Machine Learning for Health Monitoring of Uninspected Pipelines

Razwan Arshad · October 2021

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Prologue: Traditional Approaches to Integrity Management for Uninspected Pipelines

- Make the line piggable if it is uninspected due to mechanical or operational challenges
- Direct assessment – four-step process involving data alignment, condition prediction of corrosion “hot spots”, direct examination via dig-up and NDT methods, post-assessment effectiveness
- Risk based approaches – qualitative through to fully quantitative… needs subject matter expertise, may involve fitting standard pipeline failure databases to specific cases

Integrity Data Warehouse (IDW)

In-line inspection (ILI)
(metal loss, cracks, geometry, mapping)

Design and construction
(construction year, coating type, diameter, grade)

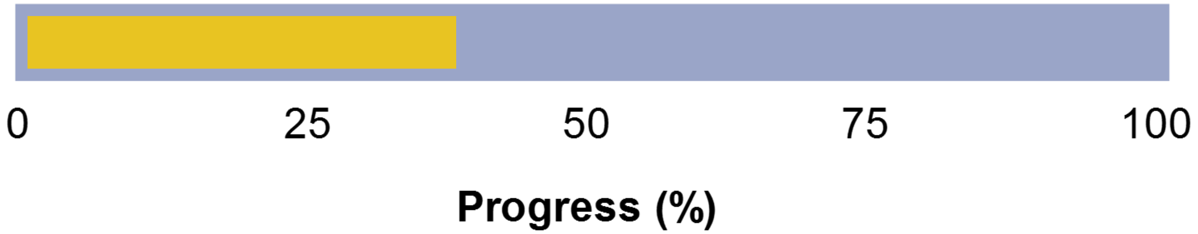
Environment
(soil properties, land use, terrain, climate)

Operations
(temperature, pressure, flow, product)

Surveys
(CIPS, DCVG etc.)

Integrity Data Warehouse (IDW)

Structured information for > 10,000 pipelines



Integrity Data Warehouse (IDW)

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- **Corrosion**
- **Cracking**
- **Bending Strain**
- **Geometric Defects**
- **Third Party Damage**

Integrity Data Warehouse (IDW)

- **Corrosion**
- Cracking
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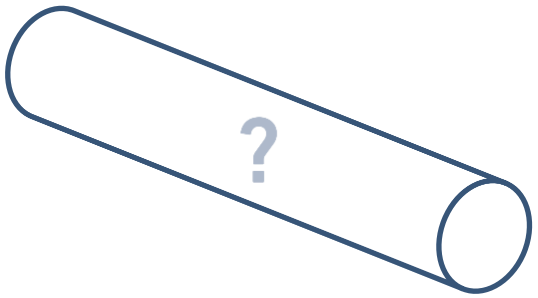
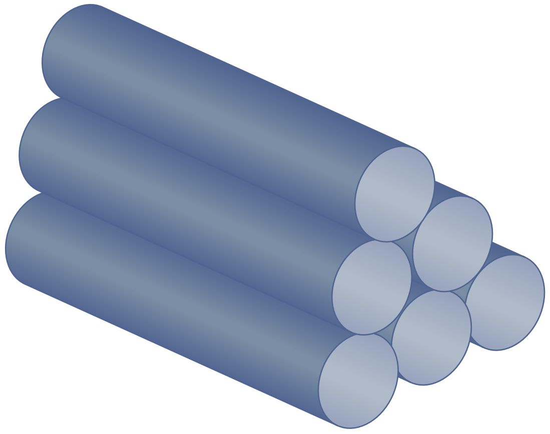
- Third Party Damage

Virtual ILI



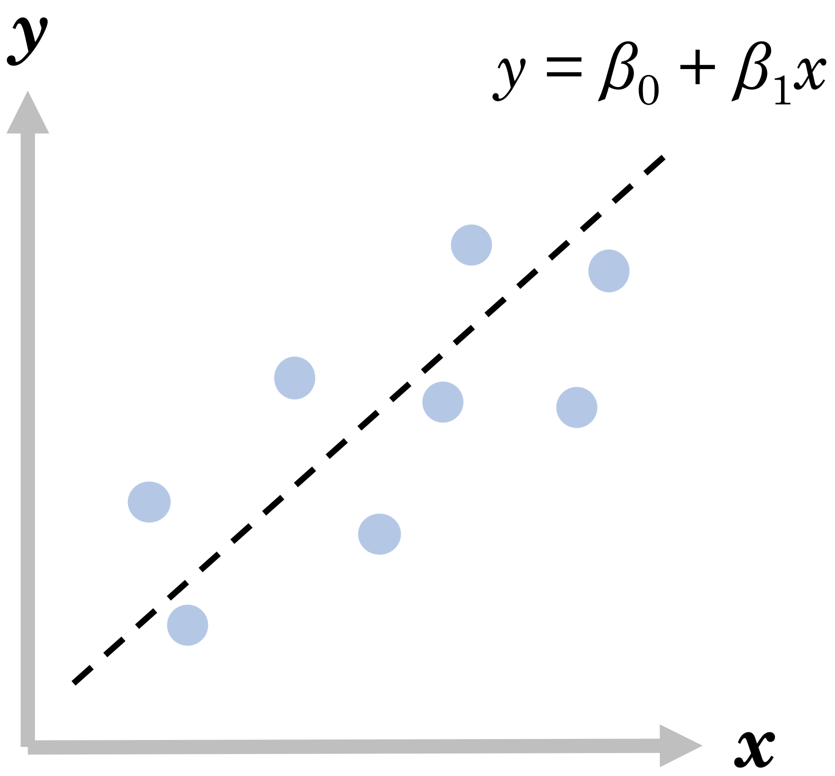
Supervised machine learning



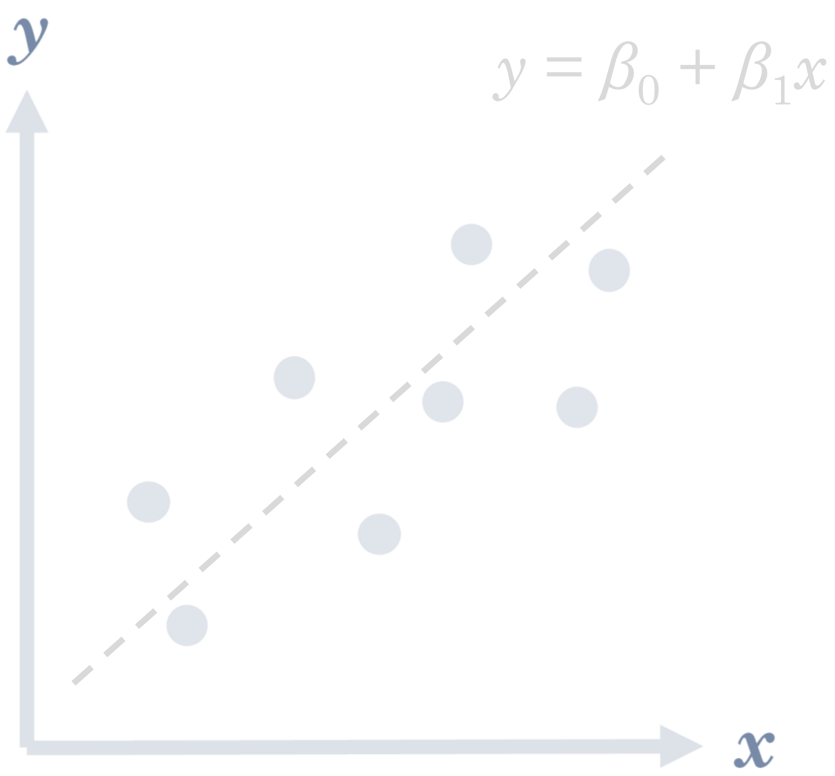
Uninspected pipeline

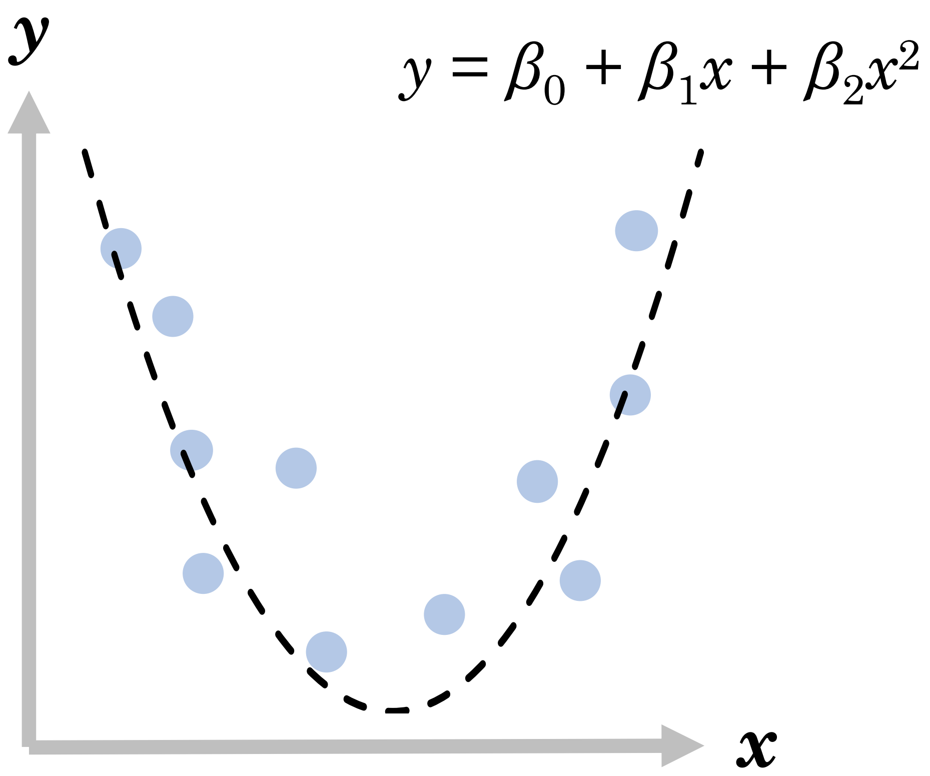
Inspected pipelines

Supervised machine learning



Supervised machine learning





Virtual ILI

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$$y = f(x_1, x_2, \cdots x_n)$$

