AI For Obsolescence Management

L'IA pour la Gestion d'Obsolescence

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Outline

1. Context
2. Preliminaries
3. Conference Paper 1
4. Journal Paper 1
5. Results
6. Conclusion and Perspective

1. technological innovation,
2. supply chain disruptions,
3. natural disaster,

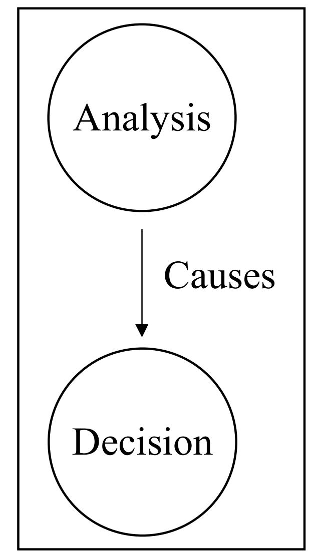
etc

1. stock,
2. last time buy order,
3. redesign,

etc

Shortage

Resolution



3 to 12+ months

Observations

1. Expert workflow is detached and unique to each person.
2. Obsolescence management process is dogmatic and changes per expert.

Objectives

1. Develop a model that unifies the obsolescence management decision making process.
2. Utilize SNCF RESEAU's obsolescence management processes as a framework.

1. **Obsolescence**

Obsolescence, pertains to the process of becoming **non-available**, **non-adequate**, and/or **non-suitable** [Zolghadri et al., 2021].

2. **Obsolescence Management**

It is the discipline that addresses obsolescence and Diminishing Manufacturing Sources and Material Shortages (DMSMS) as the service life of a product extends beyond the technology life cycle incorporated in the design [SD-22, 2021].

3. **Artificial Intelligence**

“It is the science and engineering of making **intelligent machines**, especially intelligent computer programs. It is related to the similar task of **using computers to understand human intelligence**, but AI does not have to confine itself to methods that are biologically observable.**”** [McCarthy et al., 2004]

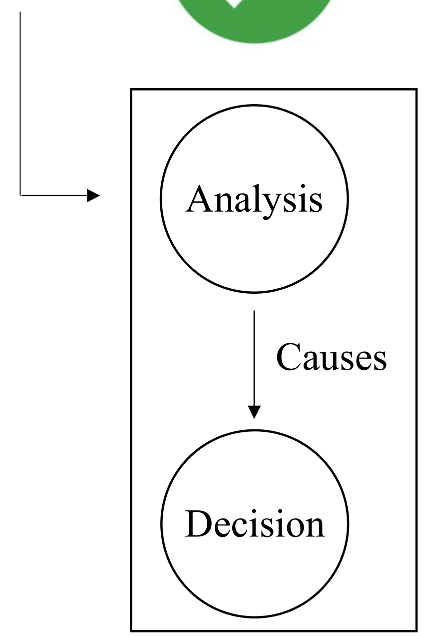
Challenges

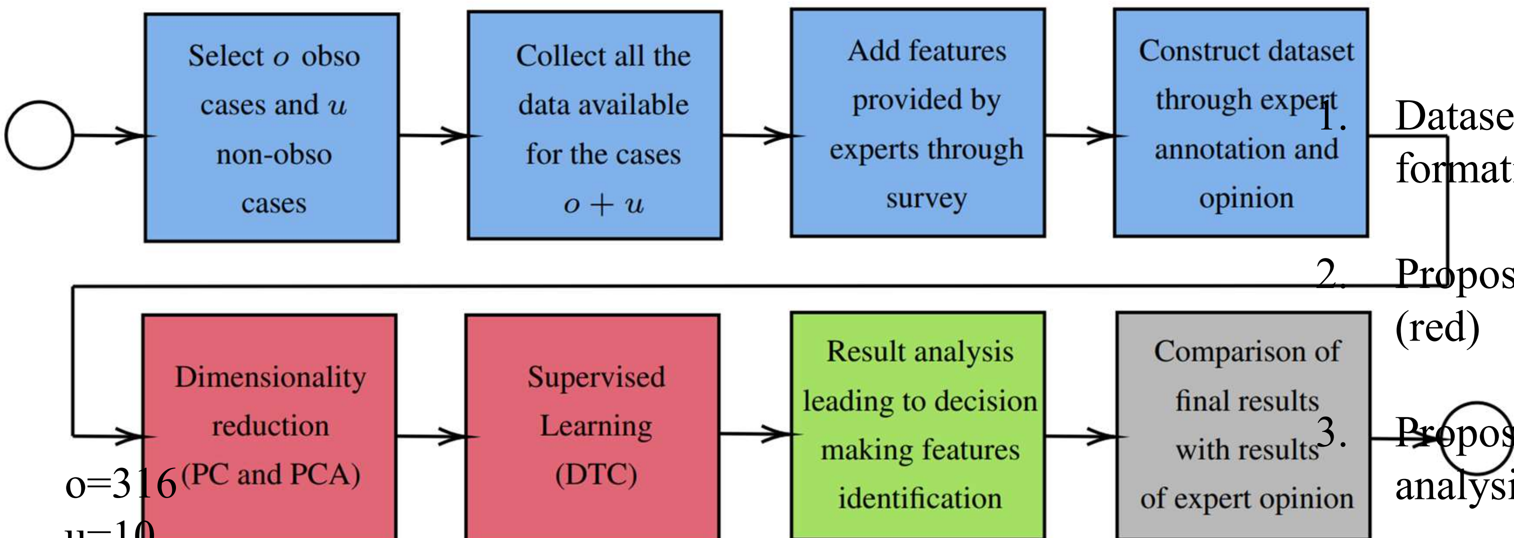
1. Create a **dataset** for obsolescence management resolution.

