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Regional economic integration and machine learning: Policy insights from the review of literature

Philippe De Lombaerde [a,b,c], Dominik Naeher [d,*], Hung Trung Vo [e], Takfarinas Saber [f]

[a] *United Nations University Institute on Comparative Regional Integration Studies (UNU-CRIS), Bruges, Belgium*
[b] *Neoma Business School, Rouen, France*
[c] *Vrije Universiteit Brussel, Belgium*
[d] *Department of Development Economics, University of Göttingen, Göttingen, Germany*
[e] *Faculty of Economics, Thu Dau Mot University, Thu Dau Mot, Viet Nam*
[f] *Lero – The Irish Software Research Centre, School of Computer Science, University of Galway, Galway, Ireland*

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Abstract

Due to its focus on prediction rather than causal inference, machine learning has long been treated somewhat neglectfully in the economic literature. For several reasons, however, interest in machine learning has surged recently and is slowly finding its way into the econometric toolbox. Within the economic literature, regional integration has been one of the research areas at the forefront of this development, with various studies experimenting with different machine learning techniques to shed light on the complex dynamics governing regional integration processes. This paper provides the first systematic review of the literature that uses machine learning to study regional economic integration. The focus is twofold, first analysing studies along various thematic and methodological features (and the links between them), and then discussing the scope and nature of policy insights derived from the surveyed body of literature.

JEL classification: C30; C60; F02; F15; F60

Keywords: Regional economic integration; International trade; Machine learning; Artificial intelligence; Literature review

* Corresponding author.
E-mail address: dnaeher@uni-goettingen.de (D. Naeher).

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1. Introduction

Due to its focus on prediction rather than causal inference, machine learning has long been treated somewhat neglectfully in the economic literature. However, driven by a rising desire to harness big data for economic research as well as a genuine interest to experiment with new methods, interest in machine learning has surged recently and is slowly finding its way into the econometric toolbox (Athey, 2018; Athey & Imbens, 2019; Mullainathan & Spiess, 2017).

Within the economic literature, regional integration has been one of the research areas at the forefront of this development, with various studies experimenting with network clustering algorithms, artificial neural network analysis, and other machine learning techniques to shed light on the complex dynamics governing regional integration processes. Despite a period of more than twenty years with a steady flow of new research articles applying machine learning techniques to study regional economic integration, there have been (to the best of our knowledge) no attempts so far to provide a systematic overview of this growing body of literature.

This paper seeks to fill this gap by presenting the results of a systematic review of the literature that uses machine learning to study regional economic integration. After identifying relevant works, we first classify them along various dimensions, including both economic attributes (such as the studied level of integration, economic sector, and geographic region) and methodological aspects (type of machine learning algorithm). We then analyse links between these attributes and identify several interesting patterns in the usage of certain types of machine learning techniques across different economic dimensions. Finally, we use our observations to derive insights on the achievements as well as gaps in this literature which may be useful in guiding future research work in this field. We discuss thereby both the scope and types of Machine Learning Techniques, as well as the kind of policy insights to which the use of these techniques lead.

The paper is structured as follows. Section 2 provides some general background on the concept of regional economic integration and on machine learning. Section 3 describes the methodology of our systematic literature search. Section 4 presents the results of our literature review, classification, and analysis. Section 5 discusses our key observations related to methods and policy insights and their implications for future research. Section 6 concludes.

2. Background and related work

In this section, we introduce the concepts that form the background of our investigation and discuss related work of our research in two parts: regional economic integration and machine learning.

2.1. Regional economic integration

Economic integration is commonly defined as a process in which different economies work towards reducing barriers to trade and production factor mobility, coordinating or harmonizing economic policies and regulations, and pooling resources to fund common policies, institutions and public goods. Such integration can take place at different levels, including at the subnational (e.g. between different federated states), bilateral or multilateral (across countries), and global level (commonly referred to as globalization). The focus of this paper is on *regional* economic integration, which refers to economic integration at the regional level; that is, economic integration that takes place between (mostly) neighbouring countries in the same geographic area. A classic framework to analyse and compare regional economic integration outcomes are the five stages of economic integration in Balassa ((Balassa, 1962)): (1) free trade area, (2) customs union, (3) common market, (4) economic and monetary union, (5) full economic and fiscal union. This framework can be thought of as a taxonomy rather than a theory of regional economic integration.

A useful distinction is usually made between *de facto* and *de jure* regional integration (Hurrell, 1995; Higgott, 1997; Lombaerde & S¨oderbaum, 2013). This dichotomy was explicitly or implicitly present already in the early transactionalist and neo-functionalist literature on regional integration (Deutsch, 1957; Haas, 1970). It is also since this early literature, which was very much inspired by the European integration process, that the term 'integration' has been associated with the European model of integration, in which some degree of supranational institutionalisation is crucial. It is for this reason that political scientists nowadays prefer the concepts of regionalism (referring to the policies and political projects that shape regions) and regionalization (referring to the growing actual linkages via trade, investment, people mobility, identity, etc. that shape regions). Regionalism is thereby a broader concept, not strictly referring to supranational arrangements and projects, not necessarily referring to the European case, and not exclusively referring to state actors. In the economics literature, the term 'regional integration' is still the generally used concept though. A recent analysis of a corpus of comparative regionalism studies from the 1960-2020 period confirms indeed that the term 'integration' is still the one used in economic studies and that economic studies (especially the trade-related ones) are still very prominent within the comparative regionalism literature (El Maaly & Chiekh, 2022). This broad 'regional integration' term should be understood in the sense of regionalism (when *'de jure'*) or regionalization (when *'de facto'*). As a consequence, the economic analysis of regional integration can focus, for example, on the regional density of flows (e.g., using clustering or network techniques), but also on the regional density of economic agreements or the effects of regional economic policies.