Virtual ILI

$$\boxed{y} = f(x_1, x_2, \cdots x_n)$$

Target variables

- Condition metrics

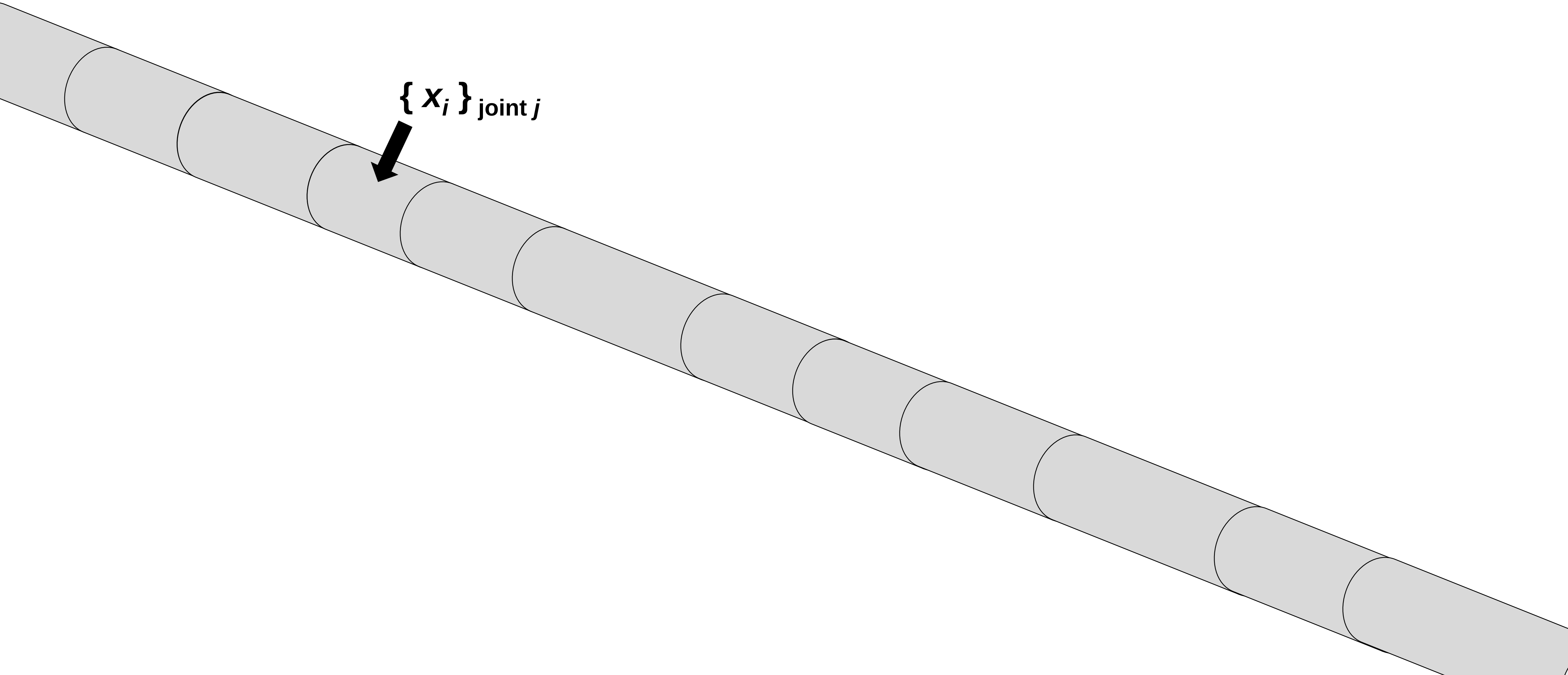
Virtual ILI

$$y = f(x_1, x_2, \cdots x_n)$$

Predictor variables

- Pipe joint properties
- Environmental properties

Virtual ILI



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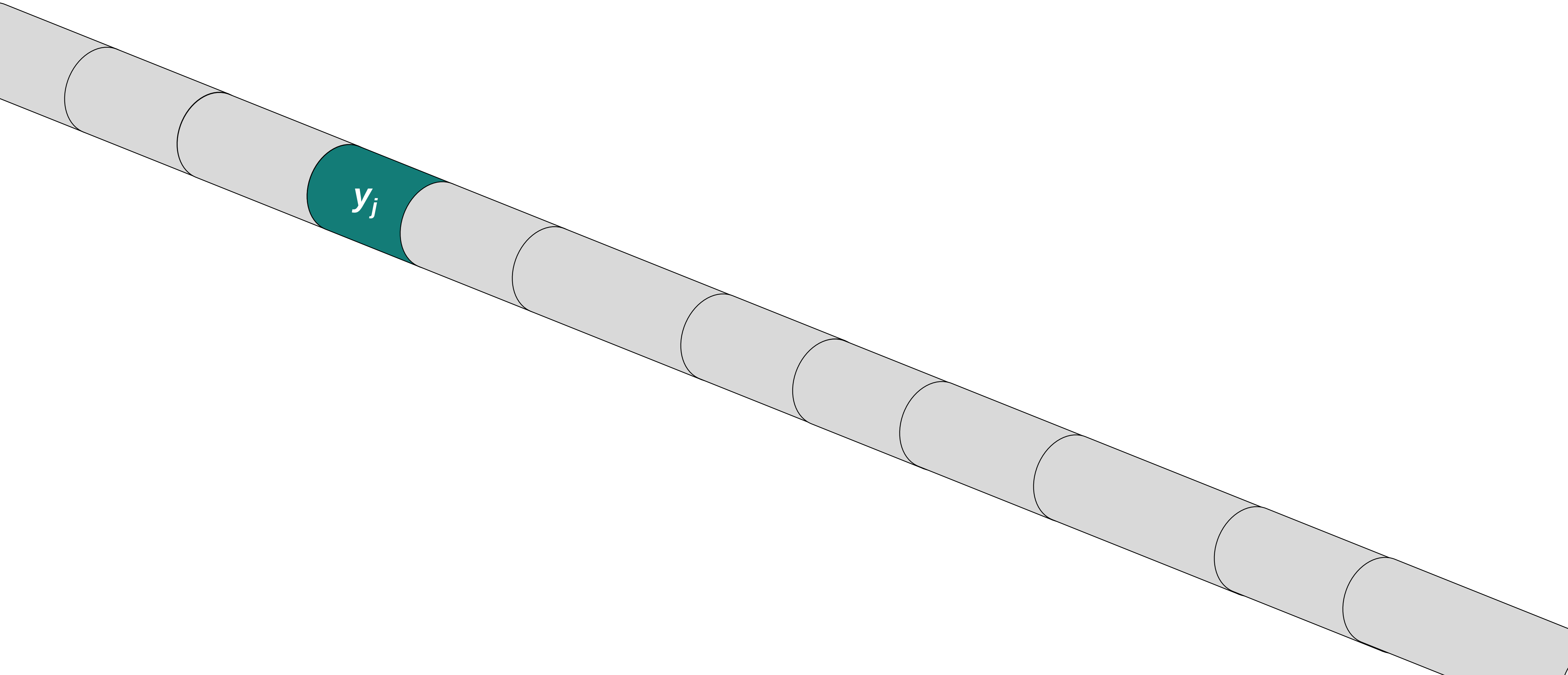

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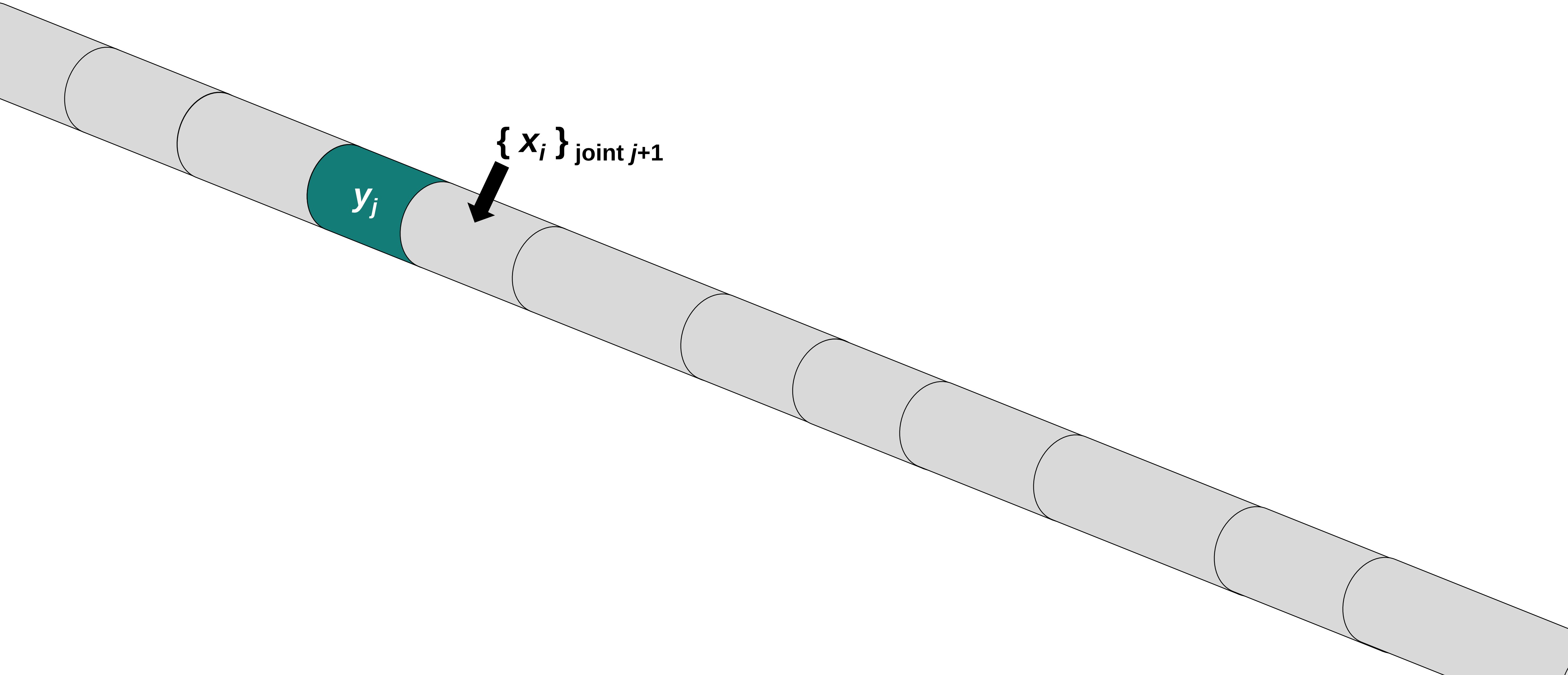

