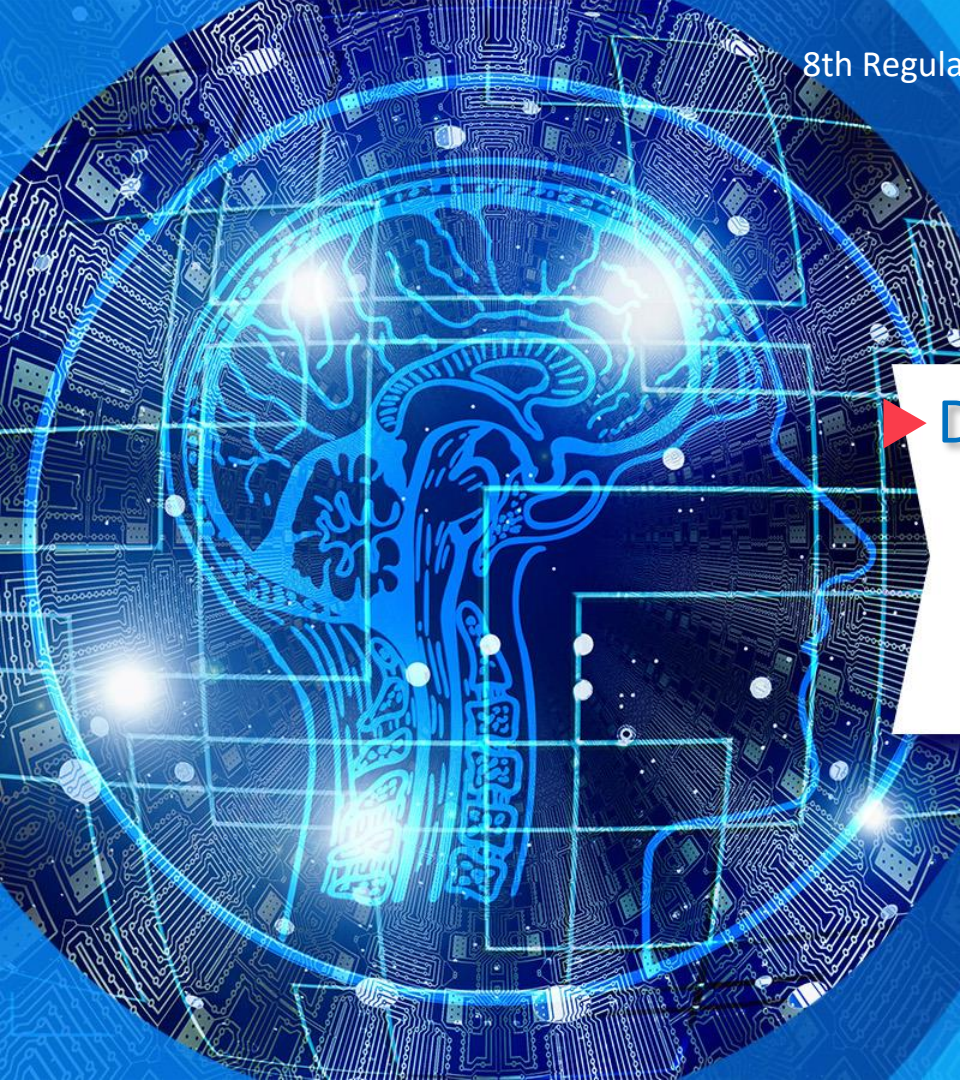


8th Regulating for Decent Work Conference  
Ensuring decent work  
in times of uncertainty  
10–12 July 2023, ILO Geneva



International  
Labour  
Organization



▶ Data Mining and Machine Learning:  
a cutting-edge technology  
supporting Labor Inspectorates to  
address undeclared work

Ada Huibregtse, Ph.D., International Labour Organization  
Eleni Alogogianni, Hellenic Labour Inspectorate