2. Understand the **impact** of difference dogmatic **features** as well as relating them to the different resolution methods.

3. Propose a **model** that unifies and best represents **expert decision making** while finding the **most optimal solution** for a given obsolescence case.

1. What are the features that play a role in the resolution?
2. How can we determine the features that play a role in the resolution?
3. How can we verify the integrity of the determination method?





1. Dataset formation (blue)
2. Proposed model (red)
3. Proposed model analysis (green)

- o=316
- u=10
- 5 classes
- 7 stock, 30 LBO, 28 minor redesign, 124 major redesign, and 126 substitution

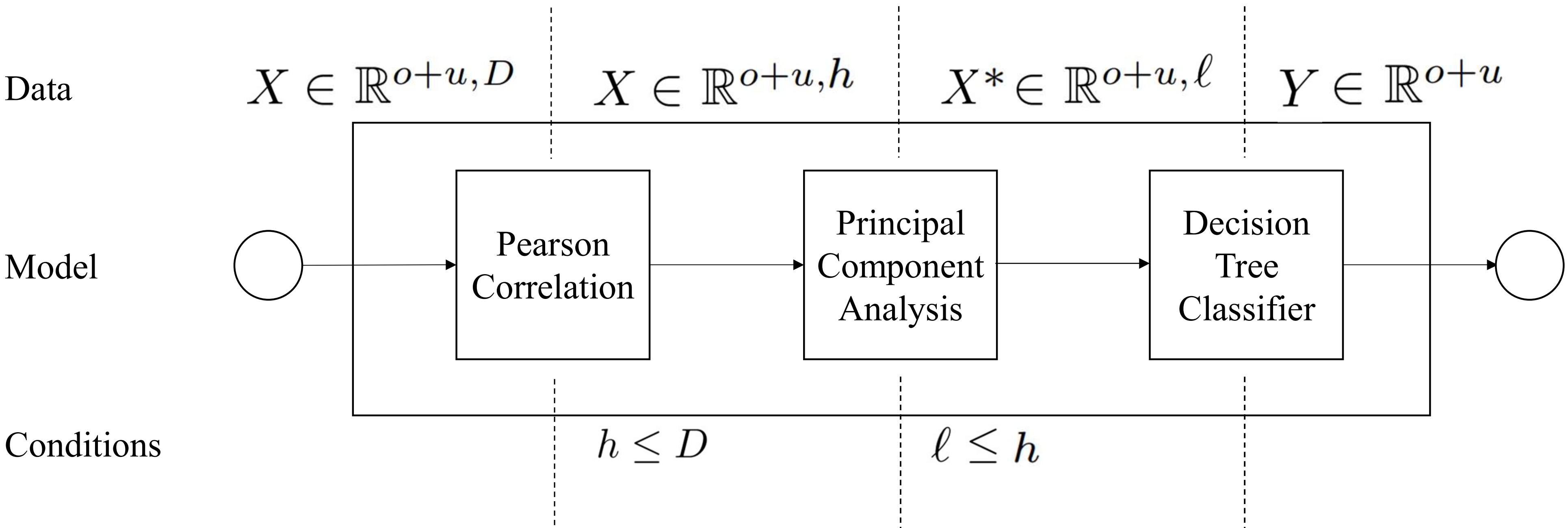
$$X = \begin{pmatrix} O \\ U \end{pmatrix} = F$$

$$O = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots \\ x_{2,1} & x_{2,2} & \cdots \\ \vdots & \vdots & \ddots \\ x_{o-1,1} & x_{o-1,2} & \cdots \\ x_{o,1} & x_{o,2} & \cdots \end{pmatrix} \quad U = \begin{pmatrix} x_{o+1,1} & x_{o+1,2} & \cdots & x_{o+1,D} \\ x_{o+2,1} & x_{o+2,2} & \cdots & x_{o+2,D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{o+u,1} & x_{o+u,2} & \cdots & x_{o+u,D} \end{pmatrix}$$

