## **Too good to be true?** Machine learning in the editing process

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### Machine Learning in Editing (MLiE)

 Research question: How can we use machine learning to improve the editing process?

 Our case: Research and development (R&D) in the Norwegian Business Sector



#### The current editing process is...

- inefficient
  - Mostly manual

- hard to transfer
  - Built on a lot of undocumented know-how

- very hard to reproduce
  - $\circ$  All that exists is a huge log



Loss in relevance and timeliness



Average time per			
editing	Hours	Man-hours	
30 seconds	8 839	5	
1 minute	17 677	10	
2 minutes	35 355	20	
5 minutes	88 387	50	
10 minutes	176 774	101	
20 minutes	353 548	202	

- Automate

Increase efficiency

- Avoid

#### Table 3.8. Data Used in Pilot Studies, Data Preparation Steps and Algorithms

Organisation	Data	Steps	Algorithms		
Editing					
Istat	Public Administration Database (BDAP) and the Information System on the Operations of Public Bodies (SIOPE)	Comparing several variables from the two sources, identifying different types of inconsistent data, list of units regarded as important to be analysed deeper delivered by subject matter experts, identifying edit rules behind such units	Decision Trees, Random Forests		
ONS	2018 Q2 and Q3 Living Cost and Food (LCF) survey data	Data preparation, calculation of the change vector, learning models to predict the change vector	Decision Trees, Random Forests, Neural Network		
	Imputation				
VITO	Quarterly data, ranging from Q1 2000 through Q1 2019	Z-standardisation of the data, feature selection for linear regression, calculating and comparing predictions	Linear Regression, Ridge Regression, LASSO, Random Forest, Neural Network, Ensemble Prediction		
Federal Statistics Office of Germany	German cost structure survey of enterprises in manufacturing, mining and quarrying	Creating missing values (several proportions, several missing mechanisms), calculating and comparing predictions	K-NN (weighted and non-weighted), Bayesian Networks, Random Forests, SVM		
Istat	Administrative information from the ministry of education, university and research, 2011 census data, sample survey data	Focusing on one region and on incomplete records, some manual feature selection, calculating and comparing predictions	MLP, Random Forests, Log-Linear Model		
Statistics Poland	Quarterly sample survey on participation of Polish residents in trips for 2016 to 2018 and some big data sources	Learning different models for estimation and comparing their predictions by several measures	Different kinds of (generalised) linear models, Regression Tree, Random Forest, K-NN, different kinds of SVM		

#### «Editing is a very realistic task for machine

#### learning algorithms»

• UNECE report 2022

UNECE

Machine Learning for Official Statistics







#### **Editing is Validation + Imputation**



Methodology for data validation 1.0 (europa.eu)



#### Data editing removes measurement error

- Overall goal:
  - Eliminate all sources of error that makes the survey value deviate from the true value (Total Survey Error)

- Goal in our study:
  - Eliminate measurement error





## Two machine learning problems constitute MLiE

• **The prediction problem**: Create a machine learning algorithm that predicts the individual responses to a survey.

• The classification problem: Create a machine learning algorithm that classifies that resulting survey dataset into *valid* and *not valid* responses.





## The prediction problem

5. Specify the expenditures for R&D performed within the enterprise in 2020. All costs shall be specified without VAT. For more information, we refer to the guidelines given on the last page.			
Intramural current costs for R&D			
Compensation of R&D employees	000 NOK		
Cost of the [X] man-years performed by contracted R&D personnel (specified in question 3)	000 NOK		
Other current costs to R&D (without depreciation).	000 NOK		
(Acquisition of R&D services shall not be specified here, but in question 11)			
Investment costs for R&D (purchase value), without depreciation			
Buildings, property, etc. for R&D	000 NOK		
Machinery, equipment, instruments, etc. for R&D	000 NOK		
Total intramural R&D expenditure	000 NOK		

• Focus on the *intfou* variable

• Intramural R&D expenditure

- One of the main variables in the R&D survey
- The total of:
  - Compensation to R&D employees
  - Cost to hired R&D personnel
  - Other current costs
  - Investments



## Measurement error in the *intfou* variable can be categorized into:

- "Thousand-error"
- Report daughter companies' R&D
- Not having correct or enough information
- Misunderstand terminology (e.g. "own employees" vs. "hired personnel")



Data - Processed - Raw



## **Data wrangling**



- Collect and merge datasets
- Remove duplicates
- Identify and flag outliers
- Impute and/or remove missing values

#### Final: Survey timeseries 2011 - 2021



#### **Research framework**

• Y<sub>ikt</sub> = function(predictors)

- $\circ$  Y = expected value
- for enterprise *i*
- $\circ$  for variable k
- for year *t*



#### Regression

#### Y = expected R&D expenditure

#### $int fou_{it} = \alpha + \beta_1 int fou_{it-1} + \beta_2 int fou_{it-2} + \beta_3 int fou_{it-3} + \beta_4 int fou_{it-4} + \beta_5 int fou_{it-5} + \beta_6 int fou_{it-6} + \varepsilon$



## High correlation between last year and this year





## **Deciding on the model**

- Linear relationships allow for
  - OLS
  - Lasso
  - Ridge
  - ElasticNet
- Benefit: Easier to interpret than more complex models





### **Challenge: Very imbalanced data**





#### **Preliminary results**

- If a company does not perform R&D, it is unlikely to perfom R&D next year.
- Historical values account for 60% explained variables for only R&D enterprises. Something else must be causing the other 40%.
  - From interviews we suspect structual data, M&As, Demergers may play role.

	Explained variance	RMSE
Linear	0.93	9664
Ridge	0.93	9723
Lasso	0.93	9651
Elastic Net	0.80	16296

Tab 2: Model performance for all enterprises

	Explained variance	RMSE
Linear	0.60	25624
Ridge	0.60	25496
Lasso	0.60	25654
Elastic Net	0.67	23154

Tab 3: Model performance for R&D enterprises only



## **Future work**

- Increase model performance for R&D enterprises only by include more variables. Specifically, M&A data.
- Develop classification algorithm.
- Generalise methodology.





## **Other survey errors:**

- Measurement validity
  - Clear definitions
  - Good examples
  - Visit and interview enterprises
  - Training in enterprises





## **Other survey errors:**

#### Processing error

- Machine learning algorithms
  reproduce processing errors from
  training data
- Using other sources to doublecheck the training data, e.g. annual reports, call enterprises, read reports, do field research, etc.





# Thank you!



**Statistisk sentralbyrå** Statistics Norway