## Employment and Social Affairs Platform (ESAP) 2

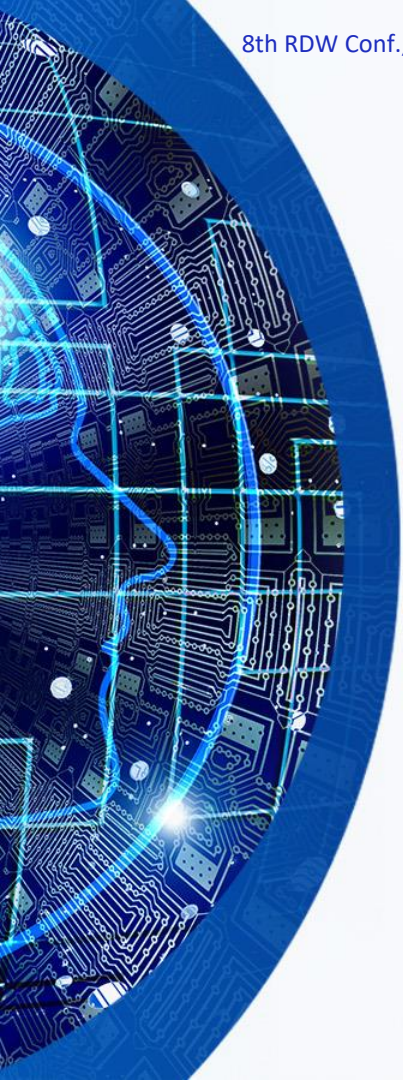

- This study was conducted as a part of ESAP 2
- Funded by the European Union
- Implemented by the International Labour Organization
- Western Balkans: Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, Serbia
- Albanian State Labor Inspectorate and Social Services (ASLISS)



## ILO and ASLISS: Intersecting Goals and Solution

- ESAP 2 Goal = ASLISS Goal: increase effectiveness in uncovering undeclared work and other labor law violations
- ASLISS proposal: Improve the existing Rules-Based Risk Assessment Tool
- ILO/ESAP2 proposal: Replace the existing one with a Risk Assessment System utilizing Data Mining and Machine Learning

# Theory

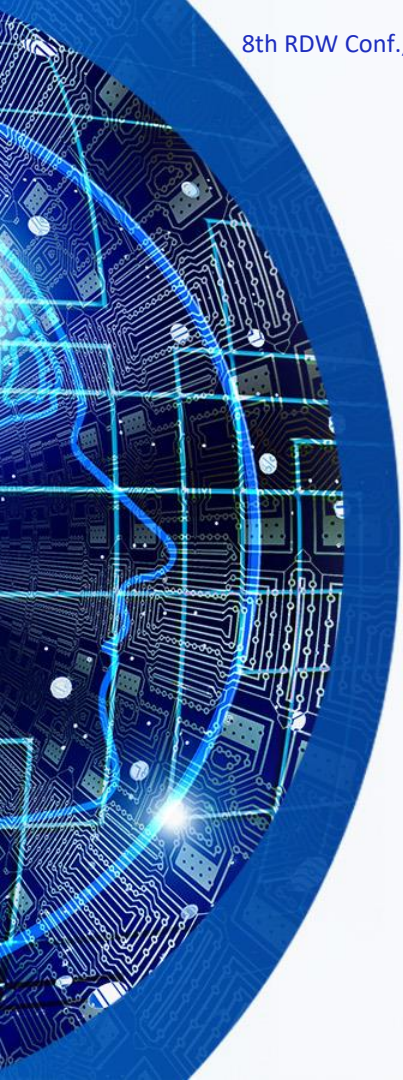
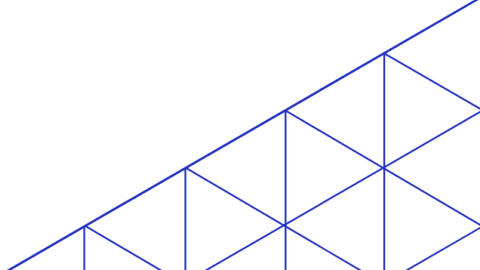
- 
- DM&ML has the capacity to:
    - Classify (patterns of compliance/non-compliance) and analyze large amounts of information about complex issues
    - With little to no induced human bias given that data is of high quality
    - Increase the accuracy of predictions of who, how frequently and when an employer is engaged in UDW
    - Generate and update knowledge about UDW
- 

# Theory

- When accurate predictions are incorporated into inspection planning, more inspection visits will identify cases of UDW than when they are not incorporated.
- Increased proportion of inspection visits identifying UDW will increase the overall institutional effectiveness.
- Increased inspection efficiency - the same input in terms of human, operation and financial resources is translated into more uncovered cases of UDW



# Theory

- 
- Assuming that labor inspection officials are interested in improving their institutions' performances, they will be willing to adopt DM&ML systems and use information and knowledge generated through these systems to identify actors, behaviors, and actions that challenge or support a labor inspectorates' probability of achieving their objectives and fulfilling their missions.
- 