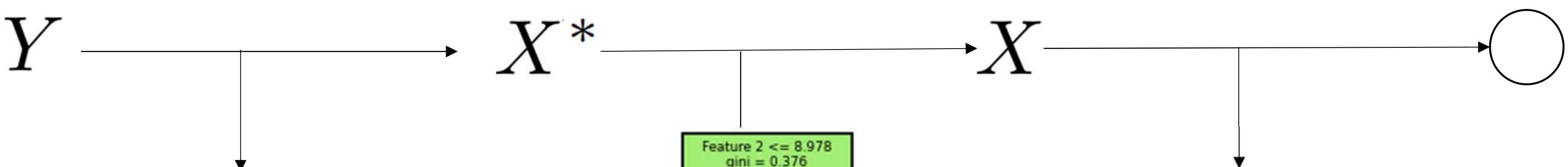
$$\begin{pmatrix} x_{1,D} & x_{2,D} & \cdots & x_{o-1,D} & x_{o,D} & x_{o+1,D} & \cdots & x_{o+u,D} \end{pmatrix}$$

$$Y \equiv [1, \ldots, N] \quad \{(x_i, y_i) \in X \times Y\}_{i=1}^{o+u}$$

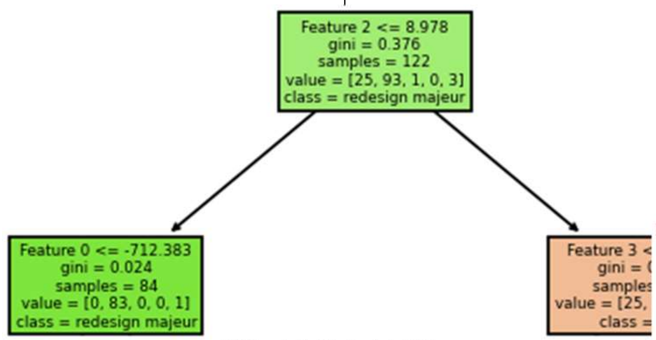
Proposed Model



Proposed Analysis Method

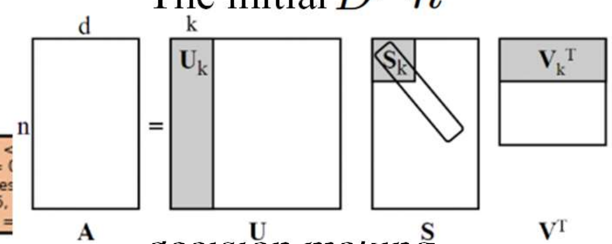


Importance is determined based on the **mean decrease** in Gini impurity of each feature [Sandri and Zuccolotto, 2010].

