Vincenzo Lanzetta

Deep learning methods for scenario analysis and predictions of complex systems

Tutor: Prof. R. Prevete Cycle: XXXVII

Year: third

My background

- MSc degree: Chemistry
- Second MSc degree (to be completed - 4 exams left): Statistics
- laboratory: AIPA
- PhD start date: November 1, 2021
- Scholarship type: no scholarship

Summary of study activities

	Courses	Seminars	Research	Tutorship	Total
Total	31	11	138	0	180
Expected	30 - 70	10 - 30	80 - 140	0 – 4.8	180

<u>Topic's relevant PhD courses:</u>

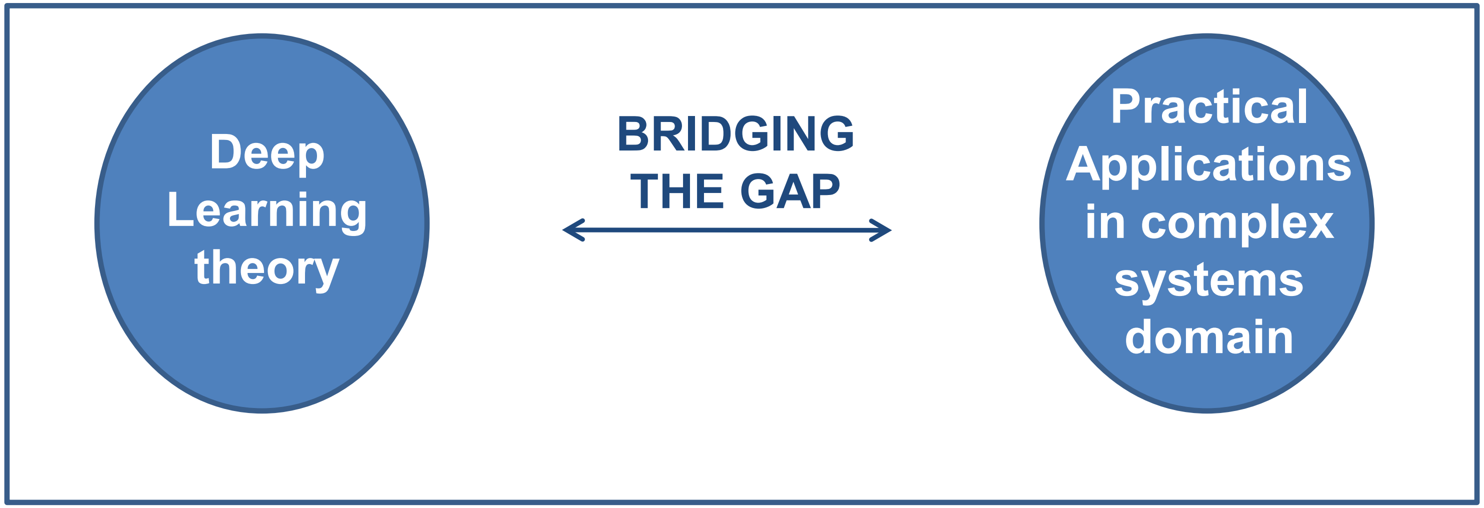
- Machine Learning for Science and Engineering Research
- Using deep learning properly
- Statistical data analysis for science and engineering research

PhD thesis overview

- Problem statement:

  Deep Learning methods for scenario analysis and predictions of complex systems.

- Objective:



Specific complex research areas, and main results

Financial markets: not linear interactions and dependencies.

Social systems: influenced by socio-economic, cultural, and political factors.

Main results	Main results
Filling the gap for **review** lack on TL(*) for financial predictions	Filling the gap between theory and adopted tools for policies purposes
Insights on TL potentiality by **experimenting**	A **new methodology** for overcoming issues of current tools

(*) TL = Transfer Learning

Agenda

Topic	Details
Part I – Transfer Learning for complex systems predictions, with focus on financial market	Problem and objective
	What emerges from literature
	Literature gap and research questions
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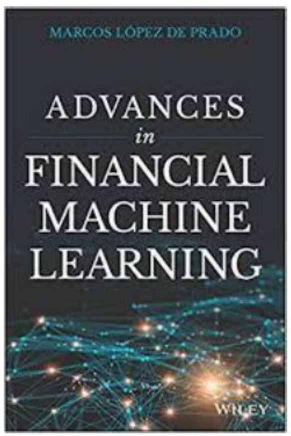
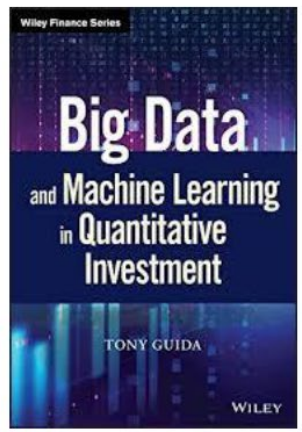
Part I – problem and objective

Problem:

*Financial industry **demands for new methods** aimed at capturing non-linear relationships, in the financial market data, for prediction purposes*

•<< A key argument for applying ML techniques to financial problems is that ML methods capture non-linear relationships in the data.>>[*]





•<< the literature regarding financial market prediction using machine learning is vast>> [**]

•<<there is a wide range of ML techniques being successfully applied to many areas in the development of quantitative investing strategies[*]

Objective

***Reviewing** and **experimenting** TL approaches for financial market predictions*

(*) S. Emerson et al., 2019
(**)B. M. Henrique et al., 2019

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Part I – what emerges from literature

Financial market data
Depending on fundamentals, noise and news
Not linear in nature
ML(*) is better then traditional statistical methods for predictions
Neural Network as main ML tool for financial predictions
TL as a potential useful tool

(*) ML = Machine Learning

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Part I – literature gap and research questions

Literature gap
Lack of literature reviews focused on TL for financial predictions

Research questions
1) How TL has been applied for financial market predictions?
2) Which are challenges and potential future directions of TL for financial market predictions?

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Part I - methodology

Methodology

1) A **systematic review** on TL approaches for financial predictions

Systematic approach of the conducted review	
1	Definition of filters (years, subject area, search words...)
2	Defining the data extraction form (problem taxonomy, …)
3	Conducting the systematic research
4	Summary of the reviewed papers
5	Answer to research questions
6	Conclusions

2) **Experimenting** ML methods to perform financial predictions

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Part I – results (reviewing step)

Main results
TL for accelerating training
TL for over-fitting problem
TL for discovering asymmetric causal structure between domains
TL for overcoming data scarcity issue

Challenges and future directions
Number of domains for pre-training step
Factors influencing selection of source domain data
Possible error propagation issue due to sequential training
Impact of different learning mechanism on TL performance
TL within the explainable Artificial intelligence framework

Part I – results (experimenting step)

Tested dataset	
1	Daily index market data
2	Daily stock data
3	Daily Forex data
4	Hourly index market data
5	Hourly Forex data

Experimented ML Techniques	
1	Feed Forward NN
2	CNN
3	LSTM
4	CNN-LSTM
5	XGBoost

"Out of bag" features

- SPY
- 1 day timeframe
- 1 step ahead to be predicted
- **1386 data to be predicted (from jan 2007 to aug 2012)**
- BUY threshold = +0.60%

Results on an unbalanced "out of bag" dataset
• Actual frequency of class 1 = 52%
•Precision of predictions for class 1 = 64%

our AI works rationally, as its precision (64%) is better than the one of an irrational predictor (52%) that makes predictions by always predicting the same class

e on BUY signal for SPY: Class 1 means a price percentage increase > + 0,60% (+0,60% is the trained threshold) for current daily with respect to previous 1 day bar close price

Part I – results (products)

Products:

1) Paper (completed, to be submitted): <<Transfer learning for financial data predictions: a systematic review>> (arXiv:2409.17183)

2) Startup/Spin-off project: PredictionLabs.ai

Not secure | predictionlabs.ai/login

Stock Signals

SIGNAL TIME	Stock	Difference in time in minute	Starting Time	Closing Time	Target price	Take profit price	Stop loss price	Probability Prediction for Class 1	SUGGESTED STRATEGY
17/07/2023, 09:01:00	AUD_USD	60	17/07/2023, 09:00:00	17/07/2023, 10:00:00	0.68005	0.680662	0.679438	0.53	BUY

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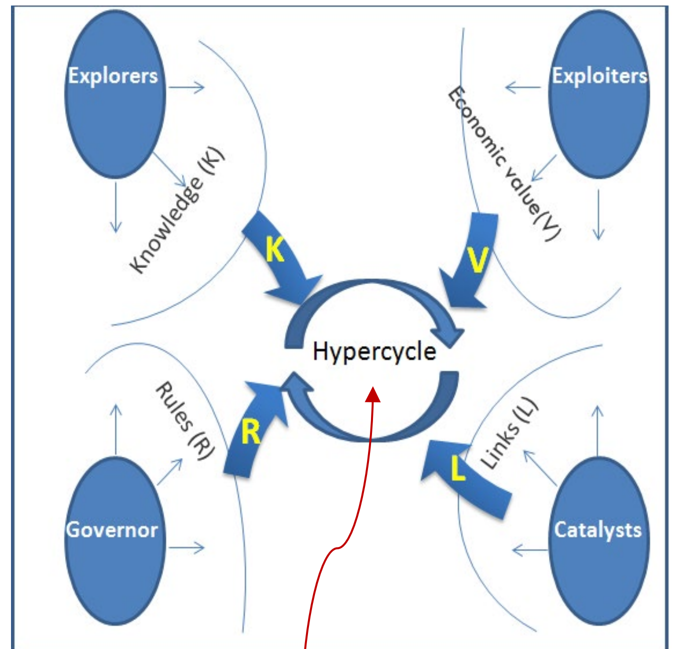
Part II – problem and objective