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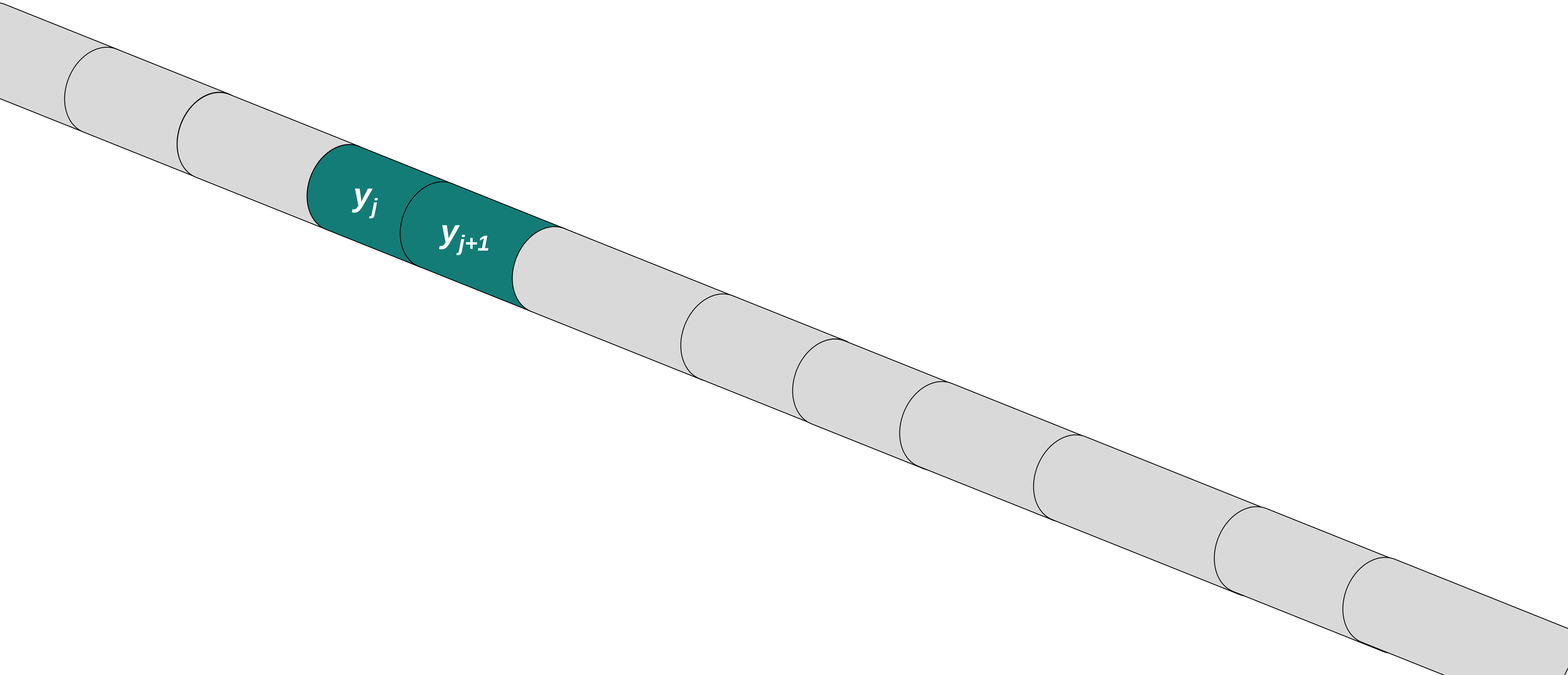

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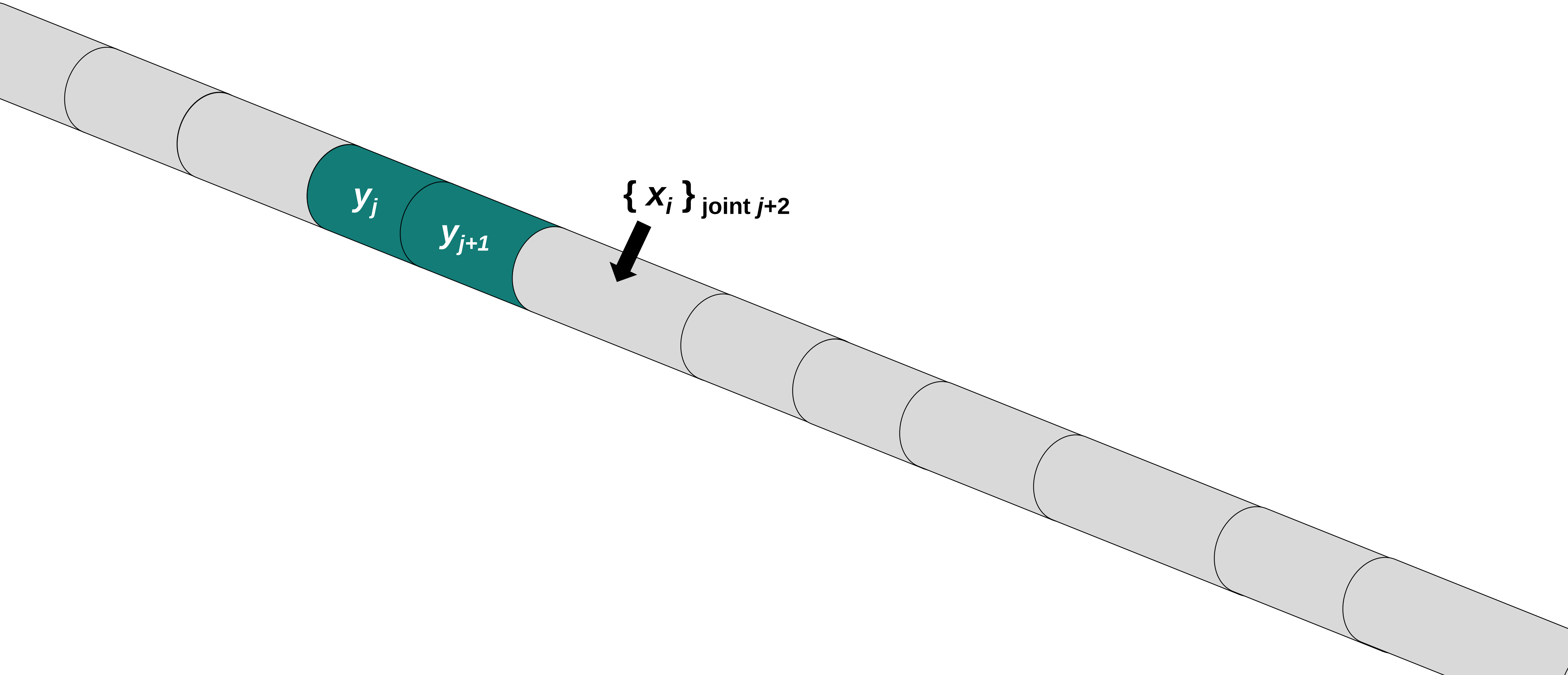