Normative theories have been formulated and developed that show under which conditions regional arrangements are welfare superior, under which conditions the regional level is the optimal level for the provision of regional public goods, and what the optimal composition and extension are of a regional economic arrangement. These theoretical frameworks include customs union theory, fiscal federalism and optimum currency area theory. They have inspired machine learning applications that have analysed the formation and optimality of real-world customs unions and currency unions (see below).

But independently of purely economic considerations and calculations, regional economic integration is relevant both from a political and societal perspective. Related events are currently taking place across different parts of the world: Europeans discussing the consequences of Brexit, people in South America debating about the EU-Mercosur trade agreement, and Australians protesting against the Belt and Road initiative. Citizens seem to be aware of the importance of regional economic integration. Authorities are taking measures reacting to cross-border challenges, such as migration, environmental degradation, and pandemics, which often require not only local, national responses but coordinated policies designed at the regional (or even global) level. Regional economic integration is also often seen as an avenue for fostering peace and stability, and triggering economic growth. Although the evidence on the successfulness of such strategies is mixed (as the ongoing war in Ukraine sadly demonstrates), policymakers continue to show great interest in the link between regional economic integration and other (economic) outcomes. The recent wave of policy-driven studies monitoring and analysing regional integration outcomes in various parts of the world is evidence of this (ADB, 2016; AfDB, 2016; Naeher & Narayanan, 2020; Naeher, 2015; Saber et al., 2022) and selected publications below).

2.2. *Machine Learning*

Machine Learning is a subfield of Artificial Intelligence that lies at the intersection of computer science and statistics. Machine learning is devoted to understanding and building methods that 'learn' as algorithms build knowledge from sample data in the form of models, thus enabling expert software systems to make and improve their predictions automatically through experience without being explicitly programmed to do so (Jordan & Mitchell, 2015). Unlike econometrics, machine learning generally studies the use of predictive models and ignores other questions such as causality, equilibrium, and feedback effects.

Machine learning algorithms can be categorized into three major types (Sarker, 2021):

1. Supervised learning: the task of learning a function that maps a given input to an output according to a collection of exemplar input training test cases with their corresponding outputs (labels). The most common goal when using supervised learning is "classification" (i.e., separating the data into different classes or categories) such as the classification of pairs of countries into allies or trade partners, and "regression" (i.e., fitting a curve on the data) such as estimating the relationship between trade agreements and export flows between countries. This type of learning is often referred to as task-driven learning.
2. Unsupervised learning: the task of analysing input data without outputs (i.e., unlabelled) without the need for human intervention. It is widely used for extracting generative features, identifying meaningful trends and structures, grouping results, and for exploratory purposes. The most common goals of using unsupervised learning are clustering, density estimation, finding association rules, and anomaly detection. Unlike supervised learning, it is a data-driven learning. Note that dimensionality reduction, despite featuring a different goal when it is used for data pre-processing, is often considered as unsupervised learning.
3. Reinforcement learning: it enables complex software system agents to automatically analyse, assess, and evaluate their particular context or environment, and take the optimal strategy to optimise their efficiency. The goal of this learning type is to leverage the feedback to maximise the reward or reduce the risk from each ultimate action taken by the agent (e.g., given the state of the stock market, do we invest money and how much do we invest?).

Table 1 provides an overview of the methods and techniques commonly associated with each machine learning type. In addition to the three main machine learning types, and to deal with the shortcomings of each type, new hybrid paradigms are starting to appear and achieve tremendous success. For instance, semi-supervised learning (Van Engelen & Hoos., 2020) which aims at combining both supervised and unsupervised learning by leveraging labelled and unlabelled data, thus alleviating issues related to the lack of labelled data and impracticality (in time and money) of manually labelling large amounts of data. Self-supervised learning (Jaiswal et al., 2020) is another paradigm for dealing with the lack of labelled data through the sequencing of an unsupervised learning technique to automatically generate label-like signals, which are fed to a subsequent supervised learning approach as ground truth.

Table 1
Machine Learning Types, Common Methods and Techniques (Shehab et al., 2022).

Type	Method	Techniques
Supervised	Classification	Support Vector Machine (SVM), NaiveBayes (NB), Neural Network (NN), k-Nearest Neighbour (k-NN), Decision Tree (DT)
	Regression	Back-Propagation Neural Network(BPNN), Support Vector Regression (SVR), Multiple Linear Regression (MLR), Partial Least Squares (PLS)
Unsupervised	Clustering	k-Means, Hierarchical Algorithm(HA), Mean-Shift, Density-Based Spatial Clustering of Application with Noise (BDSCAN)
	Dimensionality Reduction	Feature Selection (e.g., Exponential,Sequential, Random), Feature Extraction (Principal Component Analysis, Linear Discriminant Analysis, Non-Linear Principal Component Analysis, Kernel PCA, Non-negative Matrix Factorization, Self-Organizing Maps)
Reinforcement	Reinforcement Learning	Q-Learning,TemporalDifference,Value Iteration, Markov Decision

3. Methodology

The systematic literature review was performed on the full metadata fields in three databases:

(1) IEEE, which is recognized for its scientific output of technical information, especially in engineering and computer science fields, (2) ACM Digital Library, a database dedicated to advancing computer science research, and (3) Web of Science (WOS), which provides a comprehensive database of integrated and multi-disciplinary research spanning various disciplines, including natural sciences, engineering, and social sciences.