Problem:

***Need for new AI-based methods** for policies options purposes, to capture complexity behind regional innovation*



Emergence of regional innovation

Objective

New methodological approaches to grasp intrinsic complexity of regional innovation capability

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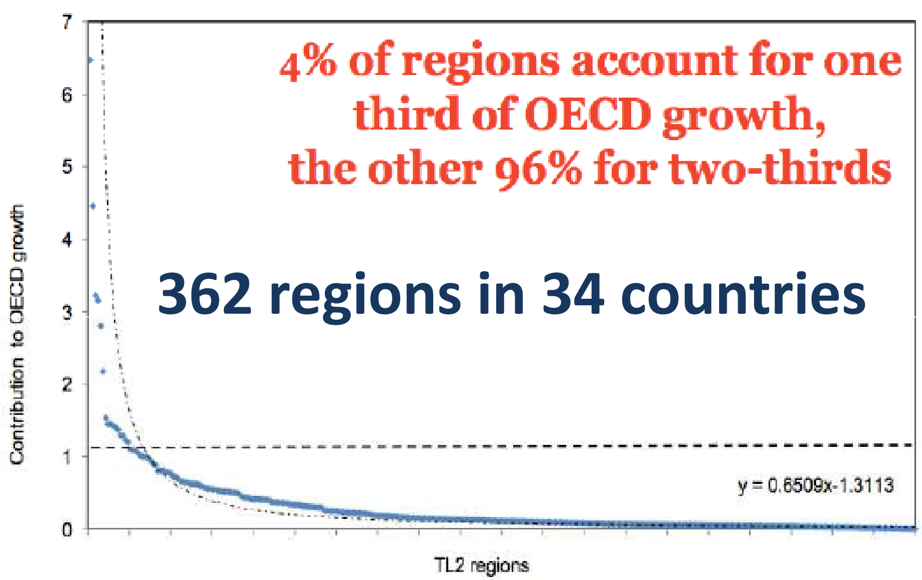
Regions as locus of innovation

Contribution to OECD growth (TL2 regions, 1995-2005)



Source: OECD (2011) *Regions and Innovation Policy*, OECD publishing, Paris based on Garcilazo , E. and J. Oliveira Martins (2010) , "The Contributions of Regions to Aggregate Growth", paper presented to the Annual ERSA Conference, Stockholm, August 2010.

Part II - What emerges from literature (2/3)

Mismatch between composite indicator methodology and complexity theory

Correlations among innovation variables

Composite indicator (*) methodological weakness of EURIS

(*) Regional Innovation Index = unweighted average of indicators normalised scores

Part II - What emerges from literature (3/3): claims

1. EURIS as tool for over-time analysis of innovation indicators, and **not for policies formulation**

2. Need to **complement EURIS with a new tool** for what-if policy options

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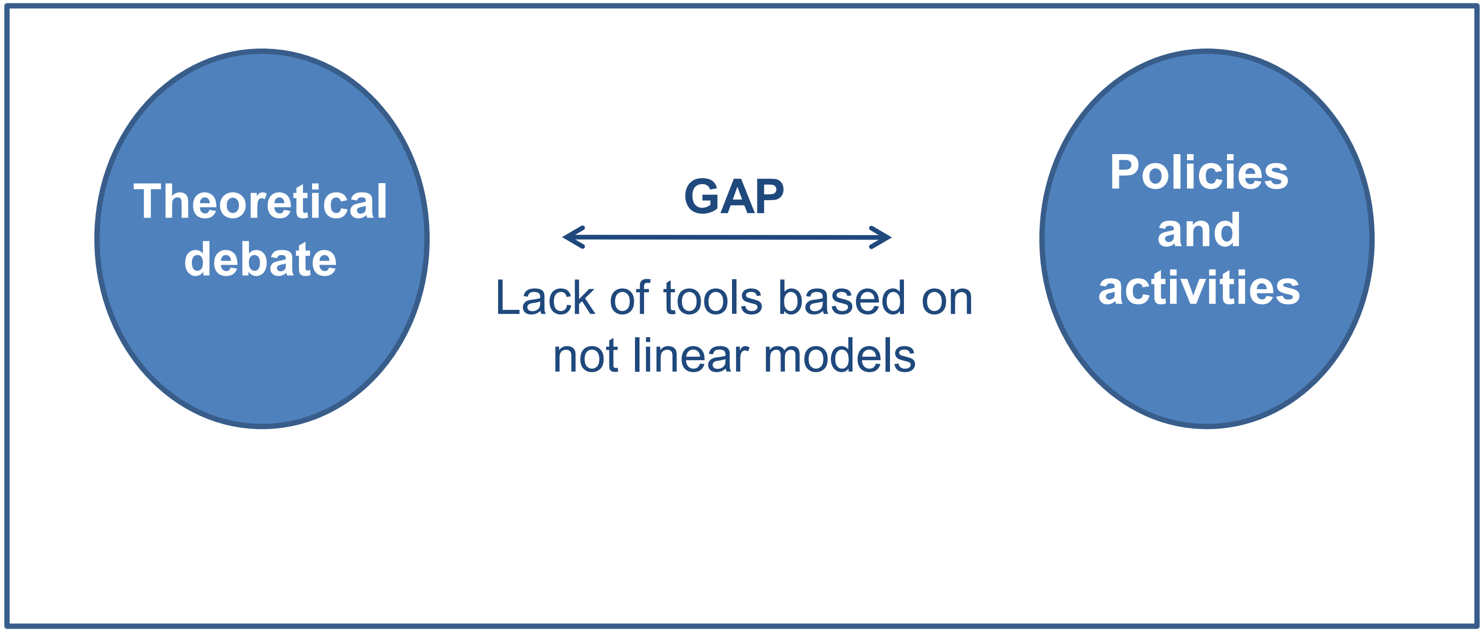
Part II - literature gap and research questions



