



ExchangeRisk

EXperimental & **C**omputational **H**ybrid **A**ssessment of **N**atural
Gas Pipelines **E**xposed to Seismic **R**isk

Post-event risk assessment for gas
pipelines at regional scale:

The Friuli case – vulnerability model and data on
the network



Flavia De Luca

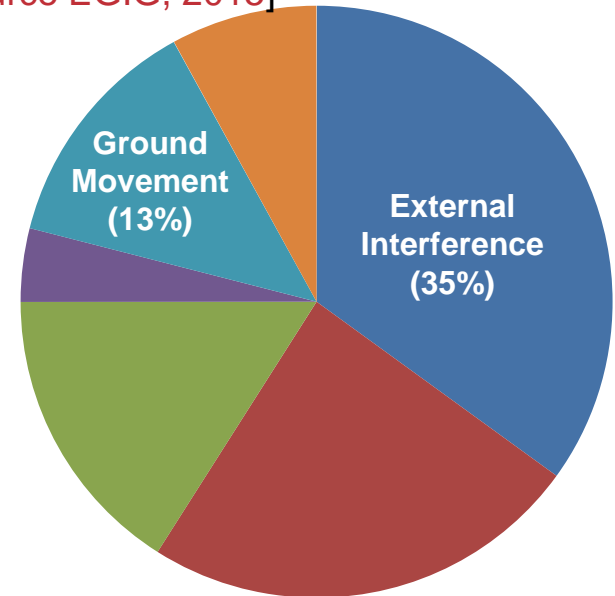
“Natural events, such as earthquakes and floods, can trigger accidents in oil and gas pipelines with potentially severe consequence to the population and to the environment. These conjoint technological and natural disasters are termed NaTech accidents [...]. Most of NaTech studies on pipelines focus on seismic risk analysis and on structural damage without considering the potential loss of containment.” [Piccinelli and Krausmann, 2013]



In the 9th report of the *European Gas Pipeline Incident Data Group* related to the period 1970-2013 is emphasized how incident caused by external interference (35% in 2004-2013) and ground movement (13% in 2004-2013) are characterized by potential severe consequences (24% corrosion, 16% construction defects/material failures, 4% hot tap, 8% other/unknown) [EGIG, February 2015]

Incidents (2004-2013)

[Source EGIG, 2015]

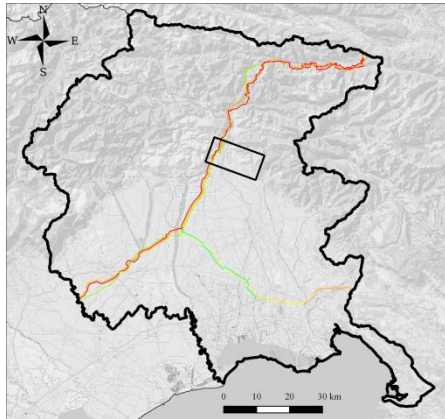


Landslides are by far the most common type causing a ground movement incidents (i.e., 85% in 2004-2013). Failure frequency decreases with the diameter class. No incidents are recorded in the whole database 1970-2013 as caused by earthquakes.

Scope of the study

In recent years, many studies have focused on the seismic performances of gas lifelines. Seismic reliability studies for short-term and long-term post-event characterization of risk and losses have proposed.

We started from the simulation-based risk assessment framework proposed by Weatherill et al. (2014) and Esposito et al. (2015) as benchmark for the state-of-the-art practice on risk of gas pipelines in Europe.



Post-event framework for **damage** and **loss** assessment at regional scale, applied to the Italian National Grid (high-pressure transport network) and to the Friuli 1976 earthquake case.

What we did?

What's new?

- Ground failure from both landslide and liquefaction in a single three-step framework
- A new machine learning classification approach for vulnerability

Literature empirical models

Fragility models can be divided in two categories, those considering damage caused by Strong Ground Shaking (SGS) and those caused by Ground Failure (GF), including fault displacements, liquefaction and landslides. For both causes we have the “classical approach” and the “industrial risk approach”

SGS

GF

$$1) RR = a \cdot IM^b$$

$$2) P(DS \geq DS_i \text{ or } RS \geq RS_i)$$

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$$2) P(DS \geq DS_i \text{ or } RS \geq RS_i)$$

1) The “classical approach” – optimized to provide consequence assessment results mainly in terms of repair expenditures

2) The “industrial risk approach” – optimized to provide consequence assessment not only in terms of structural damage but also including industrial risk consequences (e.g., release of flammable or pollutant liquid).

Literature empirical models

- 1) The “classical approach” – optimized to provide consequence assessment results mainly in terms of repair expenditures

The example of ALA (2001) vulnerability functions is considered. They are based on 18 earthquake events and employed in Esposito et al. (2013) and (2015). For steel welded joint, large D (>400mm) pipelines K_1 and K_2 are equal to 0.15.