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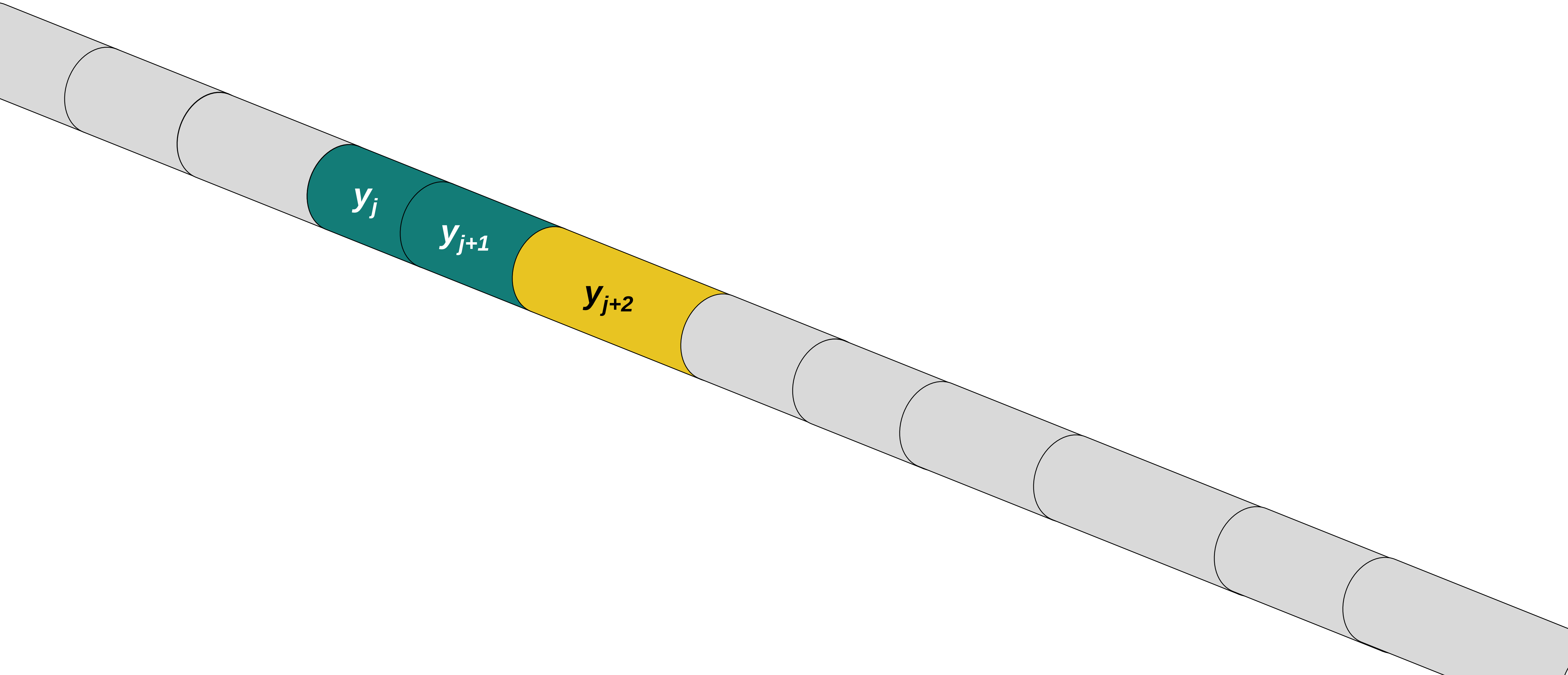

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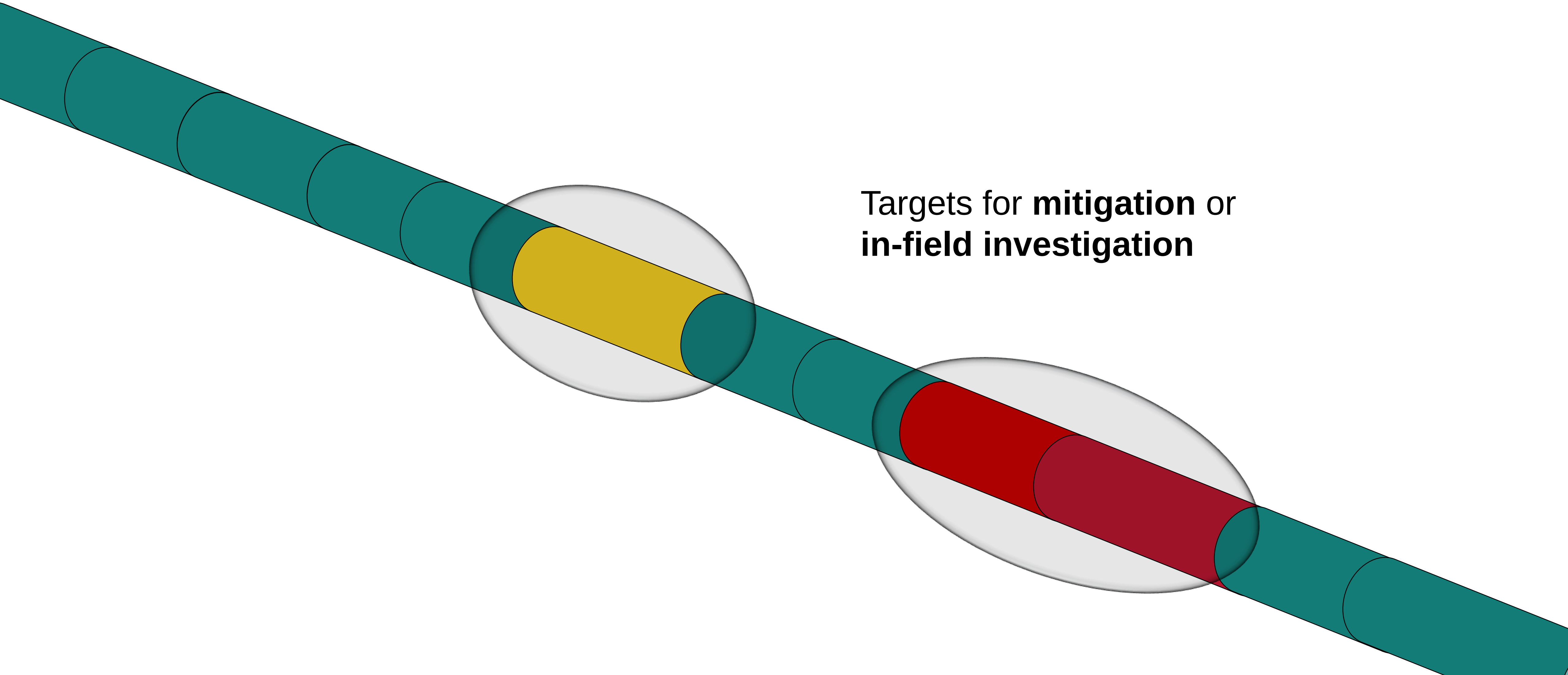


Targets for **mitigation** or
in-field investigation

Network-specific model

Network-specific model

79,336
pipe joints from gas distribution network in North America

- **In-line inspection (ILI)**
- **Design and construction**
- **Environment**
- **Cathodic protection**