Research questions
1) Which is the belonging cluster of each region?
2) What are the most effective policies for each region?

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Part II – Methodology (1/3)

Goal

How to valorize – for policies formulation – the EURIS outputs?

Output

New methodological model as synergistic tool of the EURIS

Part II – methodology (2/3)

Theoretical criteria for methodology selection

Regions grouping task	Theoretical criteria of ideal methodology	Suitable solution
Considering complexity of the innovation process	Not linear modelling	Clustering
Overcoming the information redundancy due to correlations	Grouping regions on latent variables, not correlated by costruction	Joint dimension reduction and clustering of data

Factorial K-means (FKM) - while reducing original variables to a minimal number of uncorrelated latent variables - develops dense clusters (*)

(*) minimum "within" variance of the clusters in the reduced space

Part II – methodology (3/3)

FKM detailed task	Theoretical criteria	Suitable solution
What-if tool for policy options	**Neural Networks**(*) for complex relationships between innovation latent factors and innovation labels	Complementing the EURIS with a FKM-NN tool

(*) Hajek & Henriques, 2017; de la Paz-Marín et al., 2012; Pei et al., 2022

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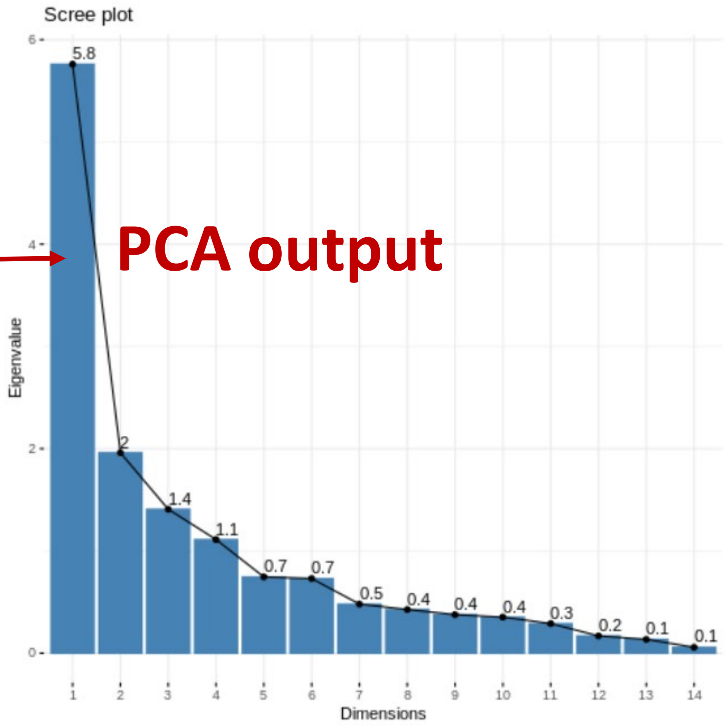
Part II – results (1/11)

Values to be used as input parameters of FKM

Clusters number	Reason
4	Equal to EURIS groups number

PCA output



Factor number	Reason
2	**PCA(*) output**, according to: - Eigenvalues greater then one rule - Scree diagram - Interpretability

(*) on standardized original variables

Part II – results (2/11)

Meaning of FKM(*) latent variables

```
Variable scores:
                                                          Dim.1   Dim.2
1.1.2 Population with tertiary education                -0.1814 -0.0848
1.1.3 Population involved in lifelong learning          -0.1226 -0.3924
1.2.1 International scientific co-publications           0.1413 -0.2008
1.2.2 Scientific publications among the top 10% most cited 0.0260 -0.4246
1.3.2 Individuals with above basic overall digital skills -0.1981 -0.3416
2.1.1 R&D expenditure in the public sector               0.6283  0.0470
2.2.1 R&D expenditure in the business sector             0.5583 -0.0758
2.3.2 Employed ICT specialists                          -0.0916 -0.0013
3.2.2 Public-private co-publications                     0.2782 -0.2327
3.3.1 PCT patent applications                            0.2617 -0.3602
3.3.2 Trademark applications                            -0.1005 -0.3239
3.3.3 Design applications                               -0.0125 -0.2420
4.1.1 Employment in knowledge-intensive activities       0.1127  0.0894
4.3.2 Air emissions by fine particulates                 0.0920  0.3718
```