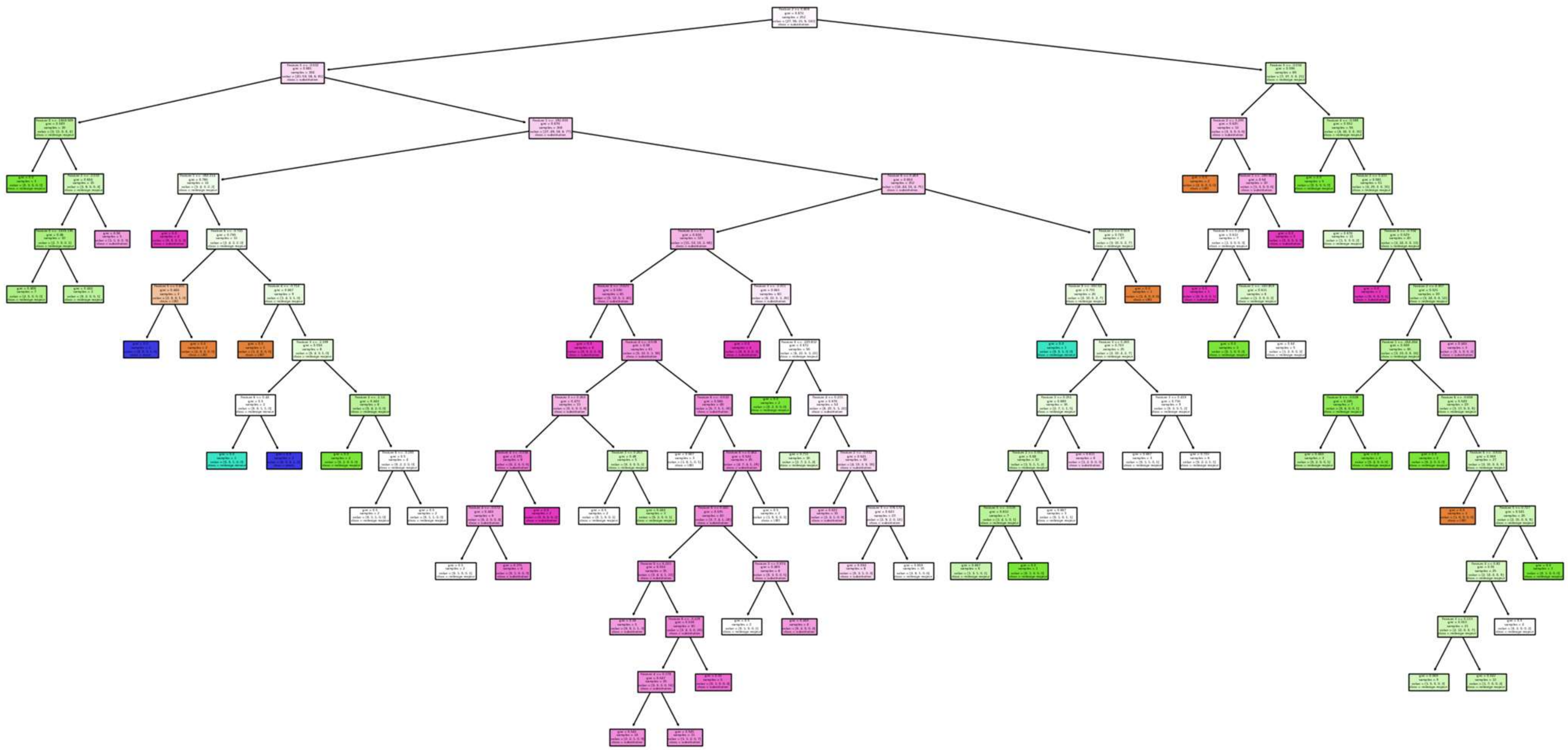


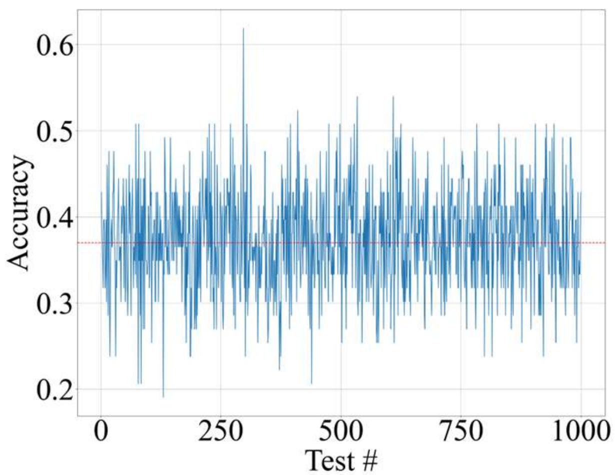
components [Goodfellow et al., 2016].

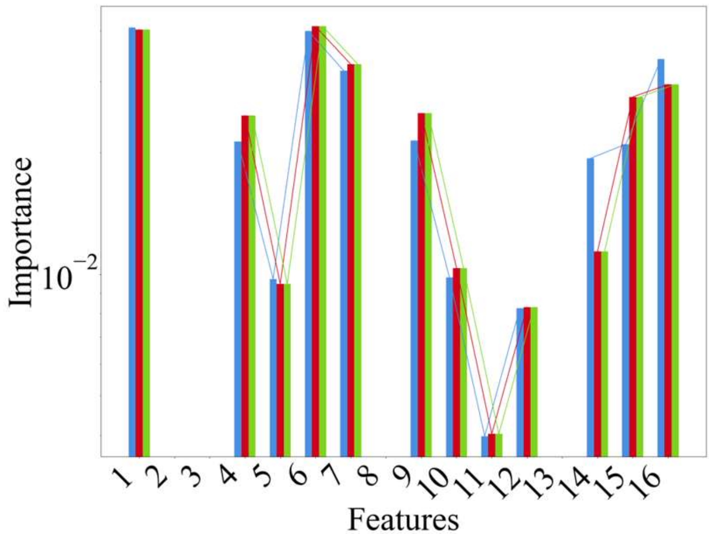
The initial $D-h$



decision making process.







- Arithmetic mean = 37.48% is similar to geometric mean = 37.00%, which implies accuracy measurments have a balanced spread, are not skewed, and are symmetric.
- Minimum accuracy = 19.05% whereas maximum accuracy = 61.90% | 40.00% on U.
- Standard deviation = 5.95% means the model is not consistent, but is not erratic.
- Similar: average feature contributions model with the highest accuracy, different: option of experts.