SGS

- $IM = PGV$
- $RR (in 1/km) = K_1 \cdot 0.002416 \cdot PGV (in cm/s)$

GF

- $IM = PGD$
- $RR (in 1/km) = K_2 \cdot 11.223 \cdot PGD^{0.319} (in m)$

Literature empirical models

1) The “classical approach” – the example of ALA (2001)

SGS

- $IM = PGV$
- $RR \text{ (in } 1/km) = K_1 \cdot 0.002416 \cdot PGV \text{ (in cm/s)}$

GF

- $IM = PGD$
- $RR \text{ (in } 1/km) = K_2 \cdot 11.223 \cdot PGD^{0.319} \text{ (in m)}$

According to HAZUS the type of repair or damage depends on the type of hazard (i.e., SGS = 0.8 leaks + 0.2 breaks; GF = 0.2 leaks + 0.8 breaks)

HAZUS (NIBS, 2004)	Damage State	Damage description	Serviceability
DS1	No damage	No break/leak	operational
DS2	Leakage	At least on leak along the pipe length	Reduction of the flow
DS3	Failure	At least one break along the pipe length	Disruption of the flow

Literature empirical models

2) The “industrial risk approach” – optimized to provide consequence assessment not only in terms of structural damage but also including industrial risk consequences (e.g., release of flammable or pollutant liquid).

The example of Lanzano et al. (2014) is considered. They are based on 20 earthquake events for continuous pipelines (CP) and segmented pipelines (SG)

SGS (for CP and SP)

- $IM = PGV$
- $RS \geq RS1$ and $RS = RS2$

GF (for CP and SP)

- $IM = PGA$
- $RS \geq RS1$ and $RS = RS2$

Literature empirical models

2) The “industrial risk approach” – example of Lanzano et al. (2014)

SGS (for CP and SP)

- IM = PGV
- $RS \geq RS1$ and $RS = RS2$ (or DS)

GF (for CP and SP)

- IM = PGA
- $RS \geq RS1$ and $RS = RS2$ (or DS)

States	Hazard	Patterns (structural damage)
DS0	Slight	Investigated sections with negligible damage; pipe buckling
DS1	Significant	Longitudinal and circumferential cracks; compression joint break
DS2	Severe	Tension cracks for continuous pipelines; joint loosening in the segmented pipelines

Literature empirical models

2) The “industrial risk approach” – example of Lanzano et al. (2014)

SGS (for CP and SP)

- IM = PGV
- $RS \geq RS1$ and $RS = RS2$ (or DS)

GF (for CP and SP)

- IM = PGA
- $RS \geq RS1$ and $RS = RS2$ (or DS)

States	Hazard	Patterns (loss of containment)	
		Gas/Vapor/Liquefied gas	Liquid
RS0	No losses	Investigated sections with negligible damage; pipe buckling	
RS1	Very limited losses: toxic ($\phi < 1\text{mm/m}$); flammable ($\phi < 10\text{mm/m}$)	Limited, time-distributed loss of hazardous substance: multiple losses ($\phi < 10\text{mm/m}$)	
RS2	Non-negligible losses	Large loss (e.g., entire tube surface) or multiple losses ($\phi > 10\text{mm/m}$)	

Literature empirical models

2) The “industrial risk approach” – example of Lanzano et al. (2014)

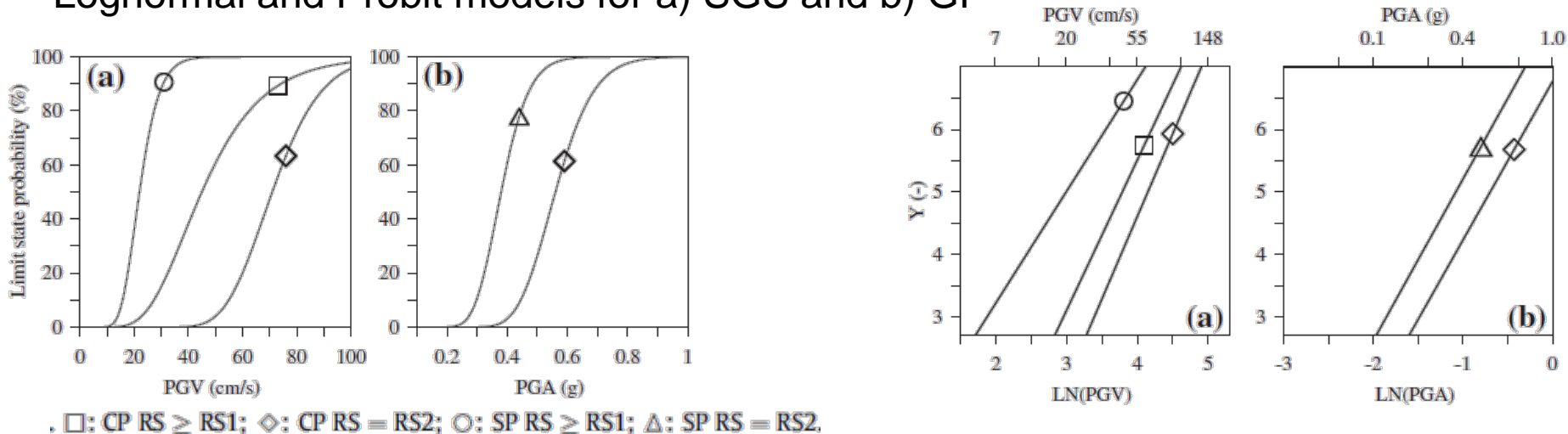
SGS (for CP and SP)