Network-specific model

$$\boxed{y} = f(x_1, x_2, \cdots x_n)$$

Target variables

- Anomaly density
- Corroded area
- Maximum depth

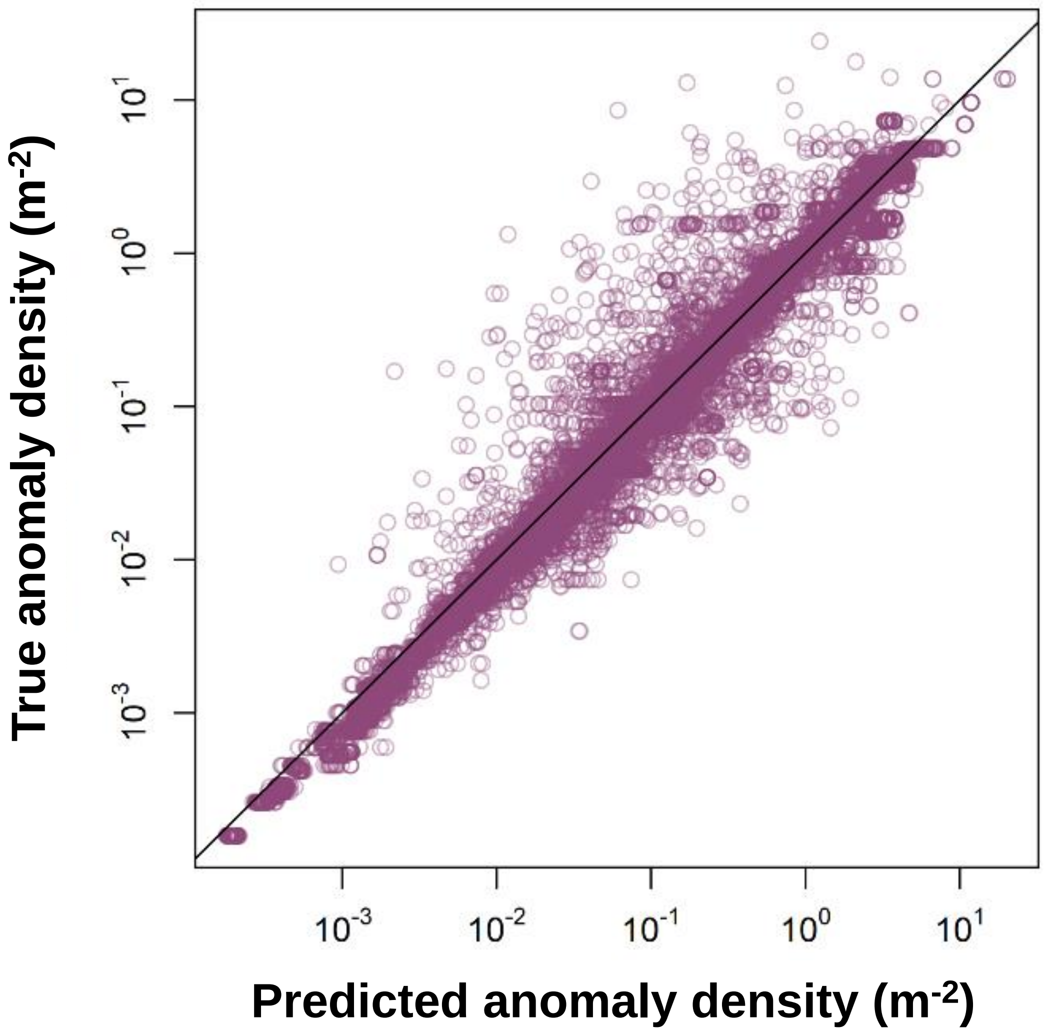
Network-specific model

$$y = f(\boxed{x_1, x_2, \cdots x_n})$$

Predictor variables

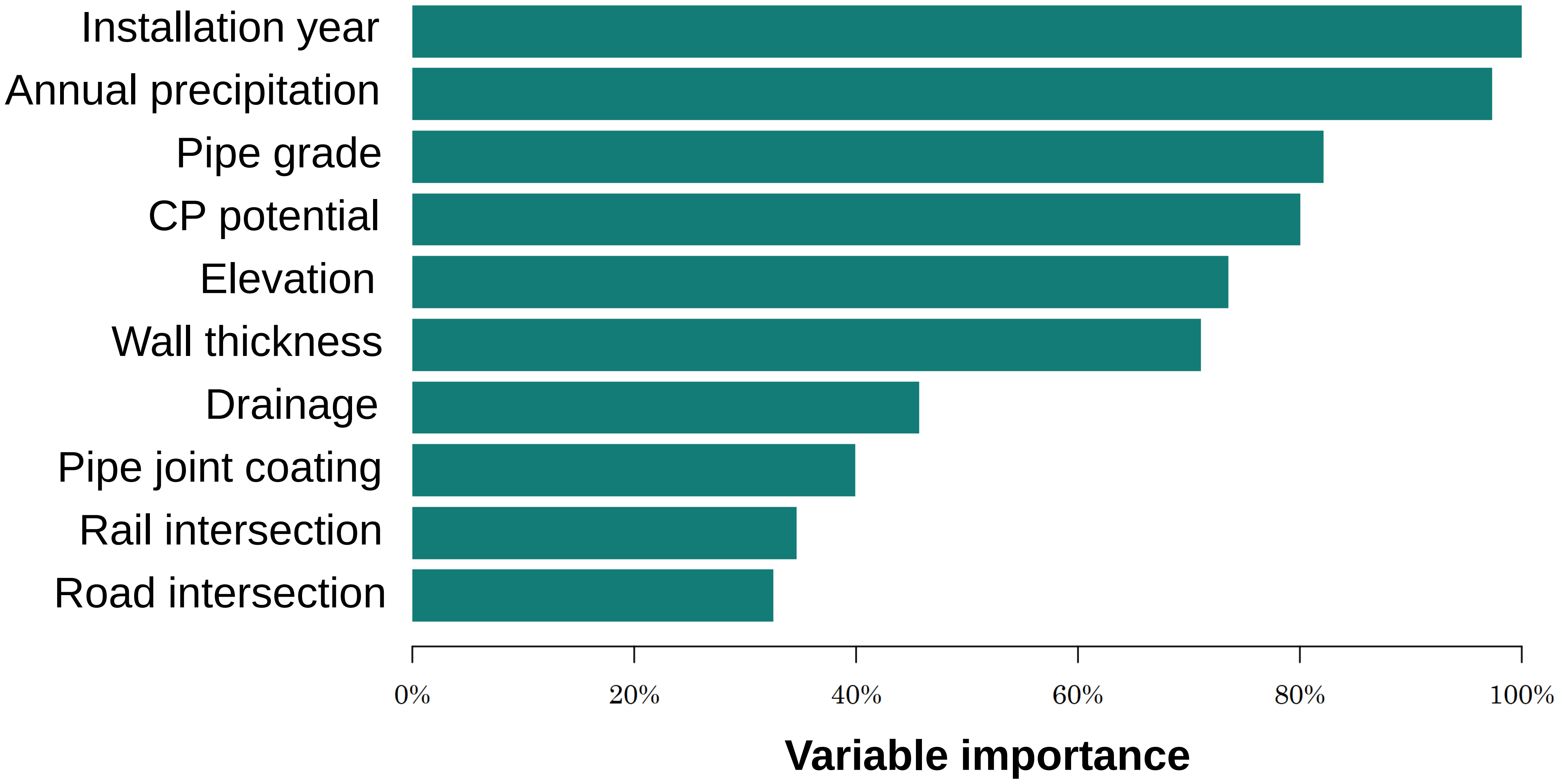
- Installation year
- Coating type (pipe body and field joint)
- Pipe grade
- CP potential
- Annual precipitation (rainfall and snowfall)
- Intersections (roads, railways, power lines)
- Terrain (elevation, slope, aspect)
- Soil properties (type, chemistry, drainage)

Network-specific model



- **99%** of anomaly density and corroded area values predicted within 1 order of magnitude
- **96%** of maximum depth values predicted within ±1 mm

Network-specific model



Network-agnostic model

Network-agnostic model

3.4 million

pipe joints from multiple operators and networks in Europe

- **In-line inspection (ILI)**
- **Design and construction**
- **Environment**

Network-agnostic model

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Network-agnostic model

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$$y = f(\underbrace{x_1, x_2, \cdots x_n}_{\text{Predictor variables}})$$

Predictor variables

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- ~~CP potential~~
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Environmental datasets – an example

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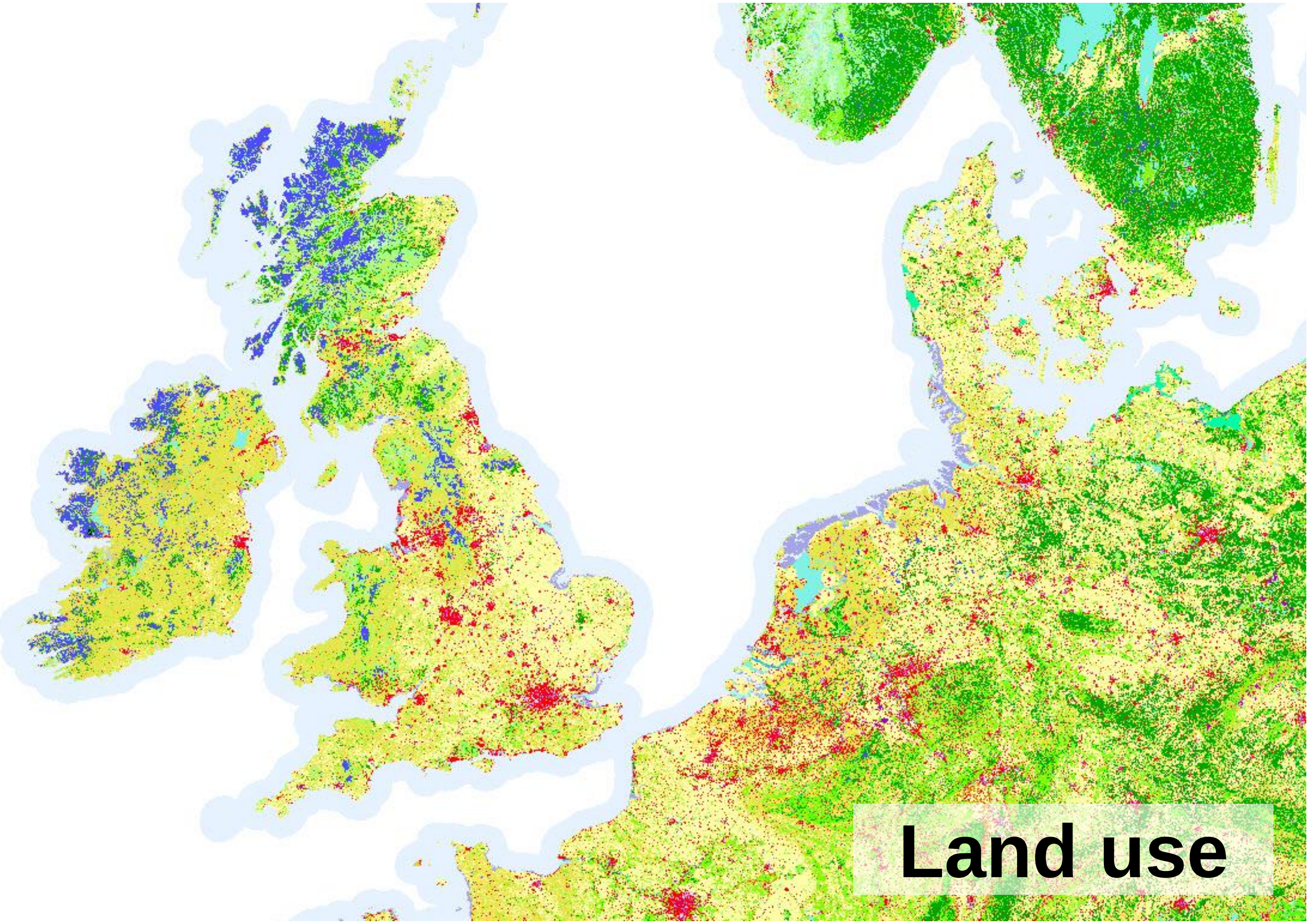
- Continuous urban fabric
- Discontinuous urban fabric
- Industrial or commercial units
- Port areas
- Airports
- Mineral extraction sites
- Construction sites
- Green urban areas
- Sport and leisure facilities
- Pastures
- Permanent crops
- Broad-leaved forest
- Glaciers and perpetual snow
- Water courses
- Water bodies
- Coastal lagoons
- Peat bogs
- Salt marshes
- Estuaries
- Sea and ocean
- Coniferous forest
- Natural grasslands
- Moors and heathland
- Beaches, dunes, sands
- Bare rocks
- Inland marshes



