Prescriptive maintenance with causal machine learning

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The challenge of maintenance

Challenge 15% – 40% of total production costs (Dunn, 1987; Lofsten, 2000)

Goal Maintenance needs to minimize costs related to:

- 🔥 **Machine failures**
- ⚙ **Maintenance interventions**

Existing work assumes certain maintenance effect

- **Perfect maintenance**
  - Maintenance makes a machine *as good as new*
  - Typical assumption in the literature, but not realistic!
- **Imperfect maintenance**
  - Deterministic effect
  - Stochastic effect
  - Machine-independent effect

➔ **Why not learn the effect from data?** = Causal inference

Learning maintenance effects from data

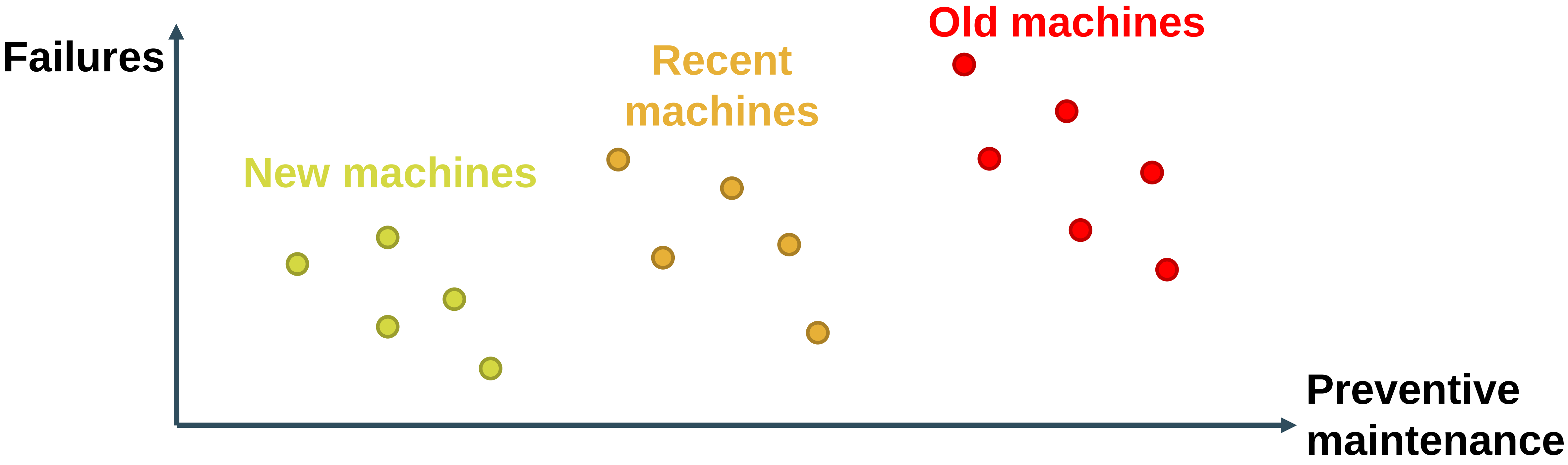
Randomized controlled trial, A/B testing

- 👍 “Gold standard” for estimating causal effects
- 👎 Expensive, infeasible, unethical