Original variables scores on selected FKM principal components (PC)

Component	Meaning	Reason
First	Level of R&D spending	Regions, that spend a lot on R&D, have positive and high values for first PC
Second	Technical-scientific "lag" of individuals belonging to a region	Regions, whose individuals have low technical-scientific capacity, have a high value for second PC

(*) FKM on standardized original variables

Part II – results (3/11)

Centroids scores analysis on FKM adopted latent variables, to understand clusters features through latent variables meaning

	Dim.1	Dim.2
Cluster 1	-0.6229	1.7000
Cluster 2	0.3154	0.0069
Cluster 3	-0.2612	-0.9912
Cluster 4	1.4111	-2.4441

Table 5: scores of cluster centroids

Clusters features

"output_ cluster from ClusPca package" result	Centroids' scores suggestions
4	Maximum level of regional R&D expenditures and minimum level of technical-scientific "lag" of individuals belonging to region
2	Medium-Maximum level of regional R&D expenditures and medium-maximum level of technical-scientific "lag" of individuals belonging to region
3	medium-minimum level of regional R&D expenditures and medium-minimum level of technical-scientific "lag" of individuals belonging to region
1	Minimum level of regional R&D expenditures and maximum level of technical-scientific "lag" of individuals belonging to region

Used dataset (without label) for cluspca function in R: Output_all_original_WITHOUT_C_VALUES_OR_EMPTY_VALUES_inserted_converted_label_without_Performance_Group.xlsx

Part II – results (4/11)

FKM clusters ranking(*)

	Dim.1	Dim.2
Cluster 1	-0.6229	1.7000
Cluster 2	0.3154	0.0069
Cluster 3	-0.2612	-0.9912
Cluster 4	1.4111	-2.4441

Table 5: scores of cluster centroids

Euclidean distance of cluster 2 and 3 – with respect to best in class cluster (number 4) – to define their ranking position

Innovation ranking among 4 clusters emerged by FKM

Assigned cluster by our methodology	Innovation ranking among clusters
4	First position
3	Second position
2	Third position
1	Fourth position

(*) based on centroids scores on FKM adopted latent variables and on meaning of FKM adopted latent variables

Part II – results (5/11)

Labelling step

EURIS labels
Innovation leaders
Strong Innovators
Moderate innovators
Emerging innovators

Assigning EURIS label names to FKM clusters, according to FKM clusters ranking

Assigned cluster by our methodology	Innovation ranking among clusters	Final label assignment of our methodology
4	First position	Innovation leader
3	Second position	Strong innovator
2	Third position	Moderate Innovator
1	Fourth position	Emerging innovator

Developed a FKM "EURIS-based" labelled dataset!

Part II – results (6/11)

Highlights on FKM capabilities

More cohesive regional groups for policymakers, with respect to the EURIS ones (*)

A NN what-if approach - on FKM "EURIS-based" labelled dataset – to define more targeted and effective policies !

(*) FKM develops a cluster allocation that minimizes the "within" variance of the clusters in the reduced space (Markos et al., 2019)

Part II – results (7/11)

Neural Network characteristics, for what-if analysis

14 features and **1912** observations (training:1146; validation: 382; test :384)

Binary label:	1 = cluster 4 (Innovation leader) "belonging"; 0 = cluster 4 (Innovation leader) "not belonging"
Scaling of the data:	MinMax procedure between -1 and + 1
Resampling method:	Undersampling
NN Architecture:	____________________ Layer (type) Output Shape Param # ==================== conv1 (Conv2D) (None, 3, 16, 32) 320 flat1 (Flatten) (None, 1536) 0 dense (Dense) (None, 100) 153700 dense2 (Dense) (None, 1) 101
Features within the Keras Tensorflow framework:	Conv2D(32,(3,3), padding = "same",activation = 'relu') Dense(100,activation = 'relu') Dense(1,activation = 'sigmoid') keras.optimizers.Adam(learning_rate = 0.01) epochs = 200 batch_size = 32
Threshold for classification	0,50 (i.e.: if predicted probability > 0,50 then predicted class = 1; otherwise, predicted class = 0)

Part II – results (8/11)

NN test set results

Confusion matrix	[333 4] [1 46]
Classification report	<table><tr><td></td><td>precision</td><td>recall</td><td>f1-score</td><td>support</td></tr><tr><td>0</td><td>1.00</td><td>0.99</td><td>0.99</td><td>337</td></tr><tr><td>1</td><td>0.92</td><td>0.98</td><td>0.95</td><td>47</td></tr></table>
Accuracy	0.987

Part II – results (9/11)