# Hypothesis

- *If ASLISS replaces the current risk analysis tool, in which variables are assigned weights based on ASLISS officials' understanding of undeclared work, with a DM and ML risk assessment system (RAS) where human judgements and biases are kept to a minimum, the RAS will generate more accurate predictions about employers likely to engage in undeclared work.*

- 
- 
- ▶ A Machine Learning application study using real-life inspection data of the Albanian Labour Inspectorate



# The Business Environment

- 
- **The Albanian State Labor Inspectorate and Social Services (ASLISS)**
    - Performs inspections on Labor Relations and Occupational Safety & Health
    - Consists of its Central Offices at Tirana and 14 local departments countrywide
    - Employs 117 labor inspectors
  - **The labor market**
    - Consists of 123.2K active businesses & 177.5K company branches
    - Includes around 553K registered employees
  - **Hence, one inspector corresponds to:**
    - 1.5K company branches
    - 4.7K employees
- 

# The ASLISS Information System

- A Case Management System, the “Matrix of Penalties” (MOP)
- Installed in 2018, used by labor inspectors to insert and manage labor inspection cases
- Contains inspection data for the period 2019 – 2022
- Biannually, a file from the Tax Authority is uploaded with the companies’ data
- Each inspection case is linked with a company contained in the Tax Authority file
- Upon inspection case completion, the inspector fills in all the related inspection findings and results

# Data Sources

## ➤ From the **MOP**:

- Inspection cases performed in the years 2021 –2022
- Data drawn in the form of statistical reports

## ➤ From the **Tax Authority**:

- The active-companies file (end of 2022)

## ➤ Inspection data from 2019 – 2020 were not used due to:

- Quality issues:
  - missing data, wrong data
  - inspections not correctly linked with companies
- The focus of the 2020 inspections:
  - Advising companies for labor law provisions related to the Covid-19 pandemic



# Data Preparation

- **Integration** of the inspection cases with company data (from the Tax Authority file)
- **Data understanding and attributes selection & creation** as per the study goals
- **Data selection:** Based on the inspection date (2021 – 2022)
- **Data cleaning:** Inspection cases with null values in selected attributes were omitted
- **Data anonymization:** All data attributes identifying companies, inspectors and employees were discarded
- **Data discretization & categorization** of the attribute values:  
For improved understandability and transparency

# Dataset Attributes

➤ 8 categorical attributes & 12,660 inspection cases

Attributes	Values	Ratio %
INSPECTION TYPE	RA_PLANNED	80.94
	OTHER_INSP_TYPE	19.06
BUSINESS SECTOR	PRODUCTION	27.64
	SERVICES	29.84
	TRADE	24.05
	CONSTRUCTION	16.86
	TRANSPORT	1.61
EMPLOYEES	EMPL_1_10	45.24
	EMPL_11_50	33.67
	EMPL_51_200	14.53
	EMPL_OVER_200	5.47
	EMPL_NOT_DEC	1.10
COMPANY REGISTRATION	REG_LESS_5	16.03
	REG_5_10	30.97
	REG_10_20	35.49
	REG_MORE_20	17.51

Attributes	Values	Ratio %
LEGAL FORM	LIM_LIAB	66.86
	PHYS_PER	29.03
	OTHER_LF	4.12
COMPANY TYPE	LARGE	81.41
	SMALL_NO_VAT	14.45
	SMALL_VAT_OTHER	4.14
REGION	SOUTHWEST_REGION	18.30
	CENTRAL_REGION	51.55
	SOUTHEAST_REGION	16.57
	NORTH_REGION	13.58
RESULT	UDW	5.81
	GREY	15.46
	UDW & GREY	2.54
	OTHER_VIOL	63.23
	NO_VIOL	12.95

# Datasets Creation for Targeted Predictive Modeling



To enhance the machine-learning process:

- We create different and **focused datasets** based on the target violations, thus:
  - We transform a multi-class dataset to several binary ones
  - We eliminate irrelevant – to the target violation – data instances
  - We enable the creation of different models for targeted predictive modeling
- In this study, we created three focused datasets:

	UDW		GREY		UDW-GREY	
	YES	NO	YES	NO	YES	NO
<b>Total #</b>	1058	1640	2279	1640	3015	1640
<b>Ratio %</b>	39.21	60.79	58.15	41.85	64.77	35.23