Environmental datasets – an example

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Discontinuous urban fabric
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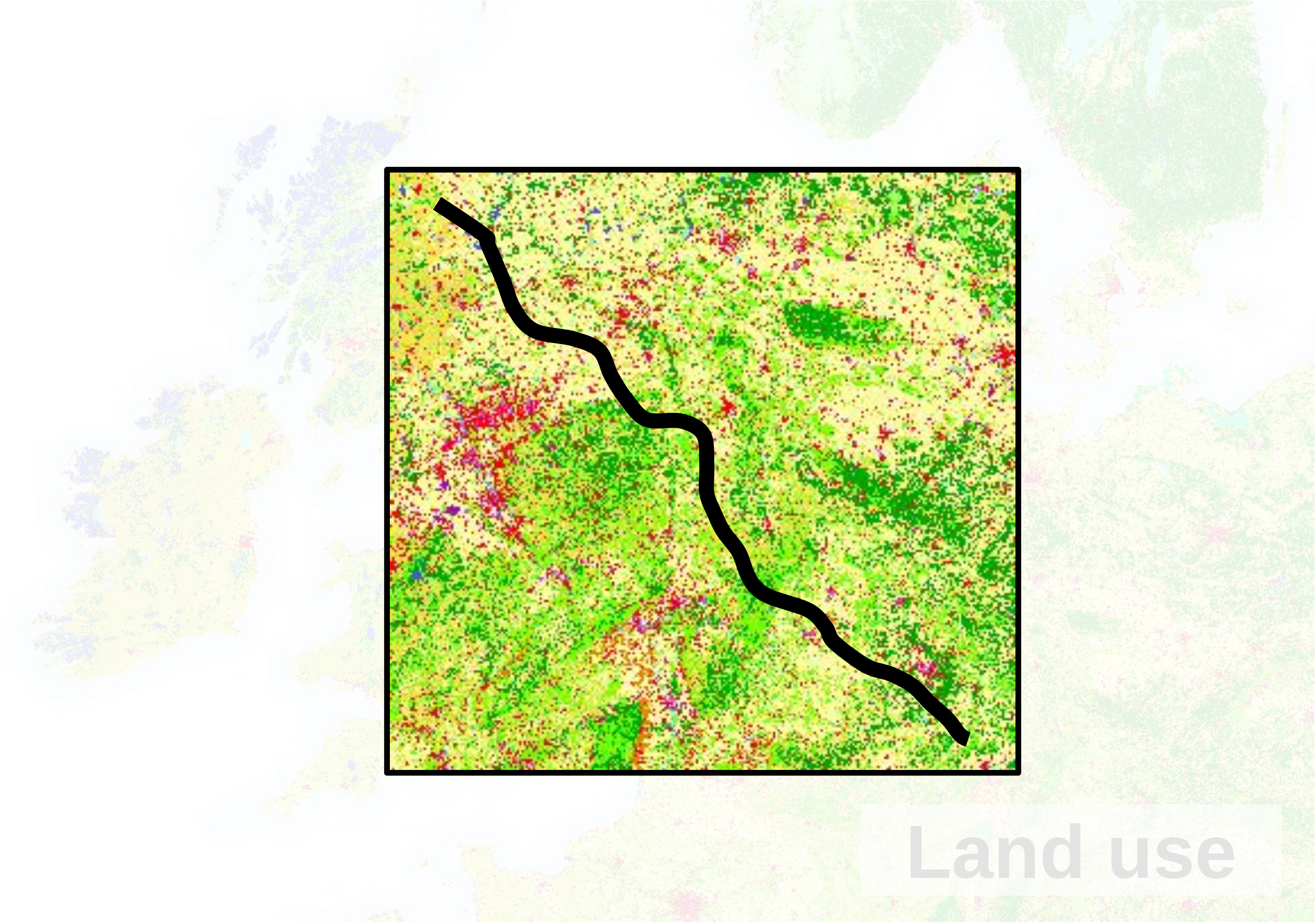

Network-agnostic model

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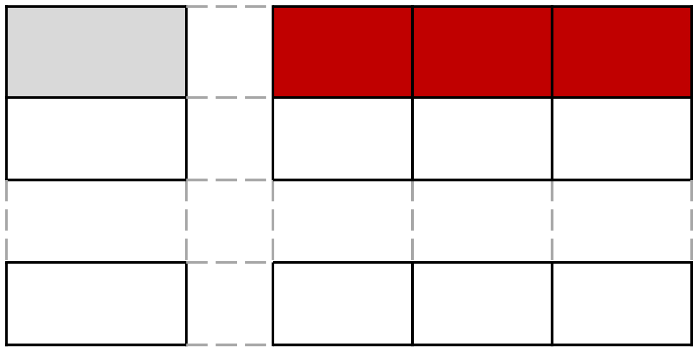
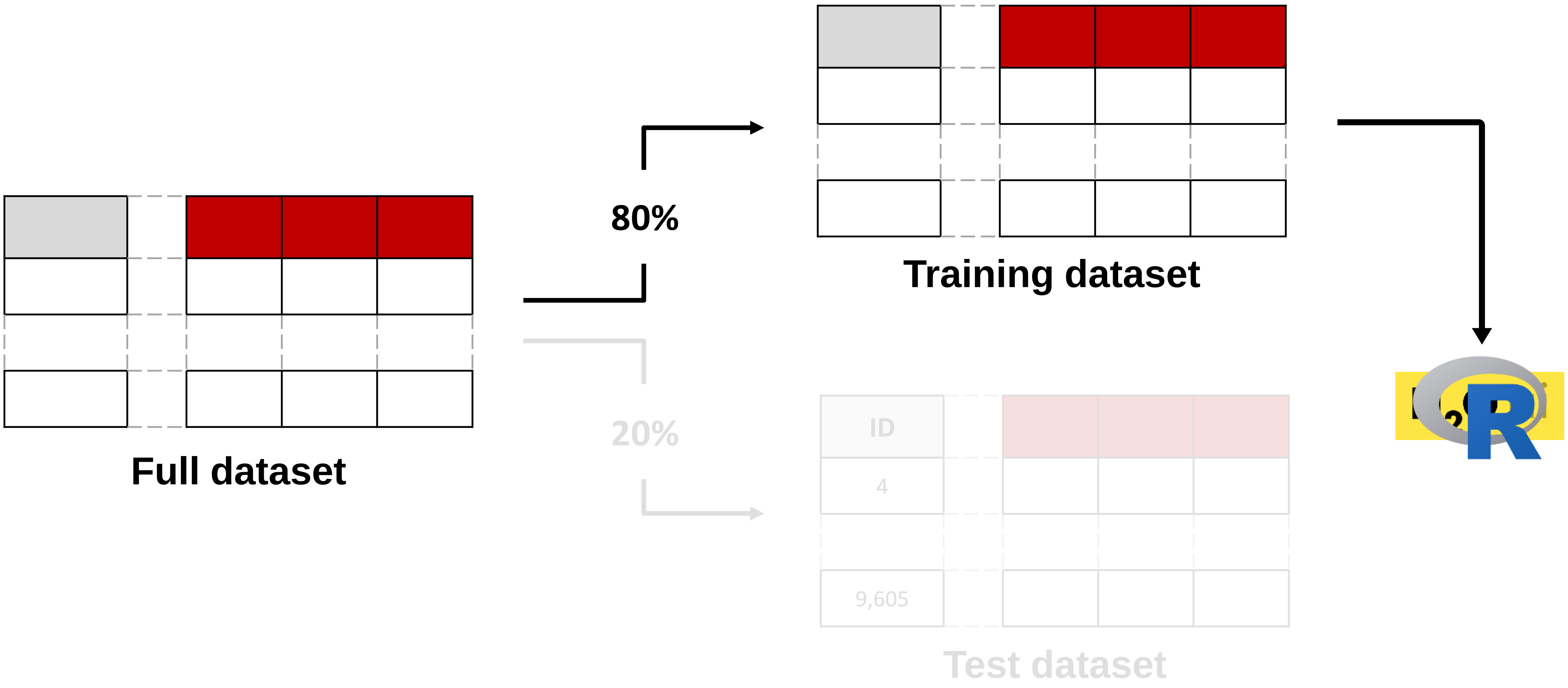
	> 30 predictor variables				Target variables		
Joint ID	Construction year	Coating type	Precipitation (mm)		Anomaly density (m^{-2})	Corroded area (%)	Maximum depth (mm)
1	1982	Tape	790		0.22	0.14	1.7
2	1982	Tape	790		0.22	0.14	1.7
3,443,896	1965	Coal tar	822		0.05	0.09	0.9