The search was conducted in May 2022. We utilized the advanced search boxes of the three digital databases for complex search queries based on all available metadata. Two groups of keywords were specified. The first group was intended to identify studies using machine learning and techniques commonly associated with artificial intelligence. Keywords in this domain included:

1. General terms: “Machine Learning”, “Artificial Intelligence”, and “Algorithm”.
2. Machine learning types: “Supervised Learning”, “Unsupervised Learning”, and “Reinforcement Learning”.
3. Additional terms: “Clustering”, “Cluster Analysis”, “Deep Learning”, “Natural Language Processing”, and “Neural Networks”.

While in principle the term “Machine Learning” and its three types should have sufficed, we added two more general terms (“Artificial Intelligence”, “Algorithm”) to maximize the success of our search query and capture high-level studies even if this resulted in several false positives (which got screened later on). Furthermore, we added the names of some popular methods and techniques to allow our search query to capture very low level studies. However, our keywords do certainly not represent an exhaustive list of all machine learning techniques, implying that our selected sample might understate the scope of the surveyed literature.

The second group of keywords comprised terms from the literature on economic integration. These included: “Multilateral Integration”, “International Trade”, “Trade Agreement”, “Regional Integration”, “Financial Integration”, “Monetary Integration”, “Currency Area”, and “Monetary Union”.

The Boolean operators “AND” (between the two groups of keywords) and “OR” (within each group of keywords) were utilized to ensure that all relevant literature associated with both groups of keywords are included. The exact query for each database is reported in Fig. 1.

The search query covered the period from 1970 to May 2022. We obtained all relevant metadata within the specific fields of interest, including abstracts, titles, publication years, keywords, bibliographic citations, author names, and others. Regarding publication types, all articles available in English were considered, including journal articles, conference proceedings, and review papers.

Following the implementation of the search query, we refined the obtained sample along the following steps, as summarized in Fig. 1. After excluding 54 duplicates, the initial search resulted in 1,130 publications. In the first step of filtering, the titles and abstracts of the publications were considered. Studies were excluded if they failed to meet one or more of the following three inclusion criteria: (1) apply machine learning techniques (e.g., studies on economic integration that used traditional econometric methods were excluded),

(2) address a research topic with economic or policy implications (e.g., studies using the term ‘regional integration’ outside the context of economic integration were excluded), and
(3) provide information on the studied level of economic integration or unit of observation (e.g., firms, states, countries). In this step, 806 articles were excluded as they failed to meet the inclusion criteria.

The remaining 324 articles were examined further based on full-text reading. The inclusion criteria were the same as in the first stage of filtering. An additional 155 articles were excluded in this step.

The remaining 169 publications all discuss some form of economic integration and machine learning. Among these, 60 articles focus on regional integration in the sense defined above; that is, relating to economic integration among (mostly neighbouring) states within the same geographic area. The other 109 articles refer to economic integration at the subnational (14), bilateral/multilateral (21) or global (74) level.

4. Results

In this section we report the results of our systematic review in three parts, focusing on (i) the level of integration, region, and economic sector, (ii) the type and techniques of machine learning, and (iii) patterns that emerge in the use of machine learning for studying regional integration.

4.1. Level of integration, region, and economic sector

Fig. 2 shows the distribution of the 169 identified studies by level of integration and year. The overall positive trend in the number of studies on economic integration and machine learning appears to be mainly driven by the increase in studies at the global and regional level.