Achievements

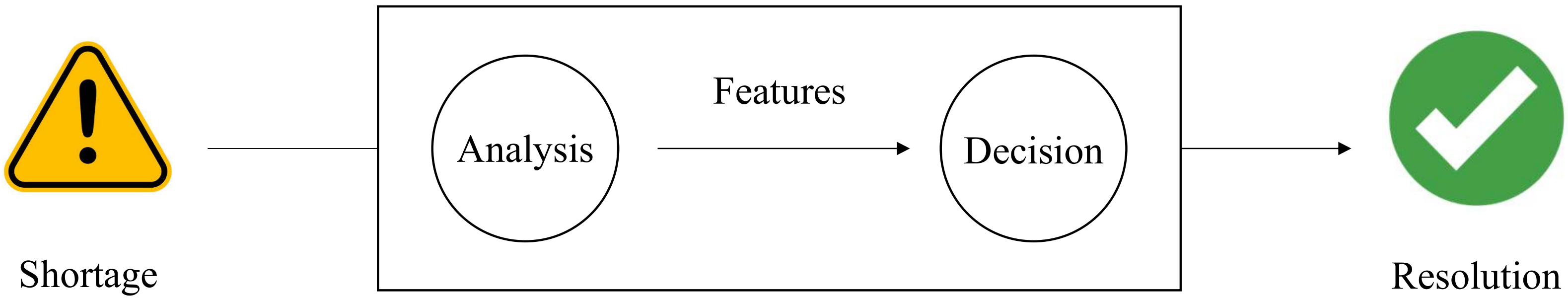
- A model that derives features affecting obsolescence resolution.
- A method for analyzing the features affecting obsolescence resolution.

Problems

- Inconsistent model due to class imbalance.
- Simple feature values affecting model accuracy.

Future work

- Augment the dataset by using generative models to generate new data.
- Add more meaningful features that correspond to obsolescence resolution to enhance the dataset.



1. How can we augment the dataset?

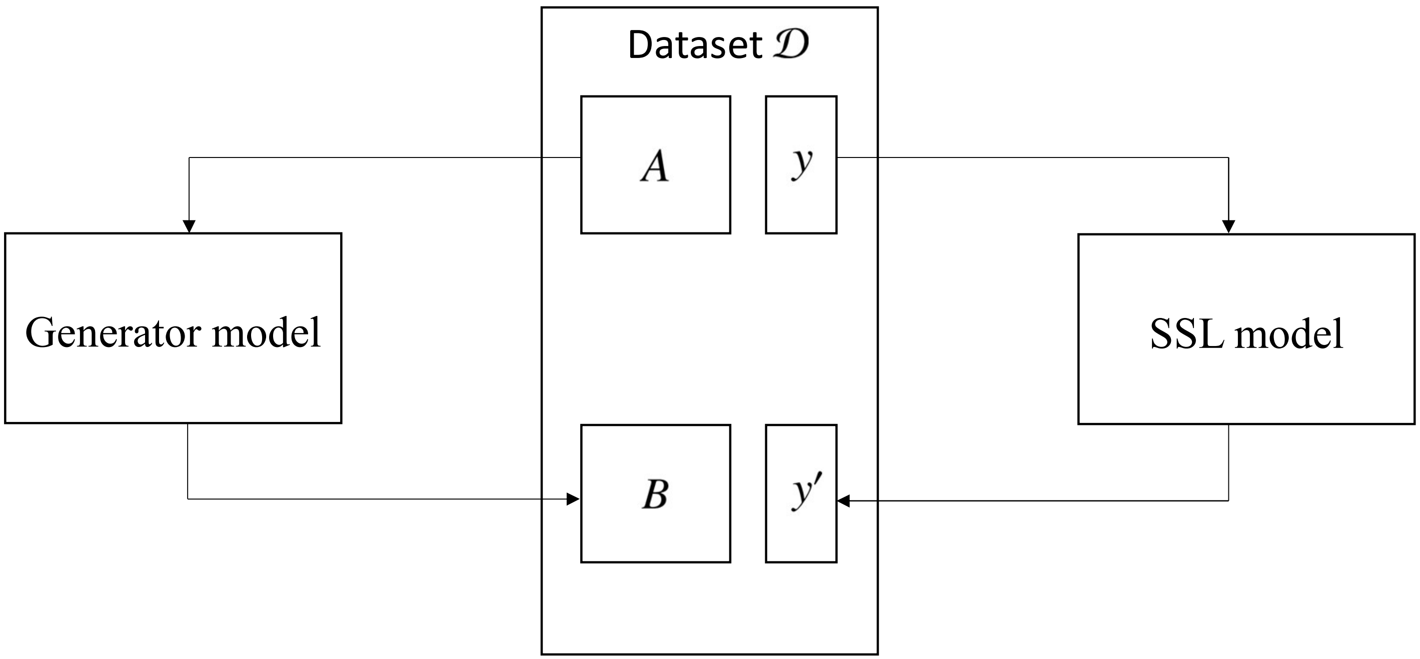
2. How can we solve class imbalance?