What-if analysis on Campania region case study (based on 2023 Campania's condition: "Moderate Innovator")

Progressive policy number	Progressive changes in innovation indicator for Campania region	Predicted probability for the belonging of Campania to Innovation Leader cluster of the Factorial K_means
1	R&D expenditure in the business sector (from 2023 value of CAMPANIA: 0.63 - to 2023 value of HANBURG: 1.22)	2.66 e-06
2	R&D expenditure in the public sector (form 2023 value of CAMPANIA: 0.68 - to 2023 value of HANBURG: 1.04)	2.52 e-06
3	Employment in knowledge-intensive activities (from 2023 value of CAMPANIA: 13 - to 2023 value of HANBURG: 21.8)	2.8 e-04
4	Employed ICT specialists (from 2023 value of CAMPANIA: 3.03 - to 2023 value of HANBURG: 8.53)	0.39
5	Employed ICT specialists (from 2023 value of CAMPANIA: 3.03 to BERLIN 2023 value: 11.8)	0.98

98%

Campania's policies suggested path, from «Moderate Innovator» to «Innovation Leader»

Part II – results (10/11)

Capabilities of NN what-if tool on FKM “EURIS-based” labelled dataset
Showing potential effectiveness of a specific innovation policy
Showing policies path to potentially push a region into an upper cluster

Process of European regional innovation Policy-making	Details
Current	**Subjective** policies formulation [based on EURIS original dataset (*)]
Proposed	**More objective** policy formulation [through NN what-if tool based on FKM “EURIS-based” labelled dataset]

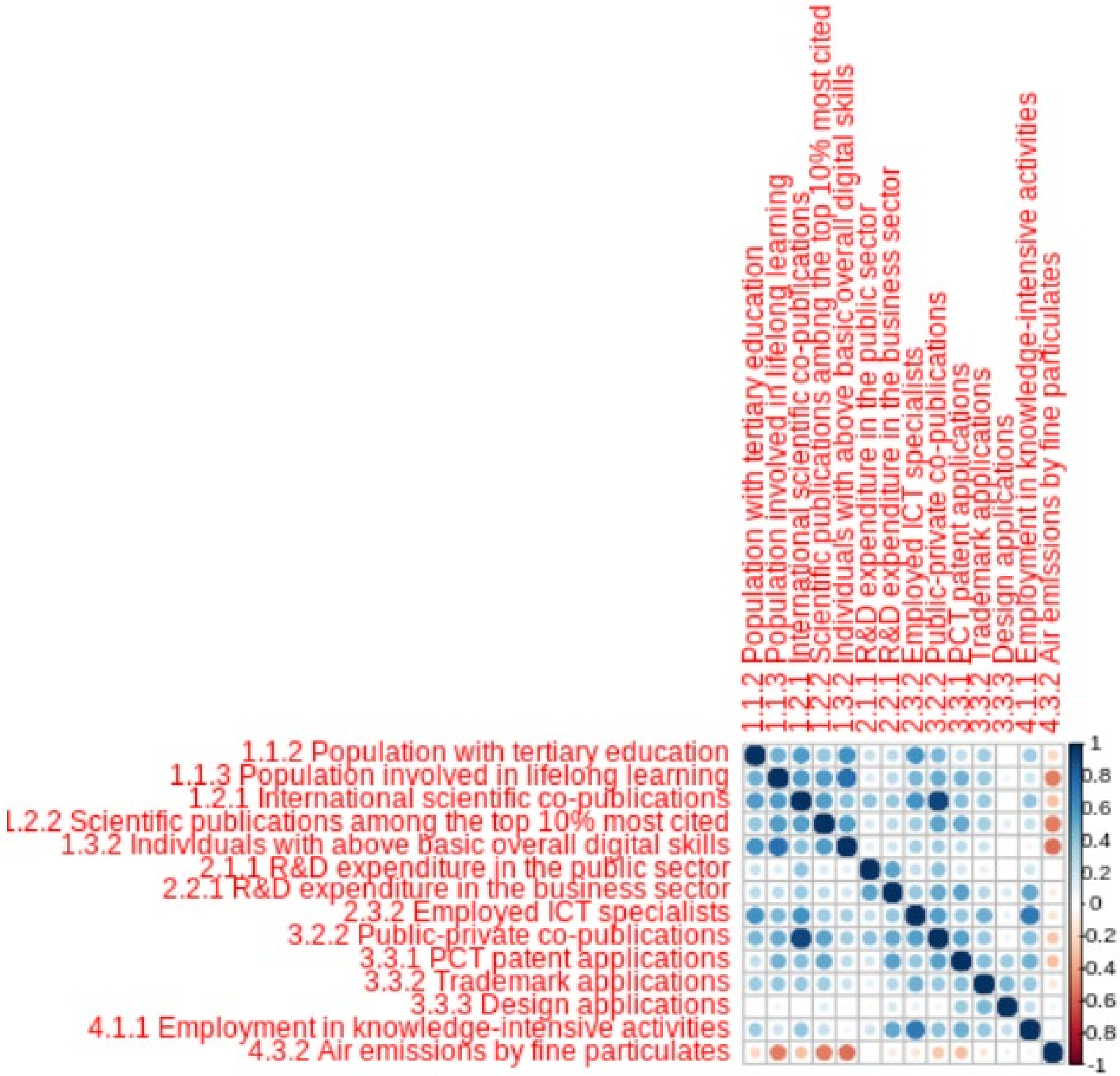
Part II – results (11/11)