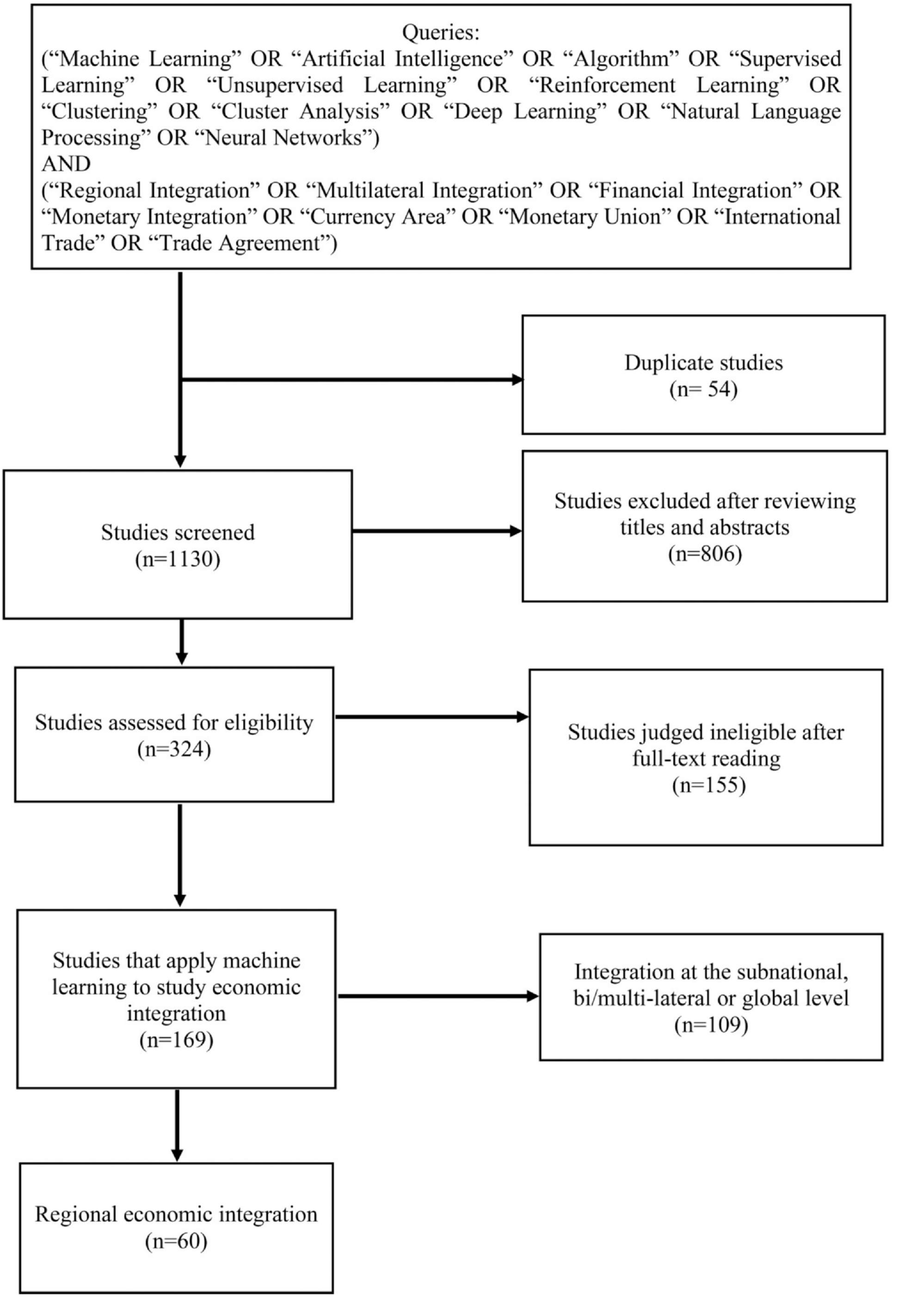

Fig. 1. Overview of systematic literature search.

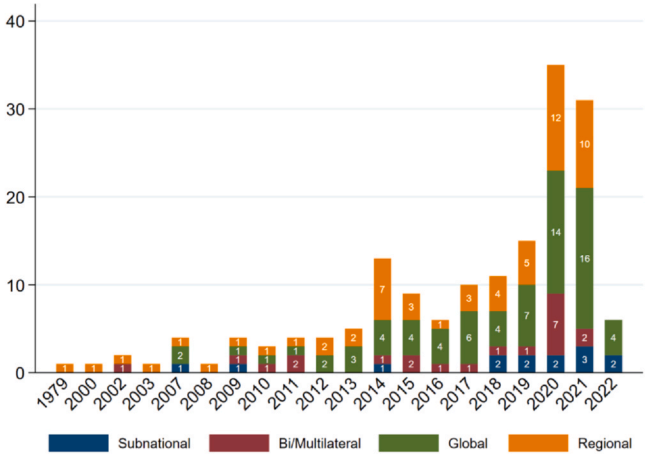

Fig. 2. Number of studies by level of integration and year (n=169).

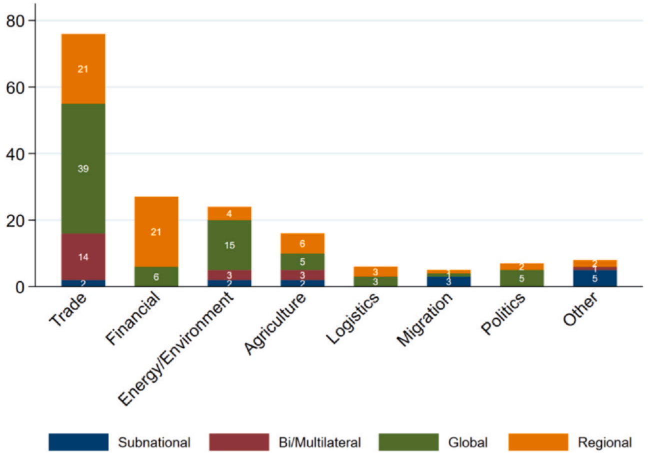

Fig. 3. Number of studies by level of integration and economic sector (n=169).

In contrast, studies looking at the subnational or bi/multilateral level are much scarcer across most of the considered time period, and only started to increase in numbers in recent years.

Fig. 3 shows the number of studies at each level of integration, disaggregated by economic sector. Most (76) of the 169 considered studies focus on trade. Around half (39) of these look at trade integration at the global level while 21 studies focus on trade integration at the regional level. Other prominent topics include financial integration (27), energy and environment (24) and agriculture (16). Interestingly, financial integration appears to be studied exclusively at the global and regional level, whereas most other sectors are studied at all levels of integration by at least some studies.

We now restrict the analysis to the sample of 60 studies concerned with economic integration at the regional level. As shown in Fig. 4, there were a few such studies published before 2012, indicating early attempts to use machine learning in analysing regional integration. Around 2012, the number of regional integration studies using machine learning started to increase, likely

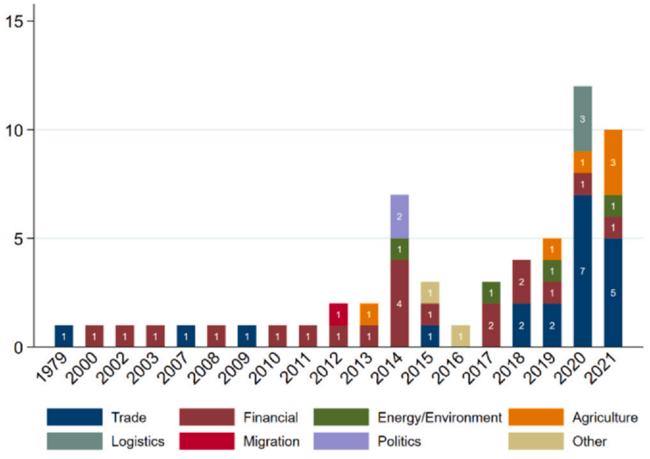

Fig. 4. Number of selected studies by economic sector and year (n=60).

facilitated (and possibly driven) by the development of more advanced machine learning techniques during this time. Fig. 4 also shows that most of these studies focus on financial (21) and trade (21) integration. In contrast, much fewer of the identified studies relate to agriculture (6), energy and environment (4), logistics (3), politics (2), and migration (1) (a full list of the papers studying each sector is provided in Table 2). At the same time, it is noteworthy that regional integration studies focusing on topics related to energy, environment or agriculture have appeared only relative recently, while most of the earlier studies are concerned with either trade or financial issues.