Network-agnostic model



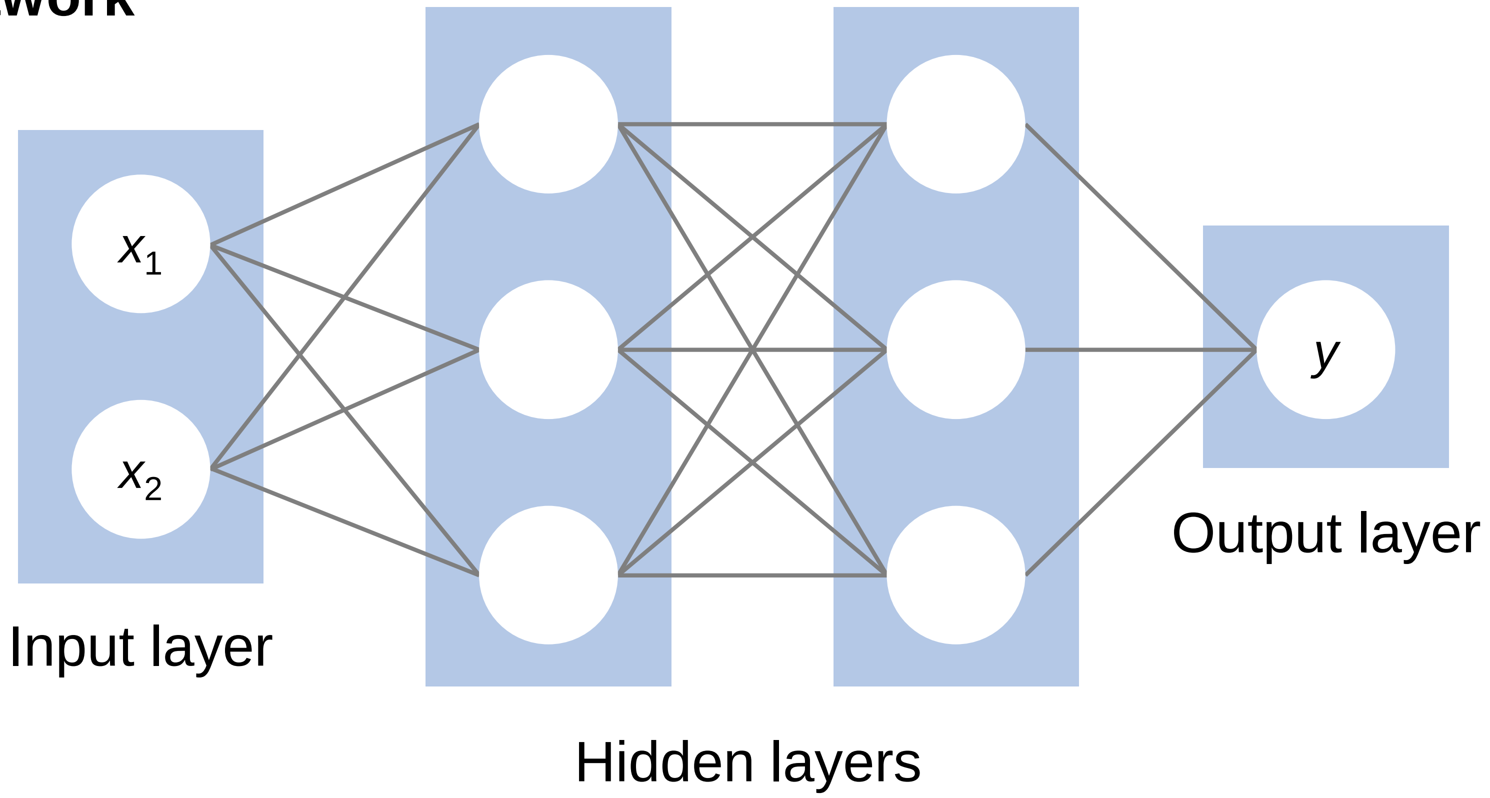
Full dataset

Network-agnostic model



Network-agnostic model

Deep neural network

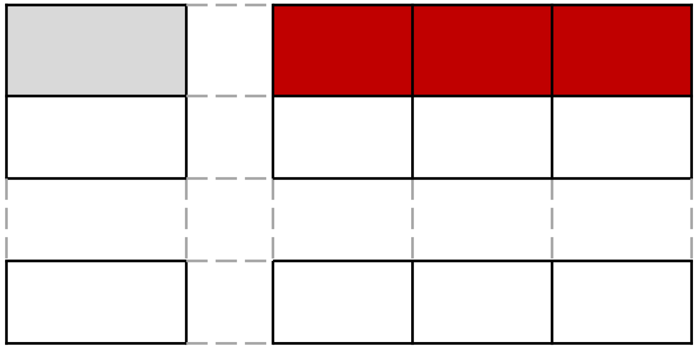


Network-agnostic model

Deep neural network

anomaly density = *f*(*installation year*, *coating type*, *annual precipitation…*)

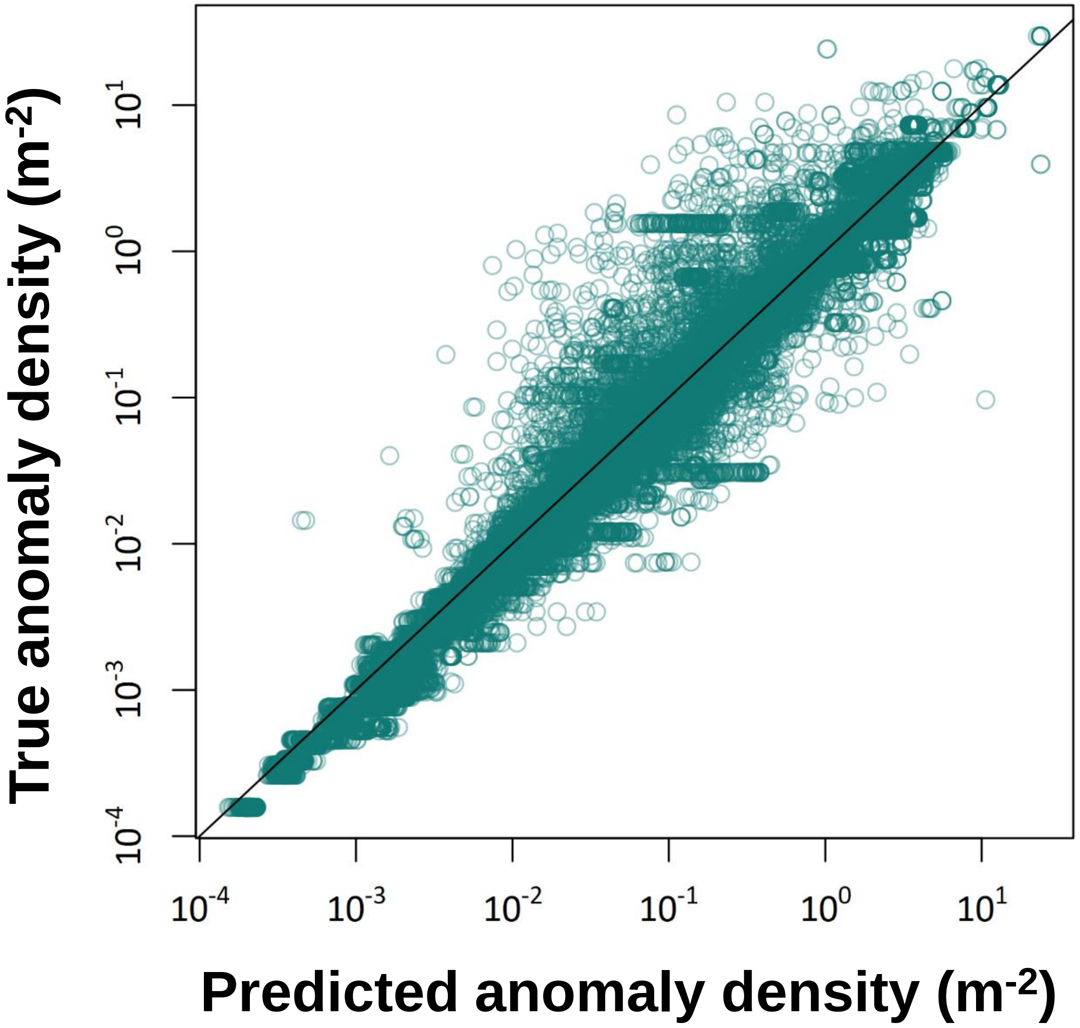
Network-agnostic model



Test dataset

anomaly density = *f*(*installation year*, *coating type*, *annual precipitation…*)