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Lognormal and Probit models for a) SGS and b) GF

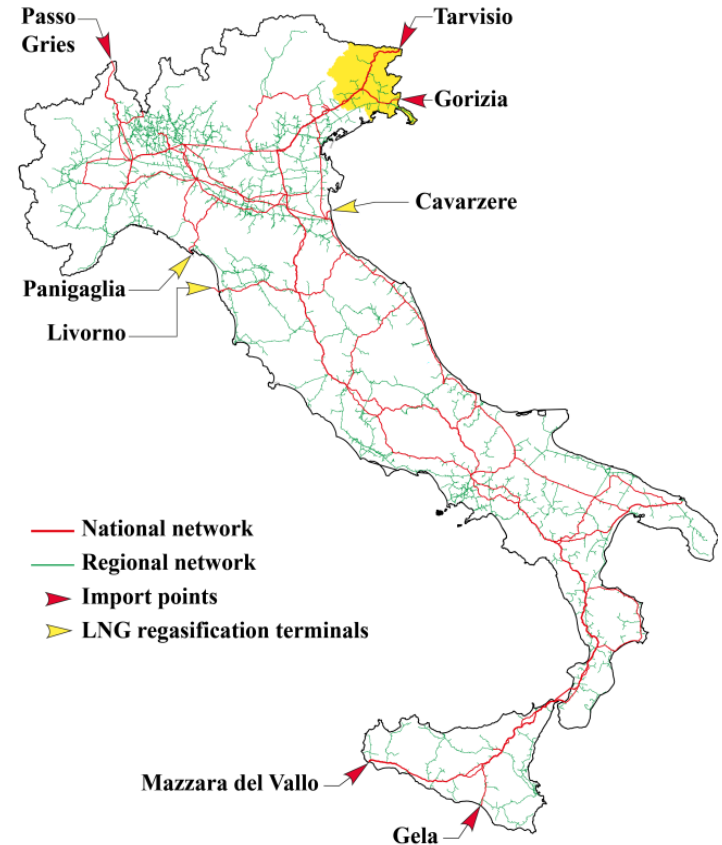


Case Study Network

Data collection

The transport of natural gas in Italy is an integrated service which involves the transport of the gas delivered to **Snam Rete Gas S.p.A.** at the entry points of the National Network up to the redelivery points of the Regional Network (in Italy this classification was made by DL164 23/05/2000).

Pipeline System	Pressure (bar)		Diameter (cm)
	Nominal	Operating	
National Network	70	50	90-140
Regional Network	25	20	25-50
Local Distribution	5	4	8-15



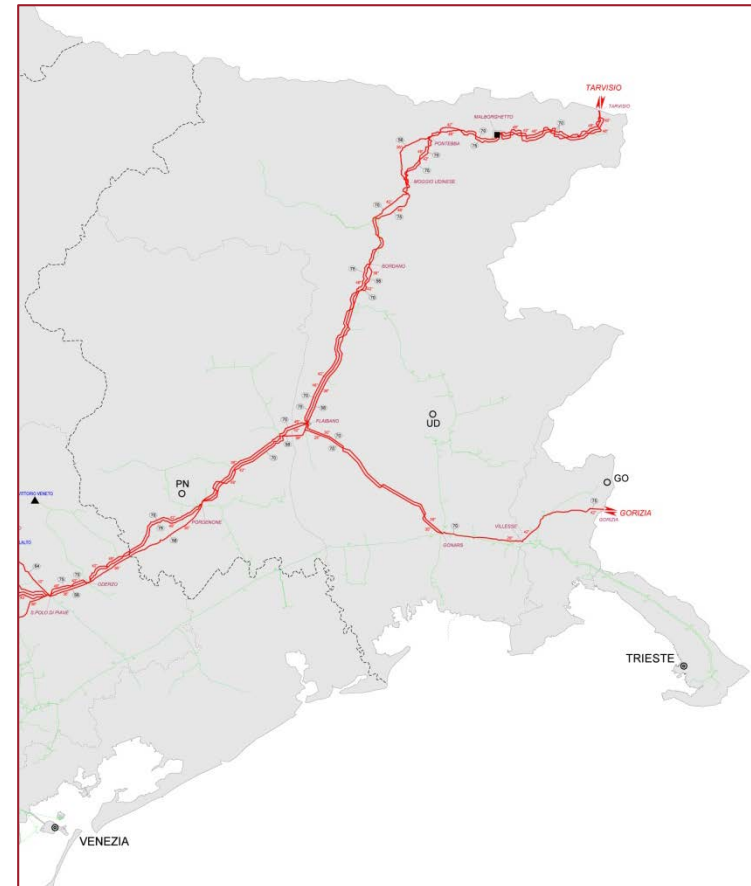
Case Study Network

Data collection

Open-source data on the Italian network were considered:

- Localization of the network (for geo-referencing)
- Diameter
- Max Operating Pressure [www.snamretegs]
- Average Buried depth 1.5m, higher than 0.90m

[Vianello and Maschio, 2014; DM 17/04/2008]