Table 2
Economic sectors and regions studied by selected papers.

		Count	Papers
Sector	Trade	21	[S1], [S4], [S5], [S6], [S7], [S8], [S9], [S10], [S11], [S12], [S13], [S14], [S15], [S16], [S17], [S18], [S19], [S20], [S21], [S22], [S23]
	Financial	21	[S2], [S3], [S24], [S25], [S26], [S27], [S28], [S29], [S30], [S31], [S32], [S33], [S34], [S35], [S36], [S37], [S38], [S39], [S40], [S41], [S42]
	Energy/Environment	4	[S43], [S44], [S45], [S46]
	Agriculture	6	[S47], [S48], [S49], [S50], [S51], [S52]
	Logistics	3	[S53], [S54], [S55]
	Migration	1	[S56]
	Politics	2	[S57], [S58]
	Other	2	[S59], [S60]
Region	Africa	4	[S29], [S30], [S32], [S34]
	Asia	3	[S7], [S9], [S28]
	Belt and Road	6	[S8], [S20], [S21], [S37], [S45], [S54]
	EU	24	[S2], [S3], [S12], [S18], [S22], [S24], [S25], [S26], [S27], [S31], [S33], [S35], [S38], [S39], [S40], [S41], [S42], [S43], [S44], [S48], [S50], [S52], [S57], [S60]
	Post-Soviet	4	[S17], [S47], [S56], [S59]
	South America	1	[S5]
	Multiple	18	[S1], [S4], [S6], [S10], [S11], [S13], [S14], [S15], [S16], [S19], [S23], [S36], [S46], [S49], [S51], [S53], [S55], [S58]

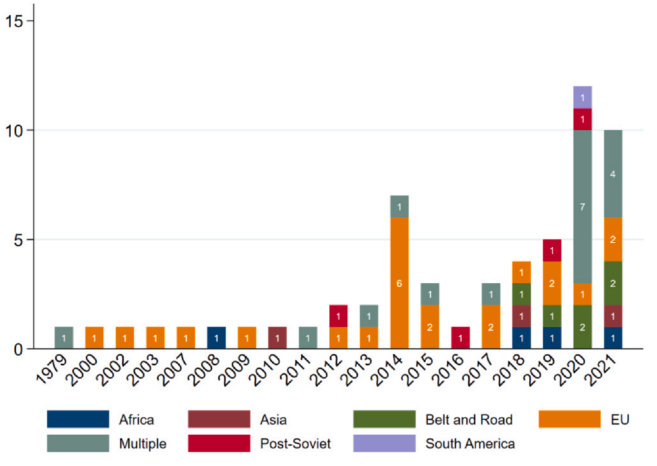

Fig. 5. Number of selected studies by region and year (n=60).

Fig. 5 shows the number of studies investigating a particular region (or comparing multiple regions) by year. While before 2010 most of these studies focused on regional integration in Europe, more recent studies increasingly look at China's Belt and Road initiative or focus on comparing multiple regions with each other. The latter types of studies often compare integration outcomes across regional economic communities or customs unions. A full list of the papers studying each region is provided in Table 2. For instance, Savchenko et al. [S1] use a tree clustering algorithm to investigate the development of regional integration groups such as the Association of Southeast Asian Nations (ASEAN), Economic Community of West African States (ECOWAS), European Union (EU), and others. In contrast, the studies by Lopez ([S2]) and Boreiko ([S3]) focus on financial and monetary integration exclusively within the EU, applying an artificial neural network approach and fuzzy cluster analysis, respectively.

Fig. 6 provides further insights by displaying the number of studies for each region by economic sector. Studies focusing on regional integration in Africa and Europe are mostly

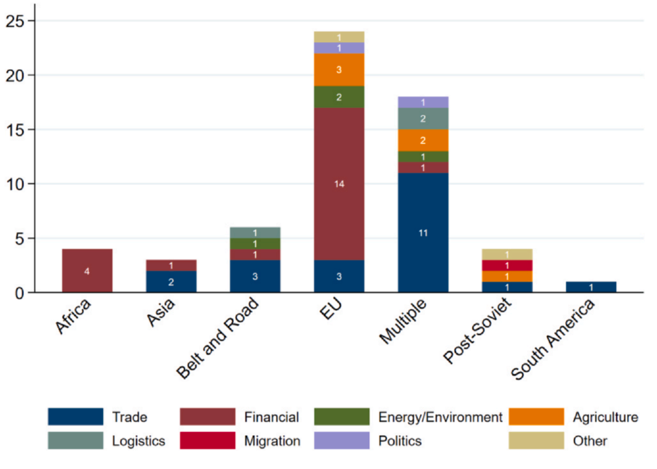

Fig. 6. Number of selected studies by region and economic sector (n=60).

concerned with financial integration. In particular, the four studies on Africa investigate the financial aspects of monetary integration in the East African Community (EAC) and West African Economic and Monetary Union (WAEMU). Similarly, many of the financial integration studies in Europe focus on the Economic and Monetary Union (EMU) in the EU. In contrast, most of the studies concerned with Asia, the Belt and Road initiative in particular, or with comparing multiple regions across the world focuses on international trade aspects. For instance, Dumor and Yao ([S20]) assess trade between China and partner countries within the Belt and Road initiative using neural network analysis. Zhang and Wang ([S15]) apply a complex network algorithm to study factors influencing the formation of regional blocks within the global trade network.