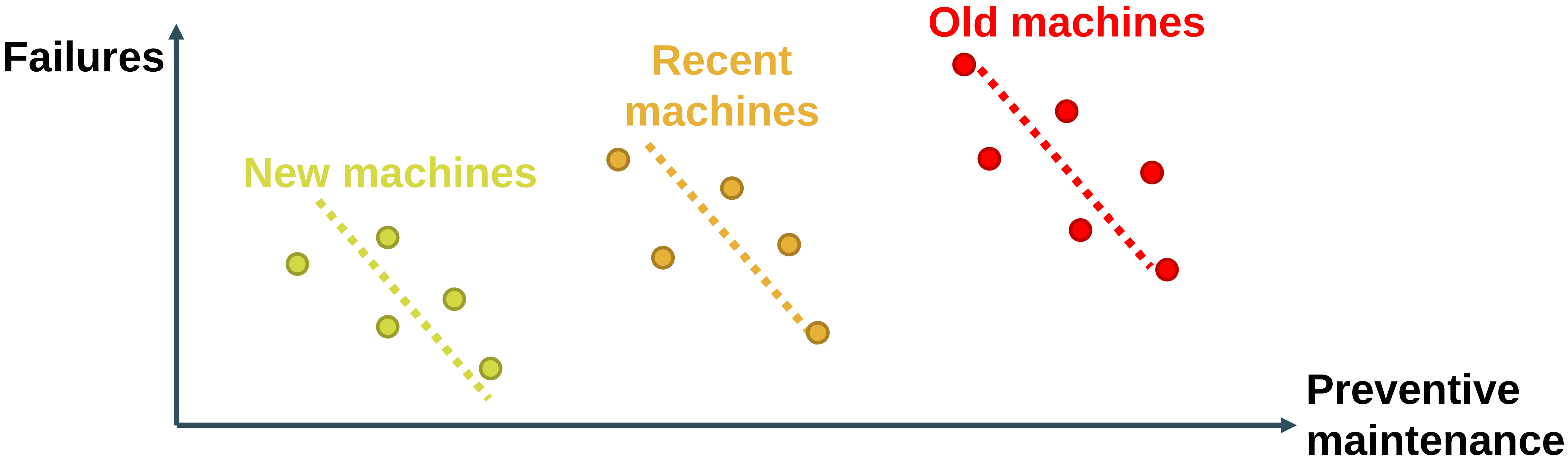
Observational data

- 👍 Cheap, readily available
- 👎 Selection bias

Learning maintenance effects from observational data

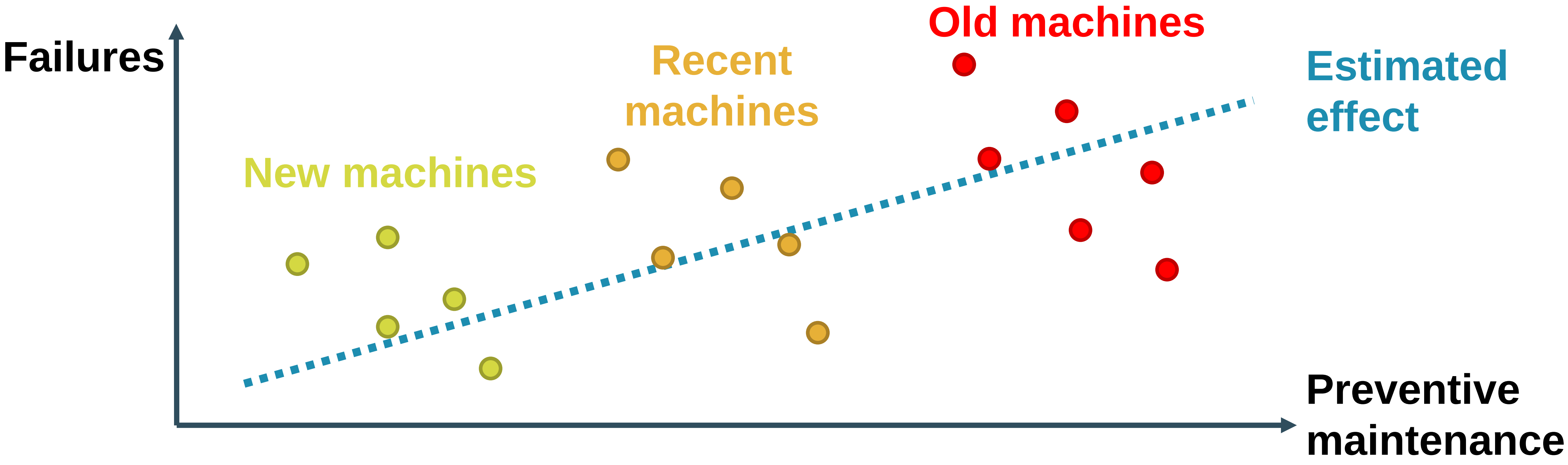


Learning maintenance effects from observational data



Learning maintenance effects from observational data

Simpson’s paradox



Problem formulation

Prior to contract start, decide on preventive maintenance frequency to minimize cost

Given contract x_i, find optimal t_i^* to minimize costs related to t_i^*, o_i and f_i

- **Machine** $x_i \in \mathbb{R}^{\mathrm{d}}$
  - Machine type, age, industry, etc.
- **Preventive maintenance frequency** $t_i \in \mathbb{R}^+$
- **Outcomes**:
  - Overhauls $o_i \in \mathbb{R}^+$
  - Failures $f_i \in \mathbb{R}^+$

