 443



Optimal threshold = 42
Optimal average welfare = 2.85
Number of treated units = 16 out of 443

AWG =
2.85 - 1.76 =
1.09

AWG =
4.24 - 1.76 =
2.48



Optimal threshold = 16
Optimal average welfare = 4.24
Number of treated units = 0 out of 443

Monotonicity of welfare
on educational attainment

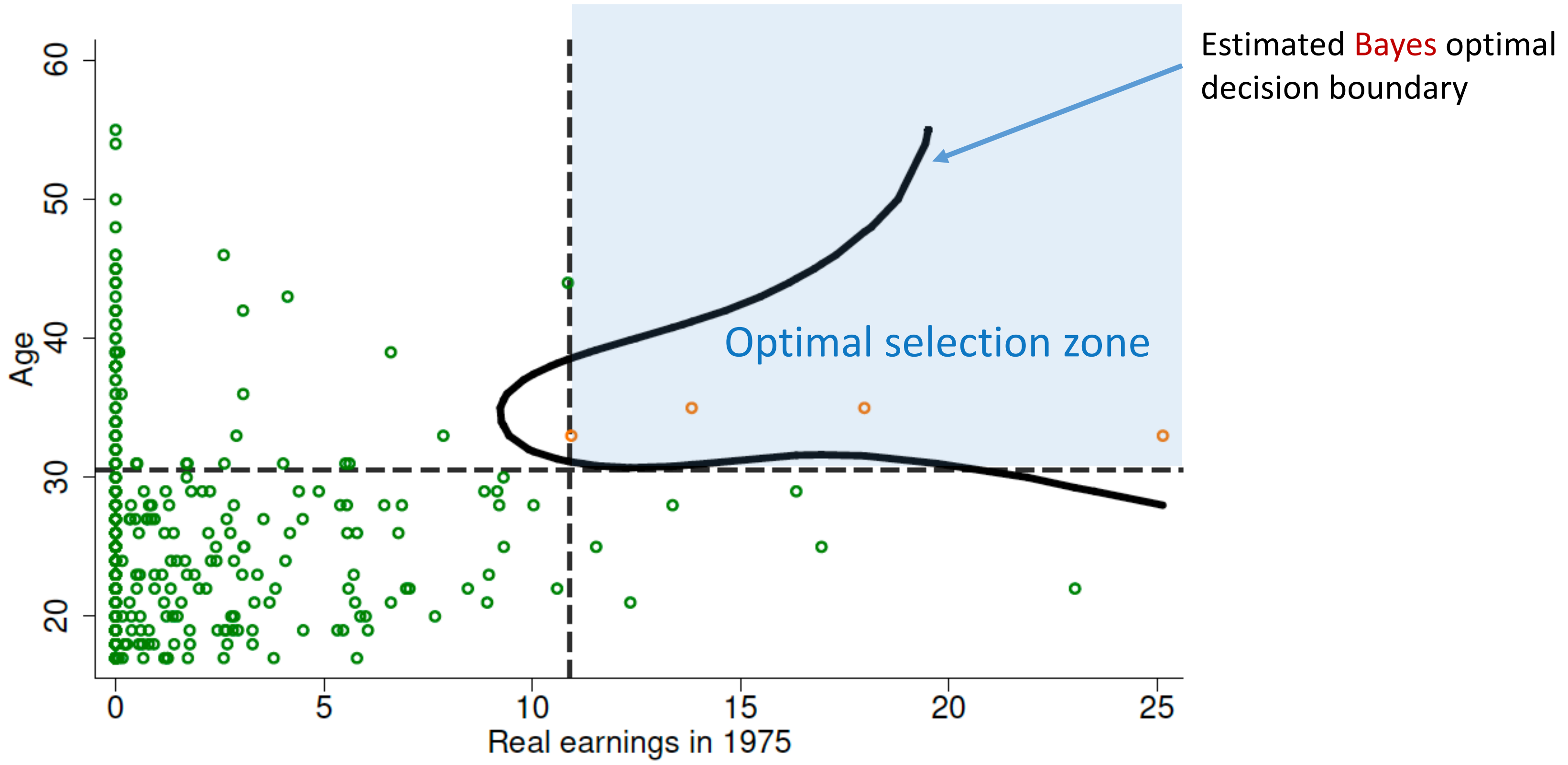
Reference ATET = 1.76
AWG = Average Welfare Gain

Constrained welfare maximization (Bivariate)

Figure 3: Computation of the policy optimal decision boundary in the bivariate case. Program: National Supported Work Demonstration (NSWD). Data: LaLonde (1986). Target variable: real earnings in 1978. Bivariate selection variables: real earnings in 1975 and age.