4.2. Machine learning

We now turn to analysing the studies obtained from our systematic review from the machine learning perspective, with the goal of identifying potential trends and patterns in terms of the types of machine learning and employed algorithms.

4.2.1. Type of machine learning

We start by analysing the type of used machine learning technique in the selected papers: supervised, unsupervised, and reinforcement learning. As lines between unsupervised and supervised learning are sometimes blurry, there are many hybrid approaches that draw from each field of study (e.g., Semi-Supervised Learning, Self-Supervised Learning, Multi-Instance Learning).

Fig. 7 shows the number and proportion of each type of machine learning across our selected papers. Clearly, there is a large domination of unsupervised learning, with 92 % (55 out of 60) papers in total. While these papers look for patterns in datasets without pre-existing labels, most of them aim to cluster their data.

Furthermore, we see that there are also papers leveraging supervised learning in studying regional integration. However, such papers are far less numerous and only represent 7 % (4 out of 60) of the identified studies. Unlike unsupervised learning, these papers are considering datasets with labels, and most of them aim to learn a model that enables them to estimate and predict the outcome of previously unseen configurations.

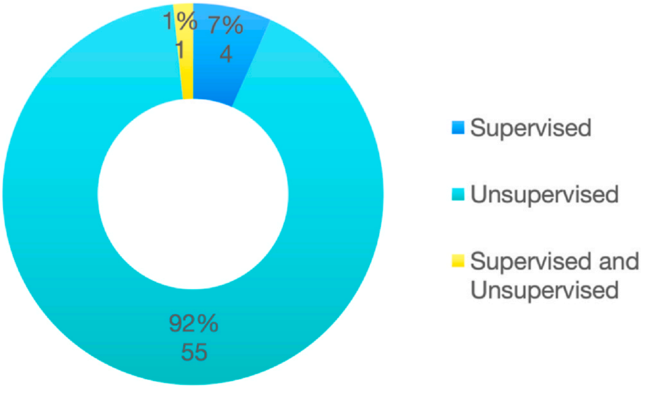

Fig. 7. Type of machine learning technique (in percentage) used in selected papers (n=60).

Surprisingly, there are no papers leveraging reinforcement learning or any hybrid machine learning approach (e.g., Semi-Supervised Learning, Self-Supervised Learning, Multi-Instance Learning), with the exception of the work by Kasabov et al. ([S42]) which uses a succession of unsupervised learning and supervised learning. The goal of Kasabov et al. ([S42]) is to develop a computational model for analysing and anticipating signals of abrupt changes of volatility in financial markets with (i) unsupervised learning modules (i.e., SOM/ESOM) for visual exploration of the annual and quarterly macroeconomic development of the EMU cluster related to the development of other clusters, and (ii) a supervised learning module (i.e., EFuNN) for the evaluation of trends in the EMU's macroeconomic indicators, such as the Euro/USD exchange rate and Euro STOXX50 index.

4.2.2. Machine learning goals and algorithms

We now analyse the goals and the algorithms used for machine learning in the selected papers, to potentially identify any trend or shift in used techniques. Tables 3 and 4 summarise the algorithms used in the selected papers for each goal (clustering, community/detection analysis, dimensionality reduction, and others).

As shown in Table 3, most papers (35) use machine learning for clustering, followed by community detection and analysis (13), whereas dimensionality reduction was employed in 9 papers. We also noticed the use of machine learning for two other specialised goals: Natural Language Processing and Ranking. Note that while community detection algorithms are very similar to clustering techniques, we preferred to segregate them as they are often techniques that are designed by researchers in the economics community to address their specific network or

Table 3
Algorithms used for unsupervised learning in selected papers.

Goal	Algorithm	Count	Papers
Clustering	Ward's Method	16	[S4], [S6], [S12], [S17], [S22], [S24],[S30], [S33], [S35], [S40], [S43], [S47], [S50], [S52], [S56], [S59]
	HierarchicalCluster-ing Analysis	9	[S5], [S16], [S19], [S26], [S27], [S28],[S32], [S51], [S55]
	K-Means	3	[S1], [S13], [S38]
	FuzzyClusteringAnalysis	3	[S3], [S32], [S36]
	Optimal Partition	2	[S14], [S29]
	WeightedExtremalOptimisation	1	[S57]
	Wavelet Clustering	1	[S34]
Community Detection/ Analysis	Blondel' Louvain	1	[S46]
	Girvan and Newman	1	[S18]
	Clauset, Newman andMoore	1	[S15]
	Spinglass	1	[S21]
	Other Cluster Analy-sis	9	[S7], [S9], [S10], [S31], [S37], [S41],[S45], [S53], [S54]
Dimensionality Reduction	Principal ComponentAnalysis	3	[S28], [S48], [S55]
	Self-Organizing Map	3	[S2], [S39], [S42]
	Non-negativeMatrixFactorization	2	[S58], [S60]
	NonmetricMultidi-mensional Scaling	1	[S49]
	Trilateration Multidi-mensional Scaling	1	[S16]
Others	NLP,ModelSummarisation	1	[S23]
	Google's PageRank	1	[S11]

Table 4
Algorithms used for supervised learning in selected papers.

Goal	Algorithm	Count	Papers
Regression	Neural Network	1	[S20]
	Bayesian Network	1	[S44]
Time Series	Neural Network	1	[S25]
RecommenderSystem	HybridS (Hybrid)	1	[S8]

graph problems. Table 3 also shows that among clustering works, Hierarchical Clustering Analysis techniques stand as the most employed techniques, with a large proportion of the works using Ward's method. However, several other clustering techniques have also been considered in this literature, including k-Means and Fuzzy Clustering. Moreover, Table 3 shows that many studies leverage dimensionality reduction techniques to deal with the large number of features in economic datasets, mainly with two goals: to process them further (e.g., using clustering [S28], [S55]) and to visualise the data cluster analysis (e.g., [S48]). Principal Component Analysis is a popular dimensionality reduction technique within the machine learning community and it is also one of the most frequently used in our set of selected papers. At the same time, we also find a consequent use of Self-Organizing Maps which are based on Neural Networks.