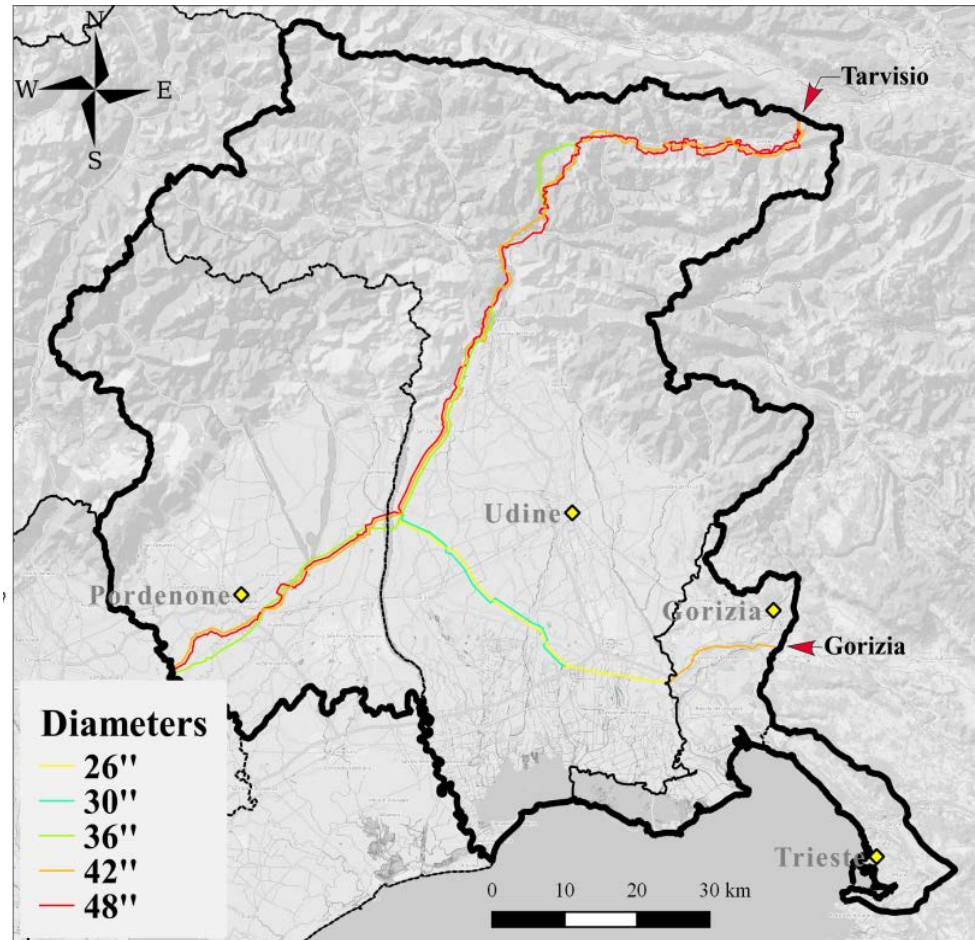


Why Friuli Region?

- Strategic (i.e., two entry points)
- High Seismicity area
- High Liquefaction Susceptibility

Total length of network considered is ~510km divided in 40m segments on average with maximum of 60m.

The scenario is purely for academic purposes since the network data are referred to 2013, and the event dates back to 1976.



Machine learning classification

- The classical approach does not fit properly for potential applications in the industrial risk field.
- The industrial risk approach provides a damage from SGS and one from GF, the envelope of the two can be too conservative and not straightforward to implement.
- What about a model providing not only the damage but also its “cause”?
- What about a model that carries out one damage level?

Machine learning classification

- The classical approach does not fit properly for potential applications in the industrial risk field.
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- What about a model providing not only the damage but also its “cause”?
- What about a model that carries out one damage level?

Let's approach vulnerability with a machine learning classification!