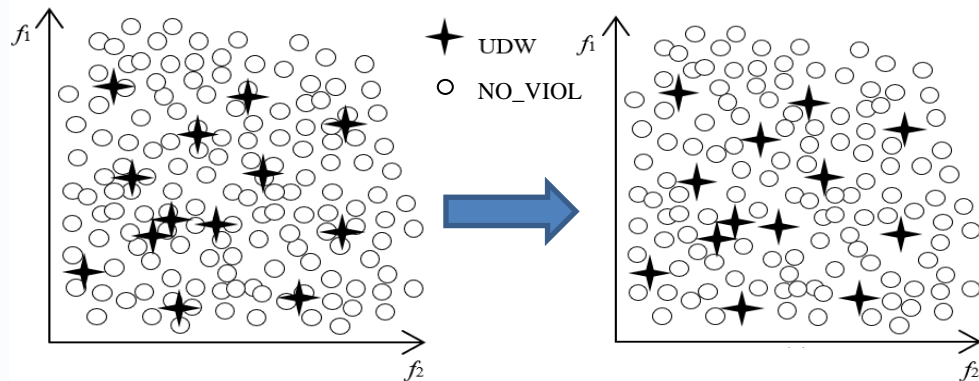
# Predictive Modeling

- 
- We employ Associative Classification (AC) to create predictive models
  - It is an advanced ML technique that combines Association Rule Mining (ARM) and Classification. It proves to offer:
    - Increased predictive accuracy compared to other DM and ML methods
    - Interpretability of the results:
      - Improving the inspectors domain knowledge
      - Enhancing the inspectors trust in the models' outputs
  - It produces Class Association Rules (CARs) of the form *if-then*
  - Training & testing is based on the **Stratified 10-fold Cross Validation method**
  - At the end of the process, classification results for all data instances are collected and placed in the **Confusion Matrix**
- 

# Data Engineering for Enhanced Prediction of Violations

**Elimination of the negatives that fall on positives in the training set:**

- Applied when:
  - There is a class imbalance in the dataset
  - The cost of misclassifying positives is much higher than the cost of misclassifying negatives
- To enhance the identification of the patterns related to the positive class
- To promote the prediction to the positive class



# Evaluation Metrics

## ➤ Evaluation based on the Confusion Matrix

- TP & TN: Cases classified correctly
- FP & FN: Cases classified wrongly

ACTUAL CLASS	PREDICTED CLASS	
	YES	NO
YES	TP	FN
NO	FP	TN

## ➤ Evaluation metrics:

- **Accuracy (Acc)** =  $(TP + TN) / (TP + FN + FP + TN)$

The ratio of the correct classifications

- **Error Rate (Err)** =  $(FP + FN) / (TP + FN + FP + TN)$

The complementary value of Accuracy – The ratio of misclassifications

- **Precision (p)** =  $TP / (TP + FP)$  – model's exactness

The ratio of Positives correctly predicted to all predicted Positives

- **Recall (r)** =  $TP / (TP + FN) = TP / P$  – model's completeness

The ratio of Positives correctly predicted to all actual Positives

- **F1-score** =  $(2 * p * r) / (p + r)$

The harmonic mean of Precision and Recall

- **Specificity (s)** =  $TN / (FP + TN) = TN / N$

The ratio of True Negatives to all actual Negatives



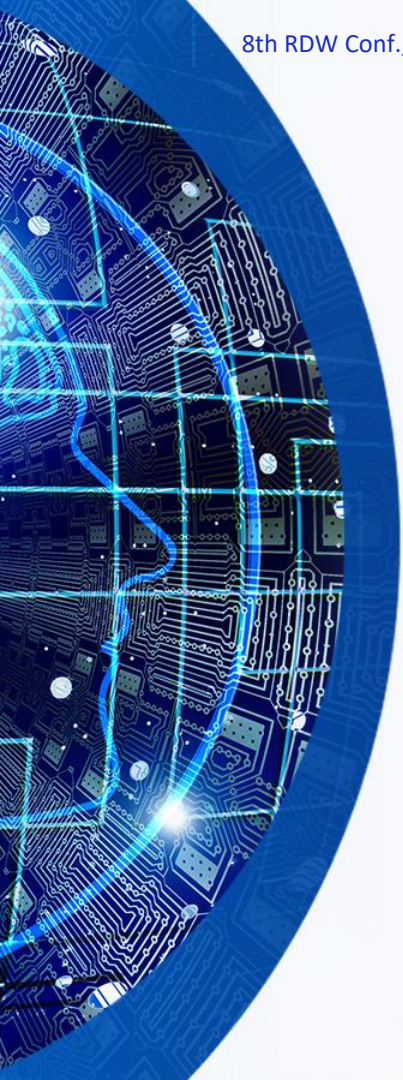
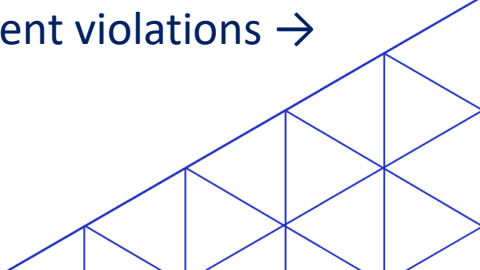
# Prediction Performance Results