Table 4 shows that, despite the low number of papers leveraging supervised learning, this handful of works leverage machine learning for diverse reasons, ranging from regression and time-series analysis to recommender system. It also shows that neural networks can be used for various goals (e.g., regression, time-series forecasting) in addition to unsupervised learning tasks through Self-Organizing Maps.

4.3. Patterns in machine learning and regional integration studies

Going further, we study the relationship between our classification of regional integration works and the employed machine learning techniques.

Fig. 8 shows the number of papers by economic sector using machine learning approaches for each goal. Clustering (the most common machine learning goal) is employed across all considered economic sectors. However, community detection, albeit very similar to clustering,

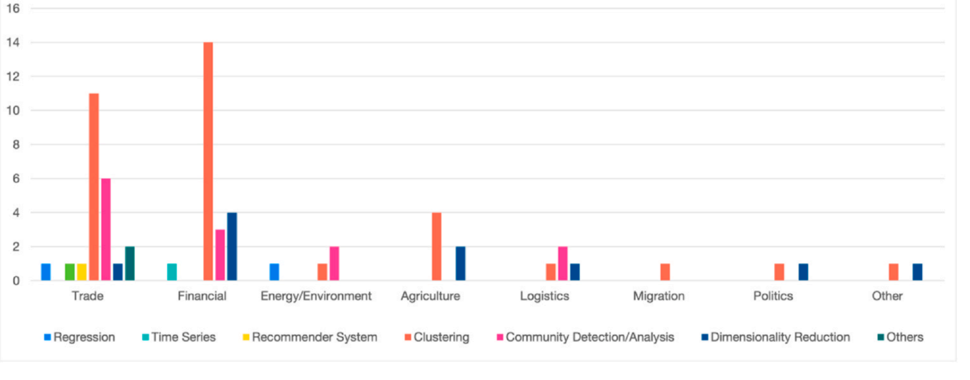

Fig. 8. Number of selected studies by machine learning technique and economic sector.

is only used in studies focusing on Trade, Financial integration, Energy/Environment, and Logistics, but not in Agriculture, Migration, and Politics. Dimensionality Reduction has also been used in studies across various economic sectors, which suggests that high dimensionality is a common problem faced by researchers in the economics field. Migration and Energy/Environment are the only two domains with no dimensionality reduction works. However, given the low number of works in these domains in general, it is hard to identify whether these domains do not have high dimensionality problems or whether they are still to be investigated using machine learning techniques.

We also see from Fig. 8 that the use of supervised learning is limited to Trade and Finance, where there is typically a substantial amount of data with corresponding outcomes, which is particularly suitable for regression and time series tasks.

5. Discussion

In this section we summarise and discuss the observations from our study, focusing first on the scope and types of machine learning techniques used in analysing regional economic integration processes and outcomes, and then on the policy insights derived from the surveyed body of literature.

5.1. Scope and types of machine learning techniques

5.1.1. Observation 1: wide use of machine learning for (regional) economic integration

We have identified a substantial number of works using machine learning techniques to study economic integration at various levels, with rapid growth in the number of published studies over the last few years.[1] This was the main motivator for conducting a systematic review on this topic. A large proportion of the works are related to regional economic integration which compelled us to focus our survey specifically on this level of integration. However, since the number of works using machine learning for regional economic integration is only second to global economic integration, we believe that conducting a subsequent survey on the use of machine learning in studying economic integration at the global level will be of additional benefit to the research community.

5.1.2. Observation 2: dominance of unsupervised learning

We have noticed that the majority of the surveyed studies use unsupervised learning to address their research questions relating to regional economic integration. This is not a big surprise as a large proportion of regional integration works are analytical and attempt to identify and understand the behaviour and interactions of countries and economic agents. We have seen that, while unsupervised learning techniques are applied to regional economic integration problems across various economic sectors and domains, applications of supervised learning techniques are mostly limited to Trade and Finance. These two domains have the advantage of being data intensive (particularly in the form of time series), making them excellent candidates for such type of machine learning. However, there are many novel machine learning types (e.g.,

[1] Note that our sample should be seen as a lower bound on the actual number of relevant publications due to (a) limitations regarding the list of keywords in our search queries (both for method-related and integration-related keywords), (b) limitations regarding the used databases, and (c) our focus on publications in English language.

semi-supervised learning and self-supervised learning) which require fewer amounts of data. Therefore, the two communities of researchers studying economic integration and machine learning, respectively, need to work further together to make use of these new techniques and address this gap.

5.1.3. Observation 3: large use of (hierarchical) clustering

The largest proportion of identified works using machine learning do so to cluster countries or economic agents into regional integration groups, with the majority of them using hierarchical clustering. Hierarchical clustering is often favoured (e.g., against k-means) as it offers stability (no random parameters), does not require prior knowledge of the number of clusters, provides an excellent visualisation of how close the regions are from each other, and is fast to execute. The use of clustering techniques encompassed all economic sectors, unlike community detection techniques which are limited to applications in Trade, Finance, Energy, and Logistics. This might be due to the fact that clustering techniques are easily accessible off-the-shelf thanks to free and widely available software tools, whereas community detection approaches are often ad-hoc, need to be tailored to a specific problem, and are hard to be repurposed to another problem.