Reference ATET = 1.74

Average Welfare Gain = 3.99 – 1.74 = 2.255



Average welfare = 3.995
Share of treated units = 1%
Optimal threshold for 'Age' = 30.5
Optimal threshold for 'Real earnings in 1975' = 10.9

Empirical welfare maximization: relevant issues

1. Monotonicity

Welfare increases monotonically with a feature
=> *too few to treat or too many to treat*

2. Sparseness

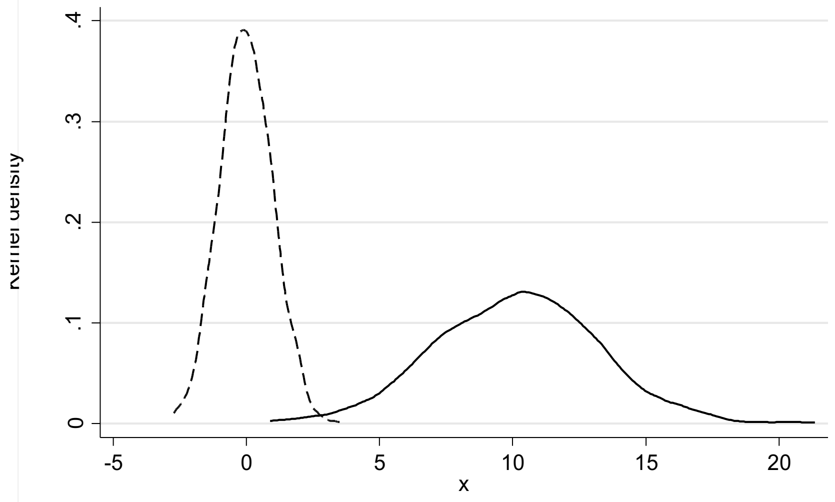
X’ comes from a *different joint distribution* than *X*

Trade-offs arising in this case, so the best to do is offering the policymaker a **“menu”** of possible treatment choices given, for example, a pre-fixed budget

SPARSENESS

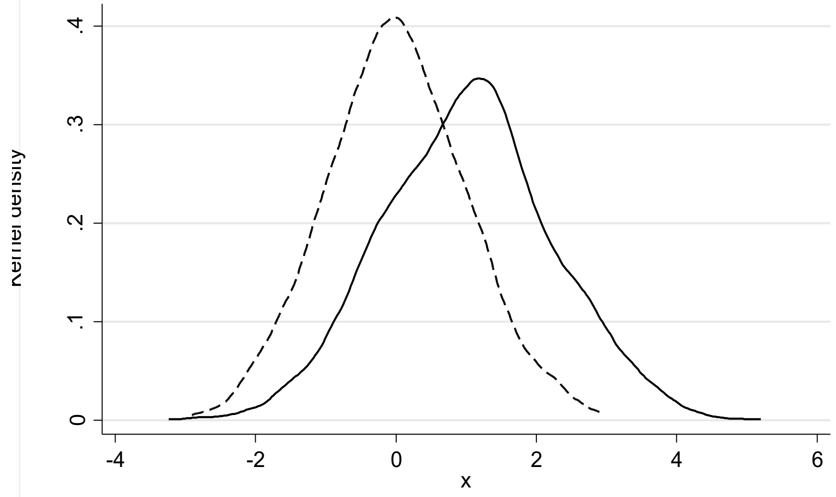
the distribution of *X* and *X'* have low overlap

High sparseness



$P(X) \neq P(X')$

Low sparseness



$P(X) \cong P(X')$

A SOLUTION TO MONOTONICITY

Trade-offs and the "menu-strategy"