- 4 models are constructed & evaluated for their prediction performance

Prediction Performance Metrics of the Models						
Model	Acc	Err	Precision	Recall	F1-score	Specificity
UDW	<b>70.64</b>	29.36	<b>63.63</b>	58.7	61.07	78.35
UDW (no overlaps)	62.19	37.81	51.11	<b>82.42</b>	63.09	49.15
GREY	64	36	65.63	<b>79.95</b>	72.09	<b>41.83</b>
UDW_GREY	66.23	33.77	69.31	<b>85.9</b>	76.72	<b>30.06</b>

- The UDW model proves highly successful (Acc):  
70.64% success >> 39.21% of the UDW dataset (current rate)
- The UDW-no-overlaps model identifies more than 82% of the UDW cases
- The GREY and UDW\_GREY models exhibit very high Recall but low Specificity: they mispredict several negatives as positives → they may trigger unnecessary inspections
- More negative cases should be included in the training data to help the models learn better

# Models Interpretability

- 
- Interpretability is achieved through:
    - Descriptive feature values understandable to the domain users
    - The use of an interpretable ML technique, such as AC
  - The models offer interpretable outputs:
    - They explain why a company should be inspected → Increasing the users' confidence in following the models' suggestions
    - They reveal the patterns linked with the different violations → Enhancing the users' domain knowledge
- 

# Findings

- Some of the CARs produced by the **UDW classifier**:

Attribute values	UDW
SERVICES, EMPL_1_10, REG_5_10, SMALL_NO_VAT, SOUTHEAST_REGION	YES
RA_PLANNED, SERVICES, REG_5_10, PHYS_PER, NORTH_REGION	YES
RA_PLANNED, EMPL_OVER_200, REG_10_20	NO
TRADE, REG_MORE_20, CENTRAL_REGION	NO

- Inspect employers in the services sector, with up to 10 employees, in operation between 5 to 10 years, with turn over small enough not to pay VAT, in the south-east region.
- Do not inspect employers in the trade sector, with more than 20 years of existence, in the central region.



# Findings

- Some of the CARs produced by the **Grey Work classifier**:

Attribute values	UDW
TRADE, EMPL_1_10, REG_10_20, SOUTHEAST_REGION	YES
PRODUCTION, EMPL_11_50, REG_10_20, LIM_LIAB, CENTRAL_REGION	YES
RA_PLANNED, EMPL_1_10, LIM_LIAB, LARGE, NORTH_REGION	NO
TRADE, EMPL_1_10, SMALL_NO_VAT	NO

- Inspect employers in the trade sector, with up to 10 workers, in operation between 10 to 20 years, in the south-east region.
- Do not inspect employers in the trade sector, with up to 10 workers, with limited liability status in the north region.

# Findings

- Some aspects of the current ASLISS inspection targeting **prove wrong:**
  - **Planned inspections are less successful** than other inspection types, yet 8/10 of the inspections are still planned by the current Risk Analysis tool

Type of inspection	Revealing UDW	Revealing GREY	ASLISS's inspections
PLANNED	7.82%	16.70%	<b>80.94%</b>
OTHER_INSP_TYPE	<b>10.61%</b>	<b>23.50%</b>	19.06%