Products:

- Paper (completed, to be submitted): <<Why do we need to complement the European Union Regional Innovation Scoreboard with a cluster-neural network tool for what-if policy analysis?>> (arXiv:2409.13316)

Thank you for your attention

Annex - EURIS variables correlations



Annex – selected variables and observations number

14 selected indicators (only those without empty values)

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Region	**1.1.2 Population with tertiary education**	**1.1.3 Population involved in lifelong learning**	**1.2.1 International scientific co-publications**	**1.2.2 Scientific publications among the top 10% most cited**	**1.3.2 Individuals with above basic overall digital skills**	**2.1.1 R&D expenditure in the public sector**	**2.2.1 R&D expenditure in the business sector**	**2.3.2 Employed ICT specialists**	**3.2.2 Public-private co-publications**	**3.3.1 PCT patent applications**	**3.3.2 Trademark applications**	**3.3.3 Design applications**	**4.1.1 Employment in knowledge-intensive activities**	**4.3.2 Air emissions by fine particulates**	**Original_label(1_innovation_leader;2=strong;3=moderate;4=emerging;)**
AT1 - Ostösterreich_2023	47.1	16.2	3077.67	11.14291	33.51037	1.23	1.57	6.499569	620.6765	3.275195	12.90797	4.041177	17	10.4488	1
AT2 - Südösterreich_2023	39.7	13.5	2292.242	9.240662	32.75709	0.97	3.6	2.926125	768.1155	5.205167	9.653948	7.133428	15.8	10.07056	2
AT3 - Westösterreich_2023	38	13.2	1610.009	9.552832	33.28731	0.54	2.25	3.033231	462.6534	5.56701	12.89236	11.61575	15.9	9.065108	2
Bruxelles-Capitale / Brussels Hoofdstedeli	56.7	14.6	5547.53	11.30148	26.40564	0.76	1.48	7.89895	869.2432	1.681718	8.191717	1.980236	19.3	9.8	1
BE2 - Vlaams Gewest_2023	53.5	10.8	2528.396	12.81744	26.74808	0.94	2.4	5.618412	414.9163	3.401118	6.778162	3.331742	16.8	10.17532	1
BE3 - Région wallonne_2023	43.4	7.5	1289.689	9.993528	25.60944	0.52	2.82	4.759663	216.3525	2.709651	5.986541	1.527734	15.3	7.803079	2
BG31 - Severozapaden_2023	20.8	1	69.72379	0.763302	6.881001	0.12	0.27	0	8.537607	0.062934	2.784404	0.127064	8.3	18.25791	4
BG32 - Severen tsentralen_2023	34	2.7	126.5325	3.071327	7.739488	0.03	0.33	1.616713	18.6469	0.348278	5.949289	5.346707	12.3	15.68516	4
BG33 - Severoiztochen_2023	28	1	230.9878	1.850038	7.979152	0.17	0.18	1.60475	27.36823	0.280003	7.023993	1.11067	11.4	14.92144	4
BG34 - Yugoiztochen_2023	24.8	1.1	98.98413	1.800458	7.651486	0.09	0.27	1.008958	25.73587	0.303161	3.931686	1.470419	10.8	13.99912	4
BG41 - Yugozapaden_2023	46.5	2.4	1025.227	2.389569	8.072771	0.41	0.87	7.42913	149.7035	0.578724	12.1418	4.359904	18.7	19.51304	4
BG42 - Yuzhen tsentralen_2023	26.5	1.8	273.9277	3.845642	8.007238	0.18	0.33	1.846478	41.70028	0.475232	7.363344	2.735345	11.3	16.64603	4
CH01 - Région lémanique_2023	51.9	22.4	7763.293	13.1032	40.4981	0.94	1.59	4.326822	1270.152	7.192005	11.05623	4.199412	15.5	8.19736	1
CH02 - Espace Mittelland_2023	48.7	22	3338.417	12.08727	39.85358	0.94	1.38	4.664693	627.0016	5.191802	5.887445	2.542039	15.8	7.65563	2
CH03 - Nordwestschweiz_2023	48.1	23	5371.08	12.78128	39.7099	0.94	7.68	5.090259	1787.843	9.240179	12.91868	3.532225	19.8	8.480301	1
CH04 - Zürich_2023	64.8	26.1	8405.01	15.735	40.85115	0.94	1.17	9.986462	1627.828	6.091659	6.935341	1.029593	21.8	8.5	1
CH05 - Ostschweiz_2023	46.1	20.5	1313.434	11.97627	40.35032	0.94	1.34	3.448131	341.4429	5.62567	7.536571	24.59748	16.5	7.651123	1
CH06 - Zentralschweiz_2023	47.7	22.1	1124.61	6.456323	40.16968	0.94	2.51	4.381551	379.2707	5.582681	22.9303	7.014456	16.5	7.590787	2
CH07 - Ticino_2023	54.2	21.3	3861.651	12.87737	40.50221	0.94	0.32	5.022908	752.454	4.877491	16.2732	4.123704	14.3	10.8	1
CZ01 - Praha_2023	59.9	10.6	5540.197	4.933775	25.36658	1.45	1.37	13.2498	864.8227	0.542578	9.55155	3.112912	26.7	12.6	1