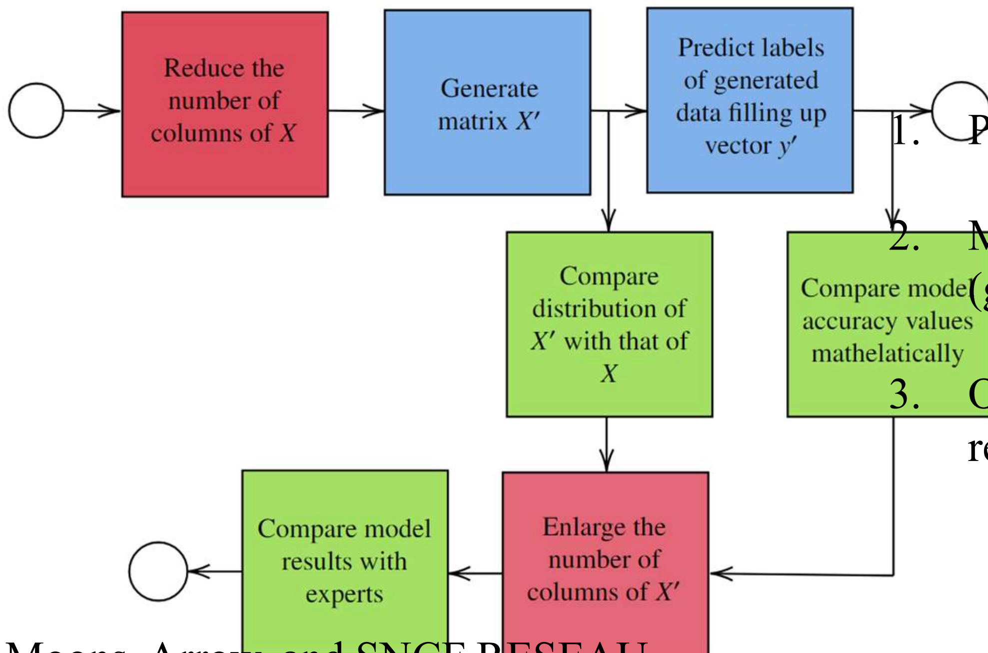
3. How can we make an optimal decision?

Challenges

1. Create a model that generates new datapoints reflecting reality.

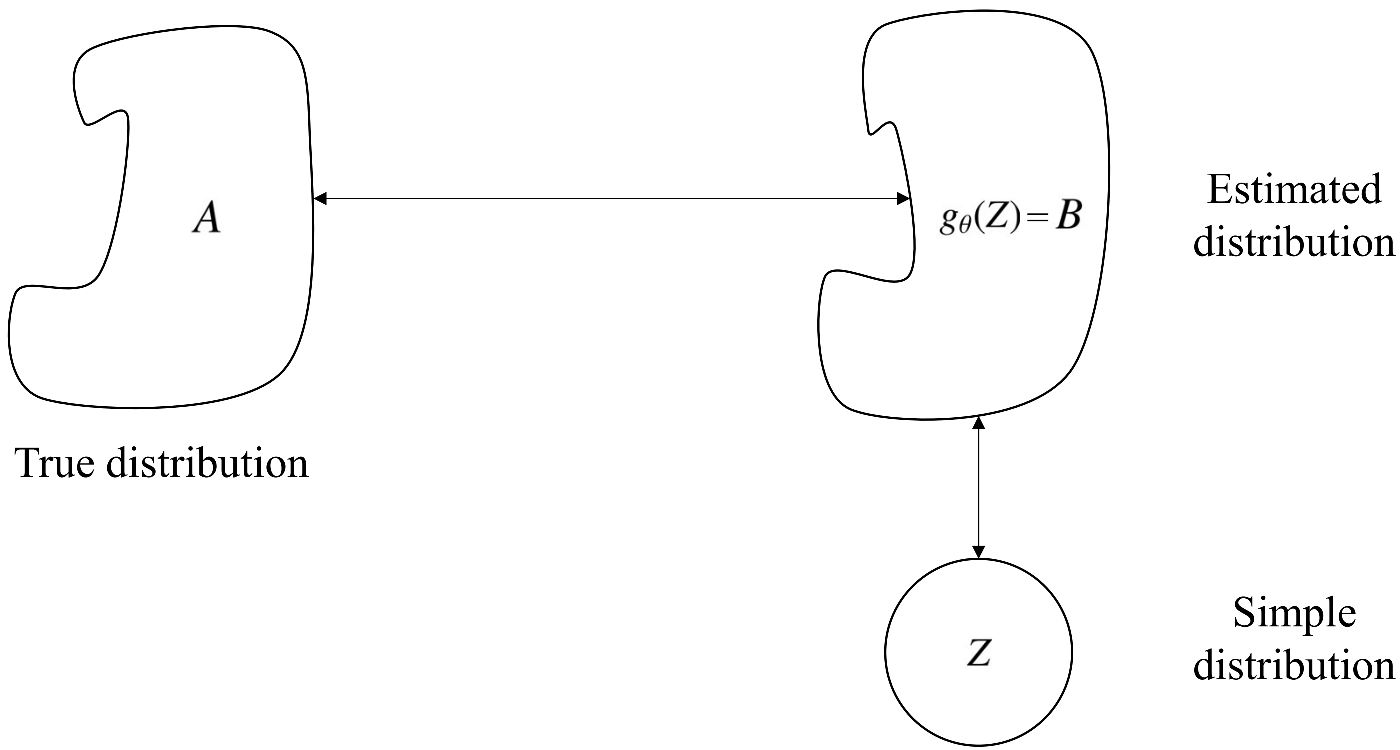
2. Create a model that makes an optimal decision.