EXAMPLE

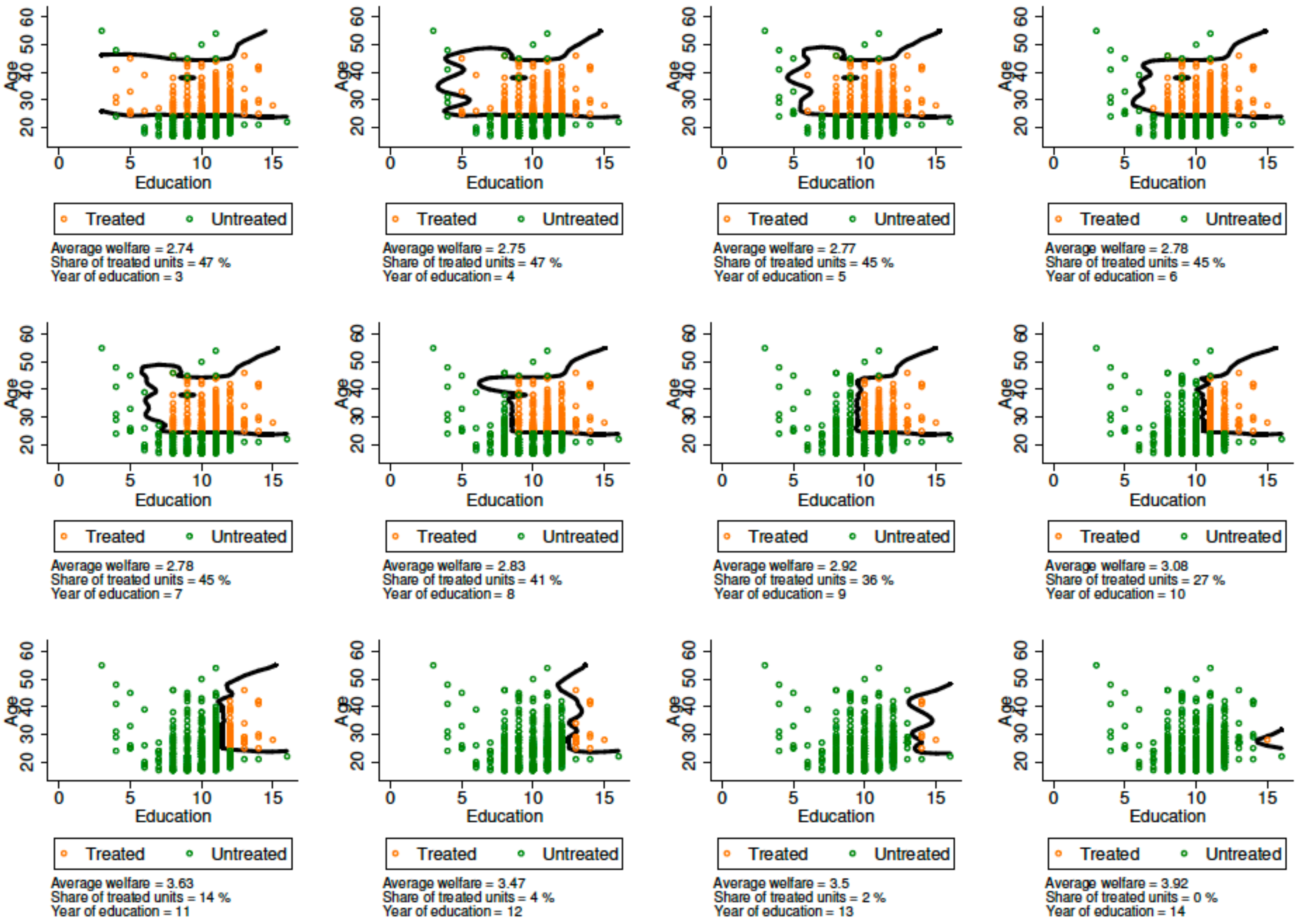
Computation of policy optimal decision boundaries in the bivariate case, when one of the two selection variables (age) is fixed at its optimal threshold, and the threshold of the other variable (education) is varying. Program: National Supported Work Demonstration (NSWD). Data: LaLonde (1986). Target variable: real earnings in 1978. Bivariate selection variables: age and educational attainment.