Observations # = all the EURIS regions per year (from 2016 to 2023)

Annex - FKM clusters compactness

<u>Quantification of the compactness of clusters:</u>

Sum of the squared distances between each data point and its corresponding cluster centroid

```
Within cluster sum of squares by cluster:
[1] 1043.6992 1708.8437  893.8419 2455.6519
 (between_SS / total_SS =  45.09 %)
```

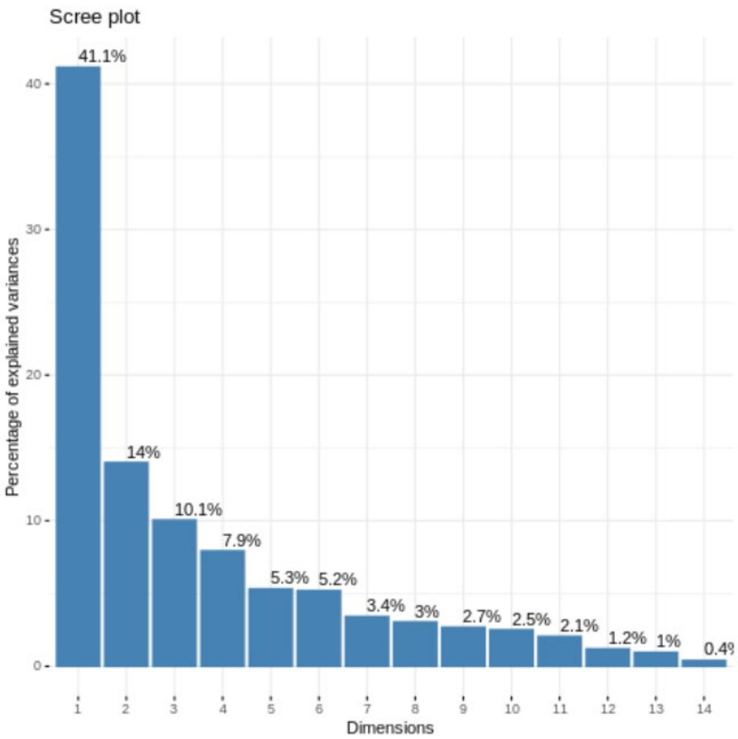
Sum of the squared distances between each data point of cluster 1 and corresponding cluster 1 centroid

Annex – PCA criteria for number of latent variables

Eigenvalues greater then one rule: keep any component that has an eigenvalue gretare then one

Scree diagram: Plot of the eigenvalue for each component and stop when an additional factor would add relatively little to the information already extracted

Interpretability: examine the interpretability of the components to only retain those providing an interpretable result from the meaning point of view



Annex – Correlation (FKM grouping and EURIS one)

FKM cluster	Correlation percentage with corresponding EURIS group
Innovation Leader	74%
Strong innovator	54%
Moderate innovator	31%
Emerging Innovator	85%

Significant disparity at the central level ("Strong Innovator" and "Moderate Innovator")

Annex - Methodology (1/3)

FKM detailed tasks	Theoretical criteria	Suitable solution
Understanding the meaning of FKM adopted latent variables	**Original variables standardization** before FKM, to study impact (scores) of original variables on principal components	FKM on standardized original variables
Understanding the FKM clusters features	**Studying centroids scores** on FKM adopted latent variables, to understand clusters features through latent variables meaning	Analyzing FKM centroids scores

Annex - Methodology (2/3)

FKM detailed tasks	Theoretical criteria	Suitable solution
Ranking the FKM clusters	**Comparing centroids scores** on FKM adopted latent variables	Comparing FKM centroids scores
Labelling the FKM clusters	Taking into account **EURIS label names**, for developing a relative synergistic tool	Assigning EURIS label names according to FKM clusters ranking

Annex - Methodology (3/3)

FKM detailed task	Theoretical criteria	Suitable solution
<<Within-cluster regional ranking>>	1) latent variables (linked to different information contents, by construction) can be **conceptually added** without issues 2) linear combination of region' s latent variables can be the index for <<**within-cluster regional ranking**>>	Ranking according to a within-cluster regional index, based on the average among latent variables scores for each region