Dataset $\mathcal{D}$
A
y
Generator model
SSL model
B
y'

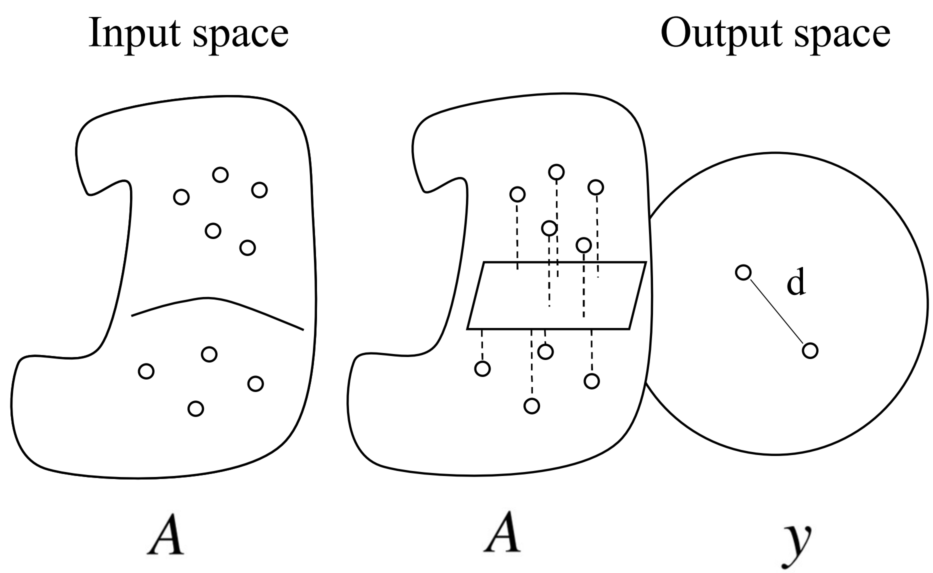


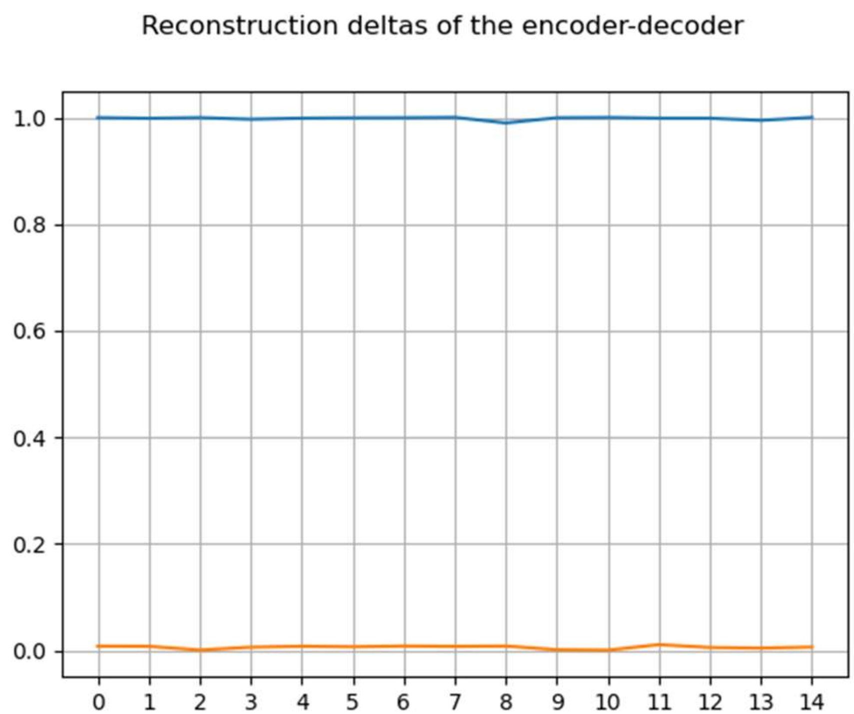
1. Proposed model (blue)
2. Model evaluation (green)
3. Original value reconstruction (red)

- Datasets: Moons, Arrow, and SNCF RESEAU.
- Generative models: Real-valued non-volume preserving (RealNVP), Generative adversatial network (GAN), Variational autoencoder (VAE).
- Semi-supervised Random Forests.