Machine learning classification

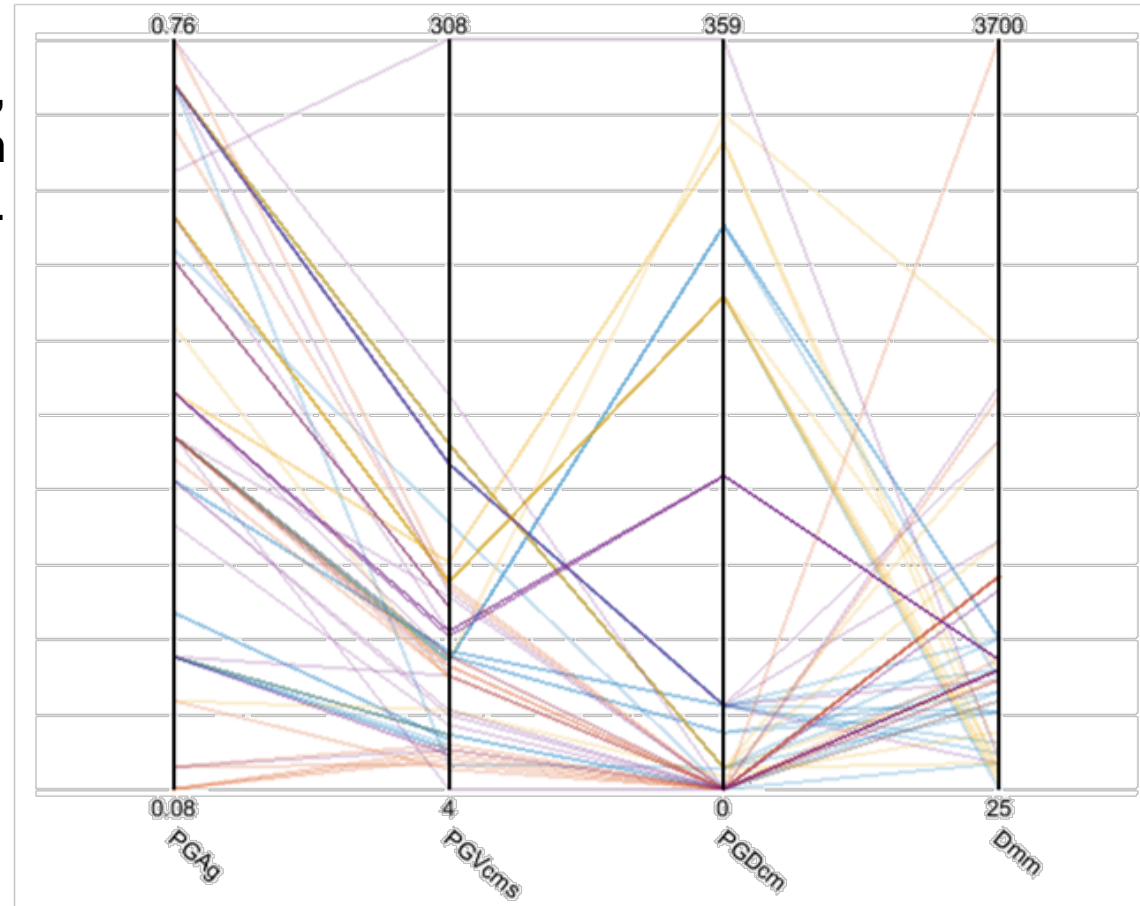
Parallel Coordinates Plot

○ 82 samples of continuous, welded joint, steel pipelines from the database by Lanzano et al. (2015)

○ 4 predictors
(PGA, PGV, PGD, D)

○ 3 predictors
(PGA, PGV, D)

○ 4 responses classes



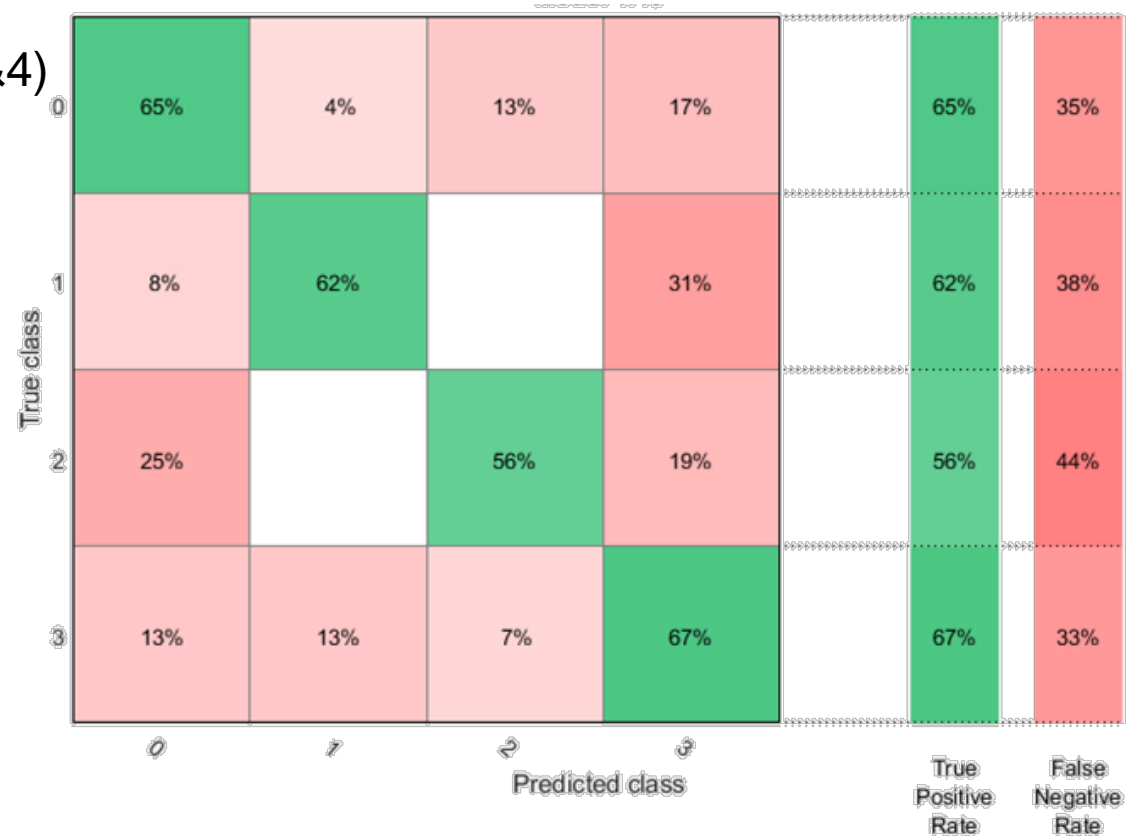
DS0 DS1-SGS DS1-GF DS2

Machine learning classification

Confusion Matrix

- accuracy **63.4%** and 62.2% (3&4) (ensemble bagged/boosted tree, 10-fold cross validation)
- 3 or 4 predictors (PGA, PGV, PGD, D)
- 4 responses