Network-agnostic model



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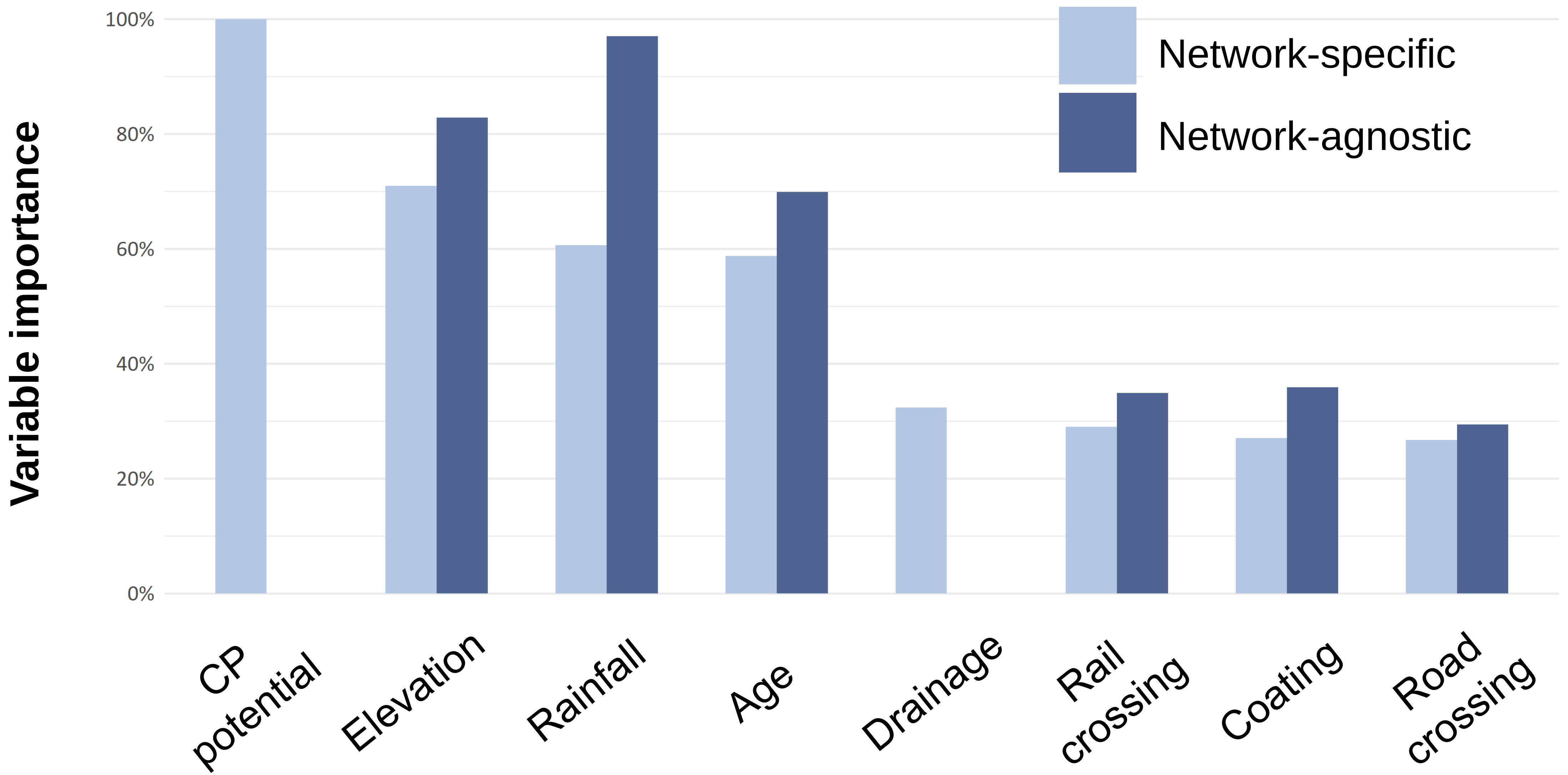
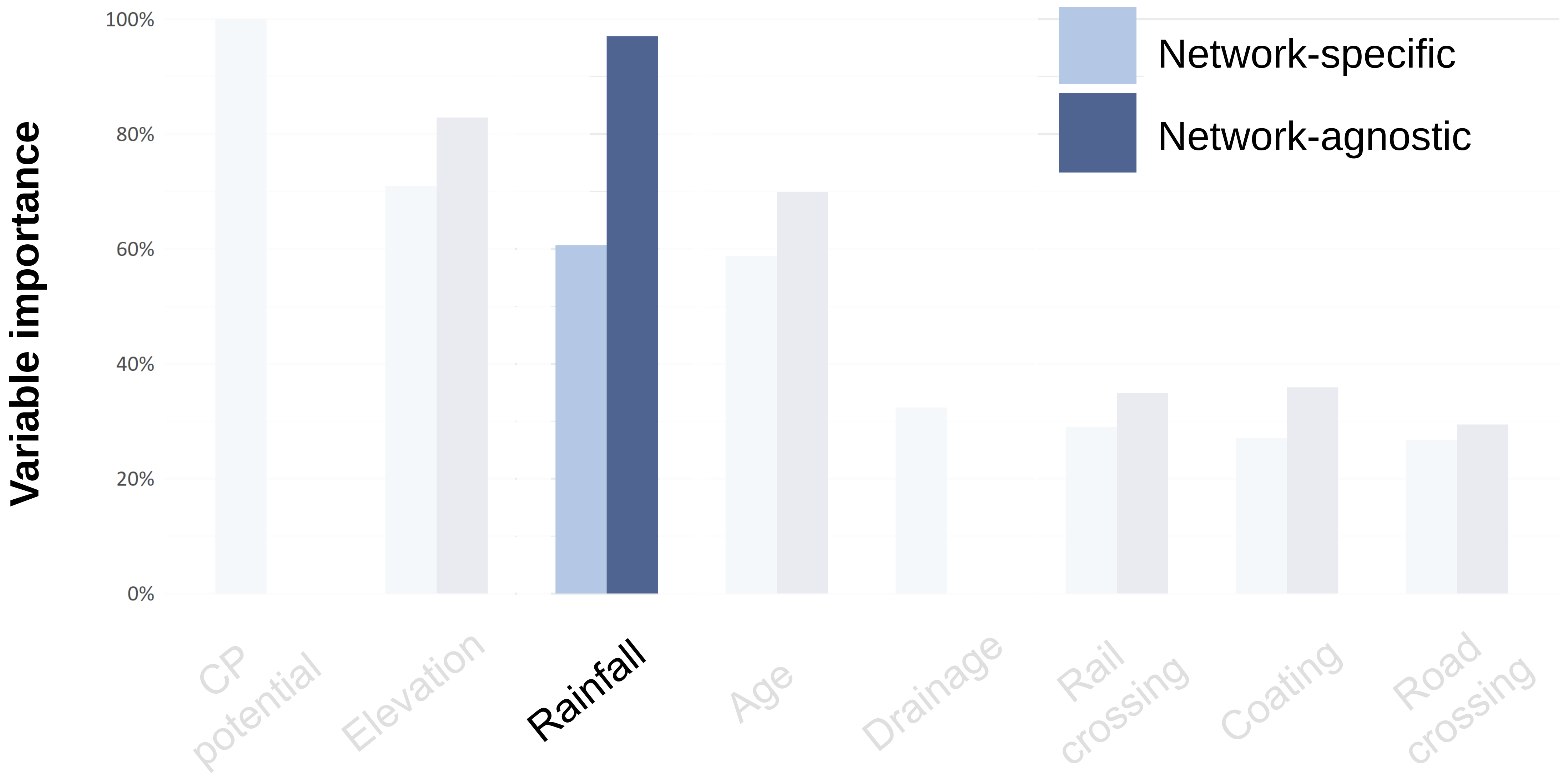
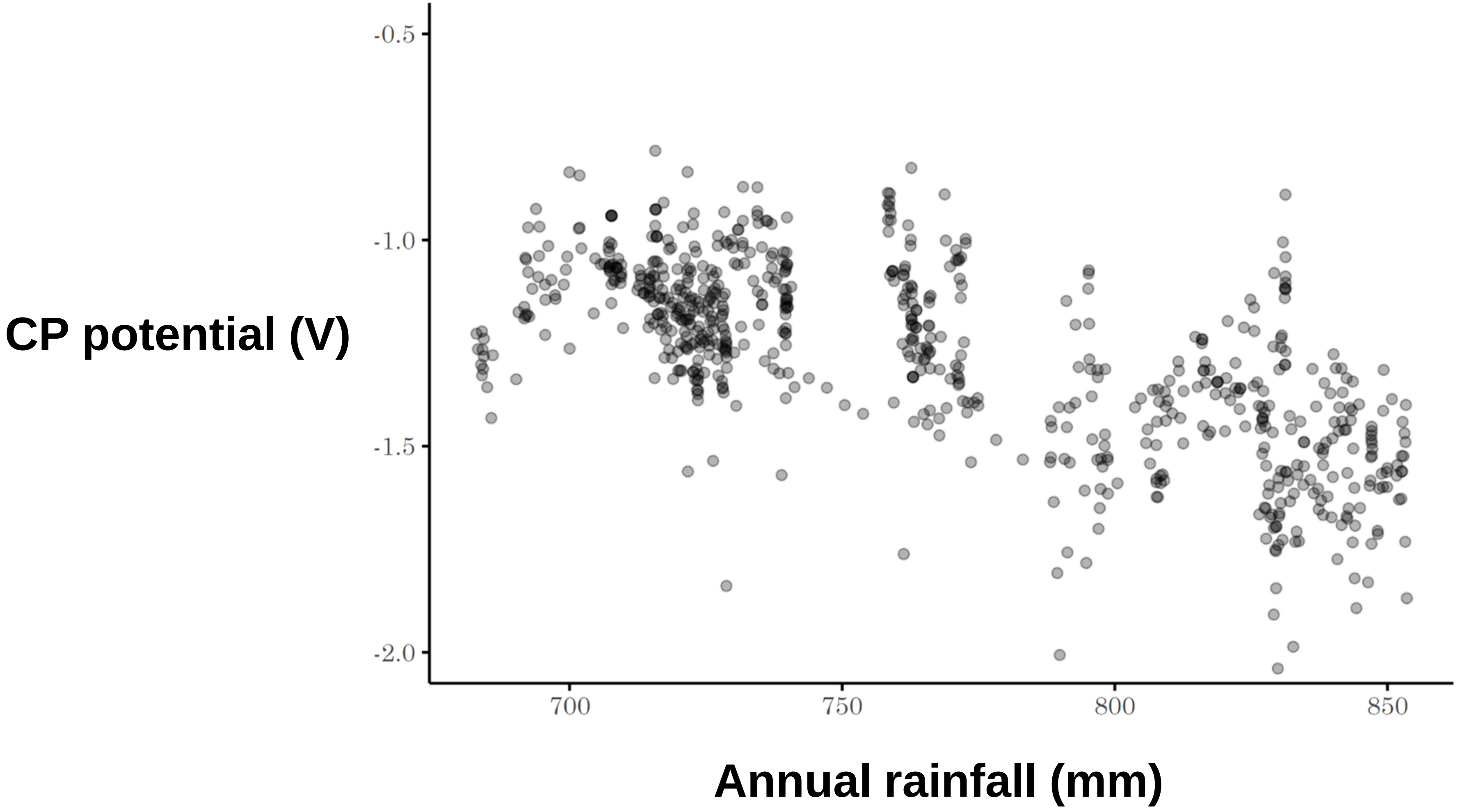
Comparison of variable importance



Variable importance



Variable importance



Conclusions

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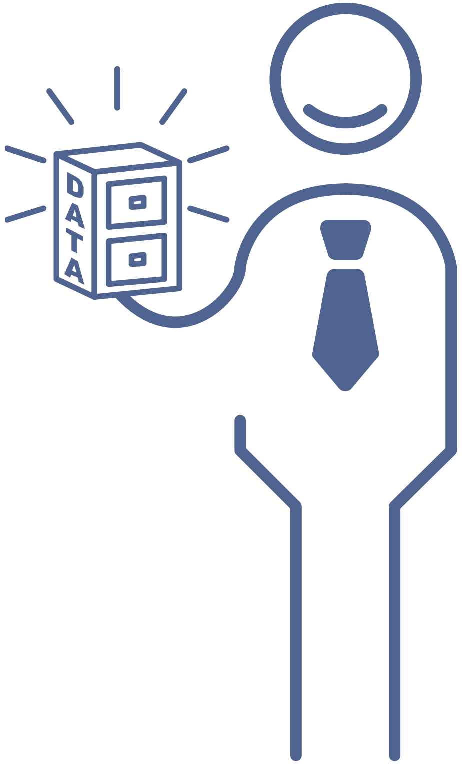

- Supervised machine learning can support integrity management of **uninspected** pipelines
- Both **network-specific** and **network-agnostic** models perform well for predicting external corrosion
- Promising application for other threats and asset types

Epilogue: Applications of Analytics to Pipeline Integrity Management

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- “Virtual ILI” – predict the condition of an uninspected pipeline
- Support dig-up planning in between ILI runs
- Quantitative probability of failure prediction to support risk based assessments
- Step two of NACE Direct Assessment – the “indirect inspection”
- Other uses…?