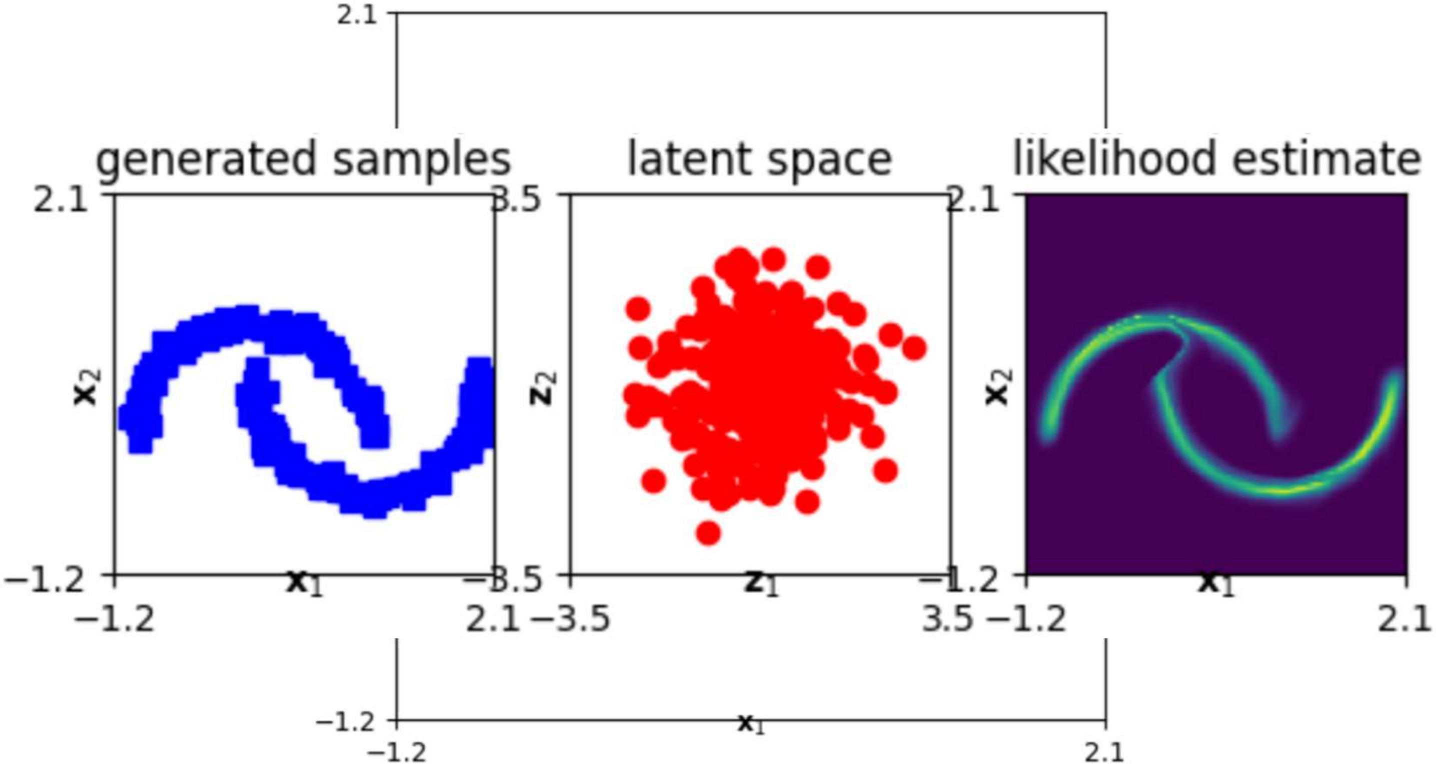

A
$g_\theta(Z) = B$
Estimated distribution
True distribution
Z
Simple distribution

1. The smoothness assumption
2. The cluster assumption
3. The manifold assumption

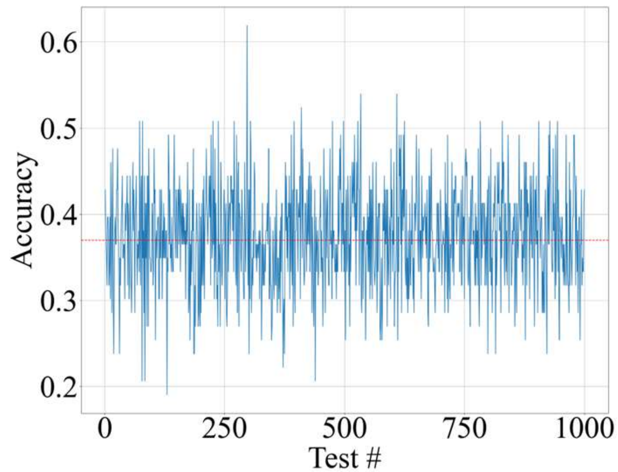




Dataset: Arrow



Dataset: moons



- Earlier model versions achieved a mean accuracy of 37% and best accuracy of 61.90%
- Initial results of current model tensting achieved a constant accuracy of **96.10%**

Achievements

- A model that generates and another that learns class distribution through SSL.
- A methodology that unifies and optimizes the decision making process.

Future work

- Test more SSL methods
- Make both the generative and SSL models work in tandem.
- Introduce a model that estimates obsolescence occurrence by introducing the concept of time.
- Introduce unseen classes to generalize the usage of the methodology by using k-shot learning.

Thank you.

Merci.