DS0 DS1-SGS DS1-GF DS2

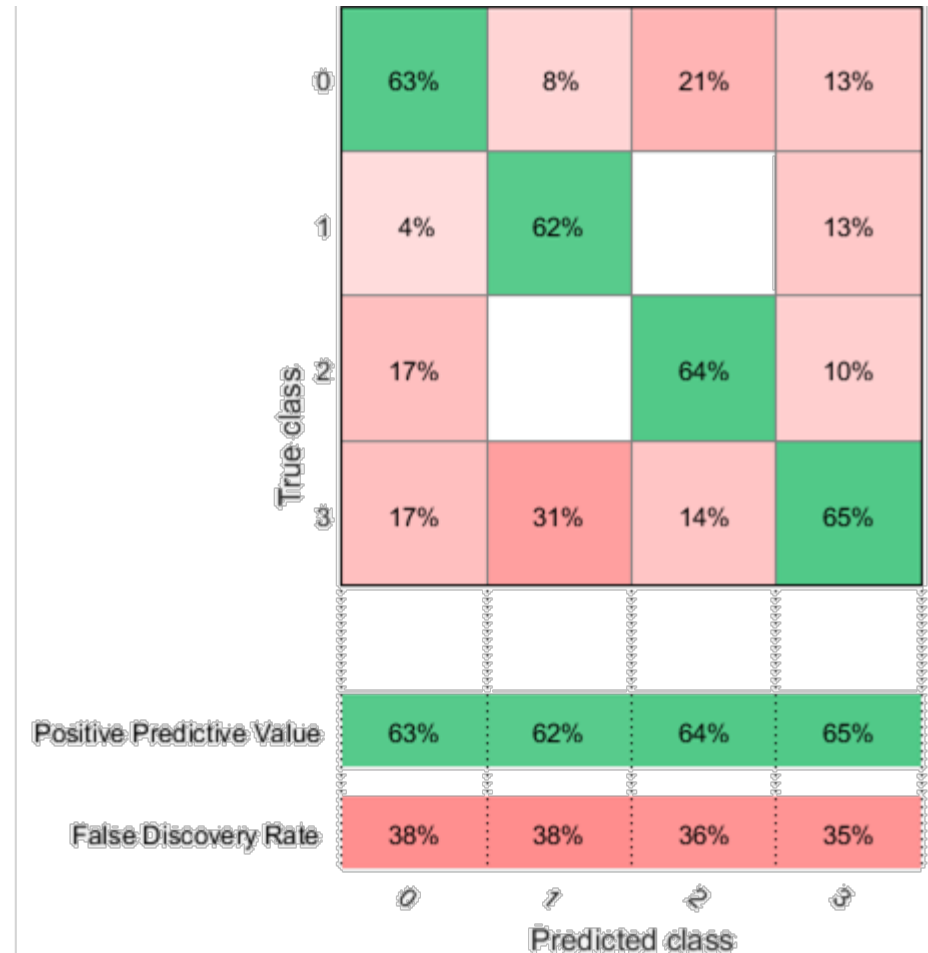


Machine learning classification

Confusion Matrix

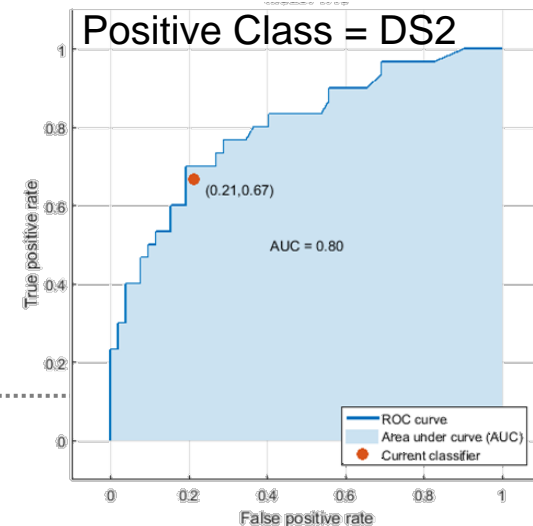
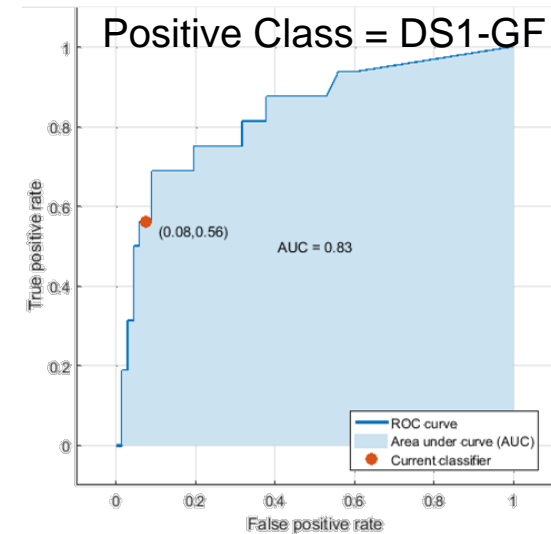
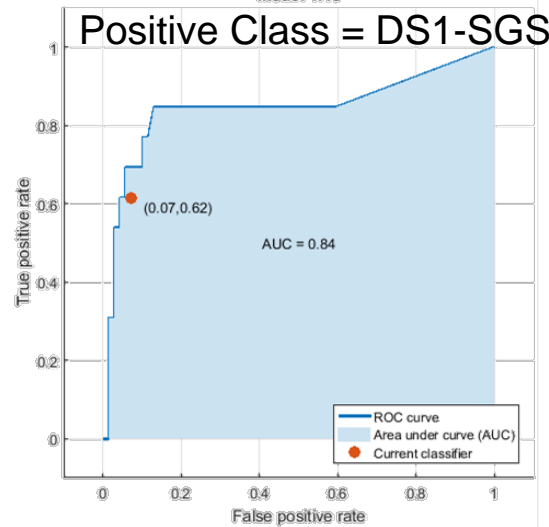
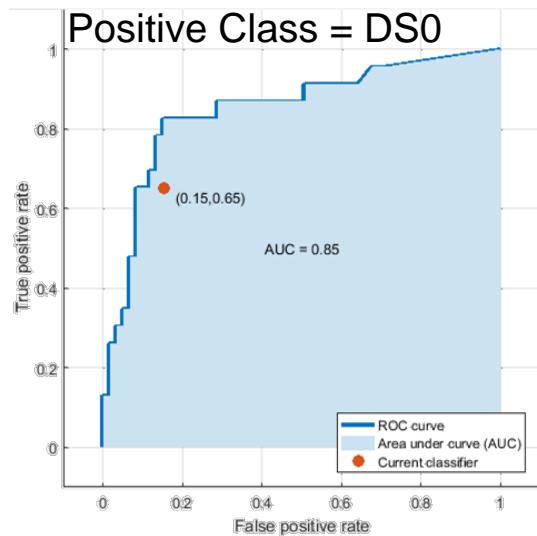
- accuracy **63.4%** and 62.2% (3&4)
(ensemble bagged/boosted tree,
10-fold cross validation)
- 3 or 4 predictors
(PGA, PGV, ~~PGD~~, D)
- 4 responses

DS0 DS1-SGS DS1-GF DS2



Machine learning classification

ROC Curves 3-predictors case (63.4%)



The Receiver Operating Characteristic (ROC) curve shows true positive rate versus false positive rate for the currently selected trained classifier. The