AGE ——————————> **set at its optimal level**

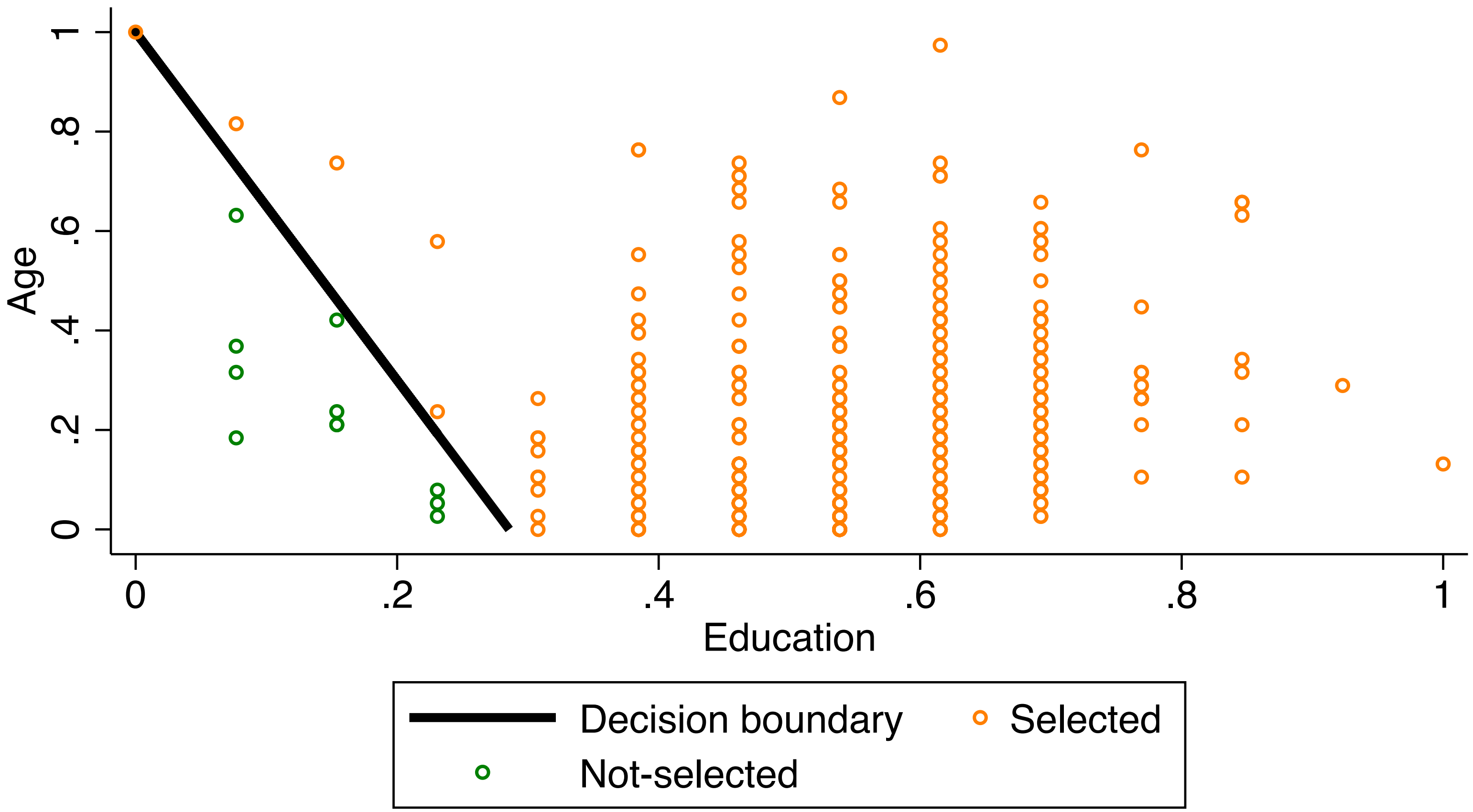
EDUCATION ————————> **free to vary**

Feature plagued by monotonicity

Trade-offs and the "menu-strategy"



OPTIMAL SELECTION WITH A Linear combination policy



Total optimal welfare =748
Total oracle welfare = 764
Regret (absolute) = 15.53
Regret (%) = 2.03
Average welfare = 2.24
Average oracle welfare = 2.23
Share of treated units = 75 %

SOFTWARE

We formed a research group for **OPL software implementation**:

Stata

Cerulli (CNR), `opl` command

R

Guardabascio (Perugia University) and Brogi (Istat)

Python

De Fausti (Istat)

Conclusion

- Optimal Policy Learning: AI/ML new frontier of policy design
- Machine Learning algorithms for estimating policy effects
- Generalization to many policy classes
- Producing Stata/R/Python software platforms for OPL
- CNR-IRCRES leading OPL development
- Future development: DATA-DRIVEN DECISION MAKING (within which OPL is a subset of model)