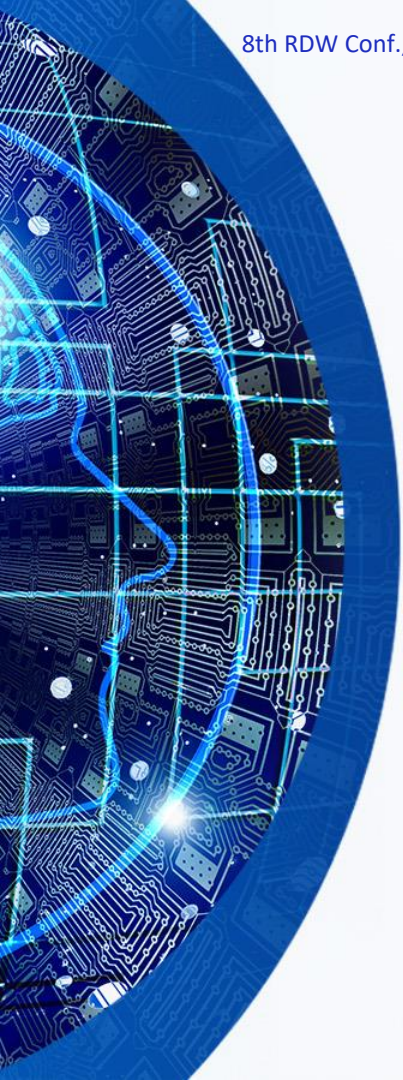

# Findings

- **The ratio of inspections per business size** does not follow the labor market businesses size rate, nor the percentage of revealed undeclared work per business size:

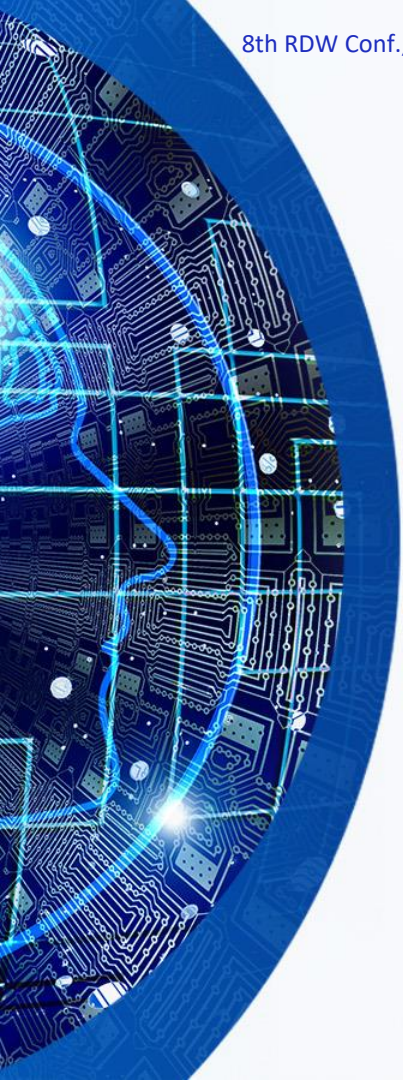
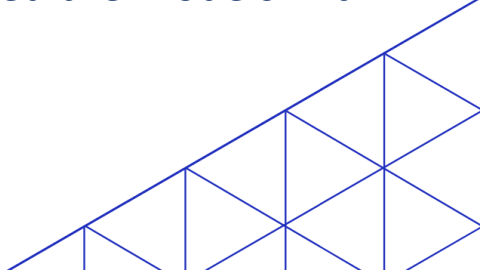
Business size (As per the number of employees)	Labor market (INSTAT 2021)	Ratio of revealed UDW	Ratio of revealed GREY	ASLISS's inspections
1 – 10 employees	93%	69.09%	43.66%	45.24%
11 – 50 employees	5.39%	22.21%	33.13%	34.33%
Over 200 employees	< 0.5%	2.08%	1.23%	5.47%



# Findings

- 
- Inspections triggered as result of any other reason except planning are better predictors of incidence of undeclared or GREY work
  - Micro- to small-size enterprises more likely to engage in UDW, while middle-size enterprises in GREY work
  - UDW and GREY work are more frequently uncovered in the Southeast – ( region less compliant or labor inspectors more rigorous?)
  - UDW is more frequently uncovered in the services sector, while GREY work in the trade and production ones
- 

# Conclusions

- 
- DM and ML can contribute in:
    - Improving the Labor Inspectorates' effectiveness and efficiency
    - Faster and smarter decision-making on resources allocation
    - Strategic planning through accumulation and update of knowledge
  - Further improvement in predicting violations can be achieved:
    - With more inspection data for training the models
    - By using data engineering to cure issues in data (imbalance, overlaps)
    - By performing some random inspections to feed the models with new labor market trends
- 



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Thank you for your attention!

Questions?

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