marker shows the values of the false positive rate (FPR) and the true positive rate (TPR) for the currently selected classifier. AUC is a measure of the overall quality of the classifier.

Machine learning classification

- accuracy 63.4% (ensemble bagged tree, 10-fold cross validation)
4 predictors (PGA, PGV, D)
- accuracy 62.2% (ensemble boosted trees, 10-fold cross validation)
3 predictors (PGA, PGV, PGD, D)
- accuracy 61.0% (ensemble boosted trees, 10-fold cross validation)
3 predictors (PGA, PGV, D_{HAZUS})
- accuracy 59.8% (ensemble bagged tree, 10-fold cross validation)
4 predictors (PGA, PGV, PGD, D_{HAZUS})

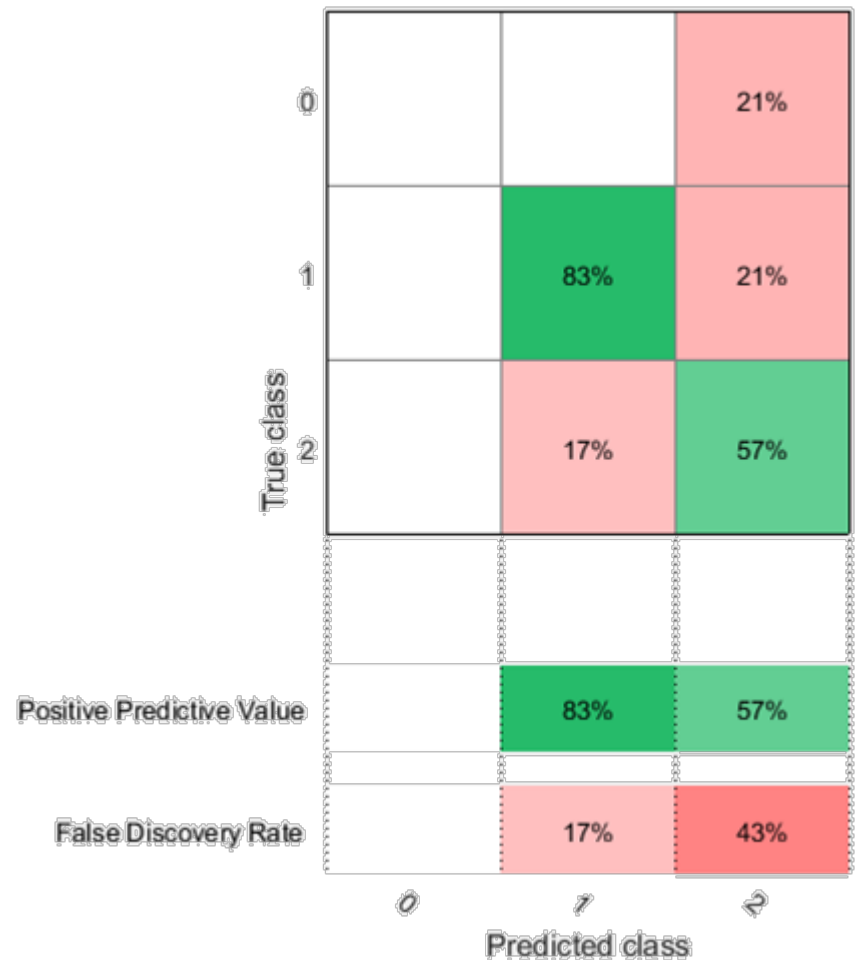
RESPONSE:

DS0 DS1-SGS DS1-GF DS2

Results for SGS only

- 26 samples of continuous, welded joint, steel pipelines from the database by Lanzano et al. (2015) for SGS
- 3 predictors (PGA, PGV, D)
- 3 responses classes
DS0 DS1-SGS DS2-SGS
- accuracy 69.2%
(Support Vector Machine Fine Gaussian, 10-fold cross validation)

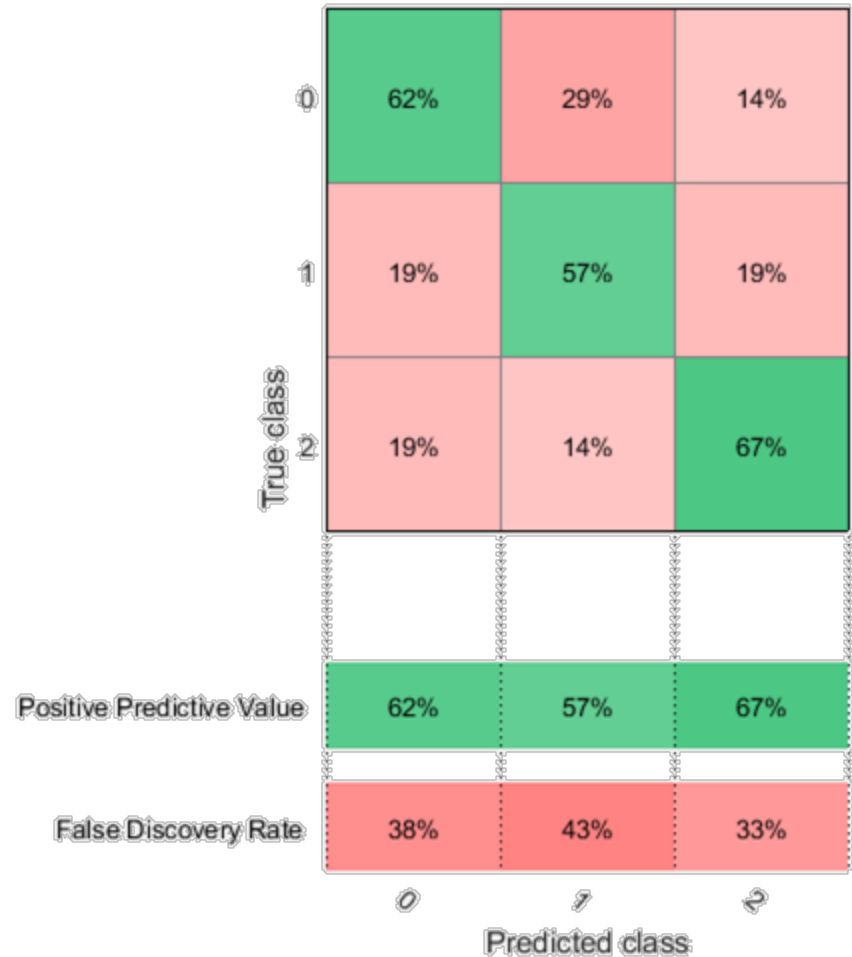
Machine learning classification



Results for GF only

- 56 samples of continuous, welded joint, steel pipelines from the database by Lanzano et al. (2015) for GF
- 4 predictors (PGA, PGV, PGD, D)
- 3 responses classes
DS0 DS1-GF DS2-GF
- accuracy 64.3% (Ensemble bagged Tree, 10-fold cross validation)

Machine learning classification



- The classification identifies the cause of a leak differentiating between DS1-SGS and DS1-GF in a single vulnerability model.
- PGD does not add much information and accuracy to the model for data considered.
- Diameter if considered as continuous variable is a better predictor

Potential Developments

- Accuracy can be improved with a different/improved data selection
- Comparison/Validation with analytical and experimental data
- Cascading risk application for fire risk



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Thanks for your attention



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Questions?



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