5.1.4. Observation 4: employing dimensionality reduction

Several identified works leverage dimensionality reduction hinting that regional economic integration also suffers from the curse of dimensionality. Indeed, there is a wide use of a variety of dimensionality reduction techniques from both linear and non-linear approaches. However, it is surprising that there is no use of feature selection approaches. This might be explained by the fact that this step is probably done implicitly by the economists based on their expert knowledge of the domain through their selection of the datasets.

Furthermore, dimensionality reduction is a very active research field in machine learning with several new techniques having been proposed recently. Since the reviewed papers mainly leverage well-known dimensionality reduction techniques, there seems to be a huge potential for collaboration between economists and machine learning researchers to bring state-of-the-art dimensionality reduction techniques to this field.

Lastly, we did not find any studies using dimensionality reduction in the context of Migration and Energy/Environment. While this observation might be due to the limited number of works in these areas in general, it could also be that these economic sectors only leverage few data dimensions, or that they are yet to leverage dimensionality reduction techniques. Additional investigation needs to be conducted to determine the real causes and identify potential for expanding the use of dimensionality reduction techniques to these fields.

5.2. Policy insights

In this section we present the main policy insights from the reviewed literature. As already suggested in Table 2, these are to be found in the monetary and financial sphere, on the one hand, and in the commercial sphere, on the other. More isolated insights are not reported here; they refer to topics as diverse as: port connectivity and competitiveness, financial innovations, pest risk analyses in the timber industry, regional agricultural policies, trade sanctions, or the evolution of a regional parliament's political agenda.

5.2.1. Observation 1: sub-optimality of the geographical extension (and stability) of regional exchange rate regimes

Since Mundell's seminal paper (Mundell, 1961) and the subsequential discussion on optimum currency areas, it is theoretically well understood that the discussion on fixed versus variable exchange rates cannot properly be held without taking the (geographical) extension of the currency area into account. A challenge is, however, to give empirical guidance to policy-makers. The reviewed papers include both *ex post* and *ex ante* assessments of regional exchange rate arrangements and intra-regional macro-economic convergence that mostly involve a variety of clustering techniques, as well as artificial neural networks. They refer, for example, to West and Central Africa ([S32]), the East African Community ([S34]), East Asia ([S28]), Mercosur ([S5]), the Portuguese escudo zone ([S26]), North America ([S36]), and the (European) Economic and Monetary Union (EMU) ([S2], [S3], [S25], [S26], [S27], [S31], [S33], [S35], [S36], [S41]). Various studies assess intra-zone economic convergence and point to the asymmetries within existing arrangements (incl. CFA franc zone and EMU) or proposed arrangements (incl. EAC), question the appropriateness of the membership of certain countries, while suggesting a regrouping around core economies and/or stronger regional fiscal policy.

5.2.2. Observation 2: imperfect financial market integration and enhanced financial sector systemic risk via regional contagion effects

A number of the reviewed studies analyse features of regional financial markets. While some studies showed the heterogeneous structure of the European capital market and banking sector ([S24], [S38], [S39], [S40]) by means of neural networks and clustering techniques, another study showed that, in the case of the West African Economic and Monetary Union (WAEMU), the joint probabilities of default of banks is enhanced by taking regional inter-bank connections (in turn, possibly leading to contagion) into account ([S29]).

5.2.3. Observation 3: sub-optimality of the geographical extension of trade policy regimes

A number of contributions aim at better explaining the structure of regional trade networks, explain the stability of specific trade relationships, assess the trade effects of regional trade agreements, or evaluate the optimality of the extension of regional trade policy arrangements. Some studies refer to single regions like the EU ([S18]) or the Post-Soviet space ([S17], [S47], [S56]), while other studies refer to multiple regions and/or the global trade network ([S1], [S4], [S6], [S10], [S13], [S14], [S15], [S16], [S19], [S46], [S51], [S57]). Different clustering techniques are used for the purpose.

5.2.4. Observation 4: potential for export development strategies in the context of the belt and road initiative

Strikingly, several of the more recent reviewed contributions refer to the Chinese Belt and Road Initiative ([S7], [S8], [S11], [S20], [S21], [S37], [S45], [S53], [S54]). The methods used include complex and neural network analysis, clustering techniques, and temporal exponential random graph models. These studies provide insights as to the structure of the underlying trade network, as well as the 'best' export development strategies for countries that are connected to the Belt and Road Initiative. In addition, the importance of port connectivity is shown, as well as the network contagion of environmental risks.

6. Conclusion

In this paper, we surveyed existing works that apply machine learning techniques to study regional economic integration. Based on a systematic literature review, we found a sizable number of works on the matter with an increasing trend in the number of studies published each year.

By focusing our study on works at the regional level (rather than the subnational, bilateral/multilateral or global level), we observed that although the number of identified works is large, most of them leverage unsupervised learning through various forms of clustering techniques, particularly hierarchical clustering. While unsupervised learning is used on regional integration problems from all considered economic domains, the use of supervised learning is mostly limited to applications in trade and finance. Moreover, several works have been identified that take advantage of machine learning dimensionality reduction techniques to deal with the high dimensionality of their data, although there is a large gap in terms of novelty of the used techniques.

It was shown that machine learning techniques can be usefully used to gain insights in a variety of policy problems in regional settings, prominently featuring monetary and financial policies, on the one hand, and trade and connectivity policies, on the other, while suggesting a series of additional opportunities to apply such techniques.

Overall, our survey identified a sizeable and growing number of works using machine learning to study regional economic integration. At the same time, we also found that there are large gaps regarding the types of used machine learning techniques and the scope of applications to different economic sectors. In sum, this points to substantive potential for future research to expand the application of state-of-the-art machine learning techniques to the study of regional economic integration and related research areas.

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