Methodology

1. Predict overhauls $o_i(t_i)$ and failures $f_i(t_i)$ using observational data

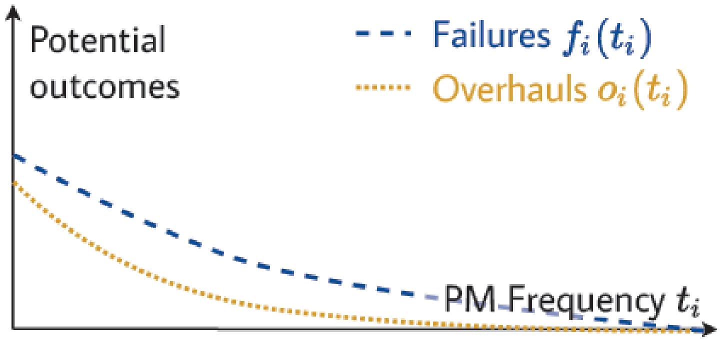
2. Decide on optimal PM frequency t_i^* to minimize expected total cost:

$$c(t_i) = c_t t_i + c_o o_i(t_i) \ + c_f f_i(t_i)$$

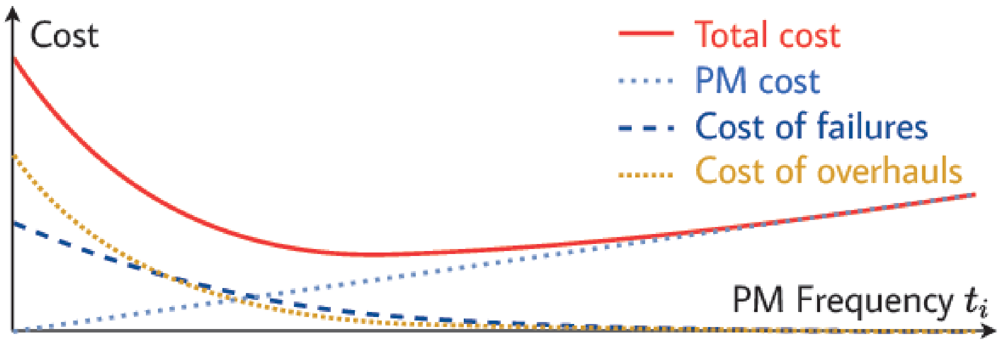
Methodology

Feature	Value
Machine type	2
Age	10.2
Running hours	2,000
Contract type	1
...	

1. Machine information $\mathbf{x}_i$



2. Predict potential outcomes $o_i(t_i)$ and $f_i(t_i)$

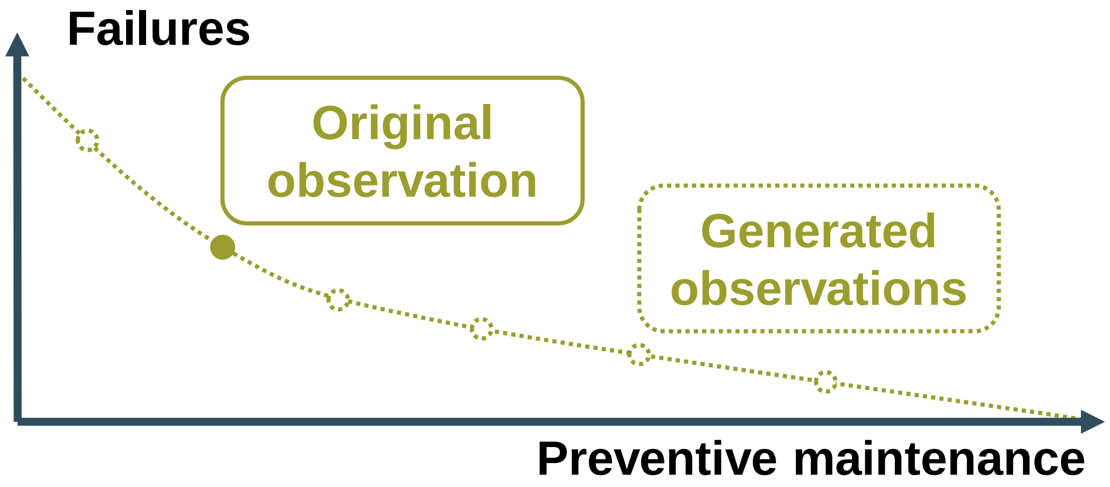


3. Prescribe the PM frequency t_i to minimize the total cost

Methodology

1. Predict potential outcomes $o_i(t_i)$ and $f_i(t_i)$ with **SCIGAN** (Bica et al., 2020)

1. Generate potential outcomes using a GAN



2. Supervised learning

Learn potential outcomes

- $\left(x_i, t_i, f(t_i)\right)\ \forall\, t_i, i$
- $\left(x_i, t_i, o(t_i)\right)\ \forall\, t_i, i$

Methodology

We propose a prescriptive, individualized maintenance approach SCIGAN-ITE:

1. Predict potential outcomes using SCIGAN: GAN → MLP
2. Optimize individual preventive maintenance frequency t_i^*

We compare against two alternatives:

Methodology	Selection bias?	Individualized?
SCIGAN–ITE	✓	✓
MLP–ITE	✗	✓
SCIGAN–ATE	✓	✗

Results

Keeping PM as is in training set:

	MISE	
	Overhauls	Failures
SCIGAN	**7.71 ± 0.60**	**14.16 ± 1.68**
MLP	10.25 ± 1.33	18.27 ± 3.65

More accurate predictions

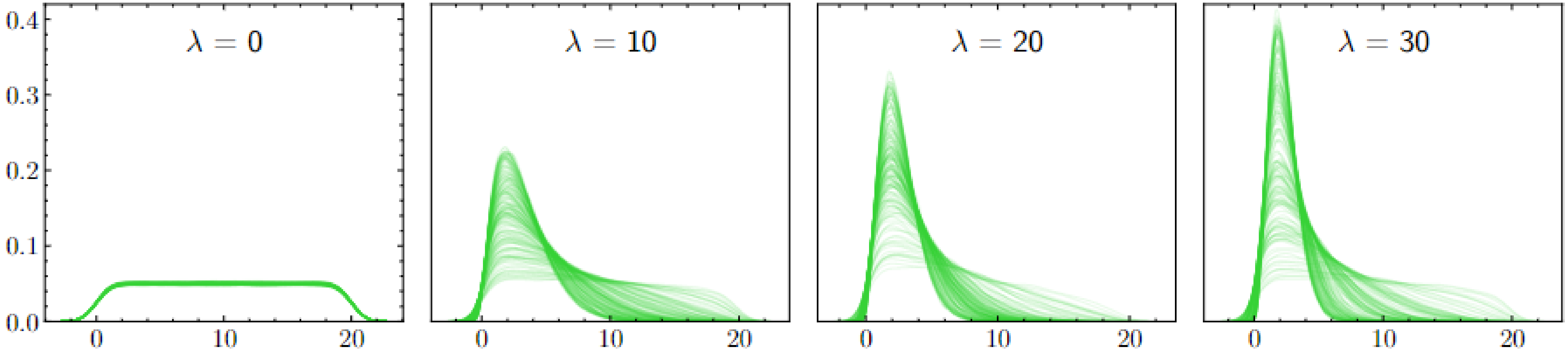
	PE	PCR
SCIGAN–ITE	**2.40 ± 0.46**	**1.07 ± 0.01**
MLP–ITE	4.36 ± 1.25	1.11 ± 0.02
SCIGAN–ATE	8.77 ± 1.07	1.24 ± 0.04

Better decisions

Results

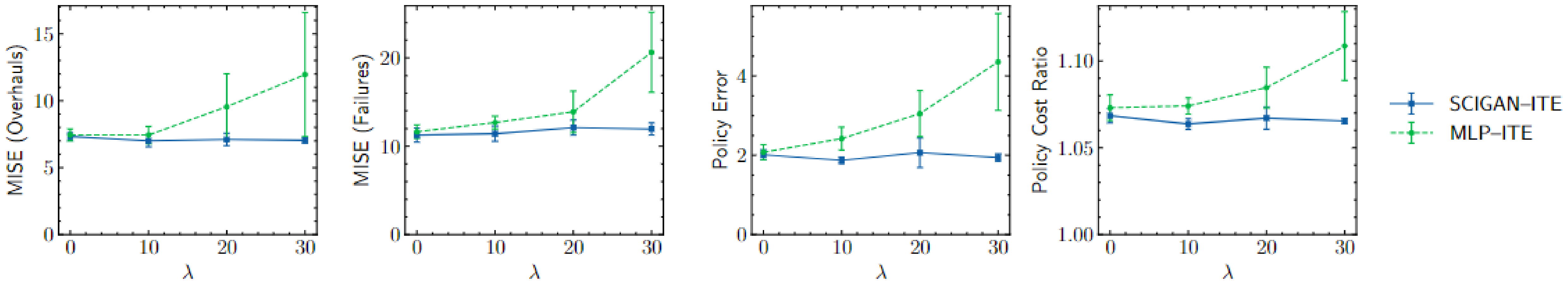
Different levels of selection bias (λ):

Randomized controlled trial ⟷ **Observational data**



Results

Different levels of selection bias (λ):



Conclusion

- Presented and validated a method for prescriptive maintenance
- Importance of dealing with selection bias
- Importance of prescribing maintenance on a case-by-case basis

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