

Autonomy is all you need

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Abstract Abstract here

1 Introduction

In recent years, the European Statistical System (ESS) has committed to leverage non-traditional data sources in order to improve the process of statistical production, an evolution that is encapsulated by the concept of Trusted Smart Statistics [28]. This dynamic is accompanied by innovations in the statistical processes, so as to be able to take advantage of the great potential of these new sources (greater timeliness, increased spatio-temporal resolution, etc.), but also to cope with their complexity or imperfections. At the forefront of these innovations are machine-learning methods and their promising uses in the coding and classification fields, data editing and imputation [14]. The multiple challenges faced by statistical institutes because of this evolution are addressed in the Bucharest Memorandum on Official Statistics in a Datafied Society (Trusted Smart Statistics), which predicts that "the variety of new data sources, computational paradigms and tools will require amendments to the statistical business architecture, processes, production models, IT infrastructures, methodological and quality frameworks, and the corresponding governance structures", and consequently invites the ESS to assess the required adaptations and prioritize them [8].

In line with these recommendations, much work has been done in the context of successive projects at the European level in order to operationalize the use of non-traditional data sources in the production of official statistics. Within the scope of the ESSnet Big Data II project (2018-2020), National Statistical Offices (NSOs) have

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been working across a wide range of themes (online job vacancies, smart energy, tracking ships, etc.) in order to put together the building blocks for using these sources in actual production processes and identify their limitations [10]. However, while a substantial amount of work has been devoted to developing methodological frameworks [7, 30], quality guidelines [17] as well as devising business architectures that make third-party data acquisition more secure [27], not much has been said about the IT infrastructures and skills needed to properly deal with these new objects.

Big data sources, which are at the heart of Trusted Smart Statistics, have characteristics that, due to their volume, their velocity (speed of creation or renewal) or their variety (structured but also unstructured data, such as text and images), make them particularly complex to process. Besides, the "skills and competencies to automate, analyse, and optimize such complex systems are often not part of the traditional skill set of most National Statistical Offices" [3]. Not incidentally, an increasing number of public statisticians trained as data scientists have joined NSOs in recent years. Within its multiple meanings, the term "data scientist" reflects the increased involvement of statisticians in the IT development and orchestration of their data processing operations, beyond merely the design or validation phases [5]. However, the ability of these new data professionals to derive value from big data sources and/or machine learning methods is limited by several challenges.

A first challenge is related to the lack of proper IT infrastructures to tackle the new data sources that NSOs now have access to as well as the accompanying need for new statistical methods. For instance, big data sources require huge storage capacities and often rely on distributed computing frameworks to be processed, which generally cannot be provided by traditional IT infrastructures [21]. Similarly, the adoption of new statistical methods based on machine learning algorithms often require IT capacities (in particular, GPUs - graphical processing units) to massively parallelize computations [29].

Another major challenge is related to the difficulty of transitioning from innovative experiments to production-ready solutions. Even when statisticians have access to development environments in which they can readily experiment, the step towards putting the application or model in production is generally very large. Such examples highlight the need to make statisticians more autonomous regarding the orchestration of their processings as well as fostering a more direct collaboration between teams, as advocated by DevOps and DataOps approaches.

A third challenge is to foster reproducibility in official statistics production. This quality criterion involves devising processing solutions that can produce reproducible statistics on the one hand, and that can be shared with peers on the other hand.

- Final challenge : encourage and facilitate collaboration - Against that background, we argue that common theme : fostering autonomy - ref innovation plateformes blabla - choix technologiques qui favorisent l'autonomie et la scalabilité - make cloud resources easily available - retext : insee + ssp - MLOps case study to illustrate - open-source project - one-stop-shop - blueprint for building other similar data science platforms

- Thème général : donner de l'autonomie
- Limites du poste de travail : littérature sur scaling horizontal / vertical

- Observation commune aux différents INS :
 - Insee / SSM : homogénéité des parcours, pourtant grande diversité d’infra, de moyens DSI → difficulté à partager des environnements, des formations → idée de fournir une “sandbox”, un commun technologique (2020) [NB : dans la continuité, sandbox à l’échelle européenne via le one-stop-shop (2024)]
 - Visions/incitations différentes DSI/statisticien → sécurité avant le fonctionnel
- Inspirations : DevOps, DataOps

2 Principles for building a modern and flexible data architecture for official statistics

With the emergence of big data sources and new methodologies offering significant promise to improve the production process of official statistics, statisticians trained in data science techniques are eager to innovate. However, their ability to do so is limited by several challenges. Central among these challenges is the need for greater autonomy — be it in scaling resources to match statistical workloads, deploying proofs of concept with agility and in a collaborative manner, etc. Against that background, our aim was to design a data science platform that not only manages big data efficiently but also empowers statisticians by enhancing their autonomy. To achieve this, we delved into the evolving data ecosystem in order to identify significant trends with the potential to overcome the aforementioned limitations¹. Our findings indicate that leveraging cloud-native technologies, particularly containers and object storage, is key to building infrastructures capable of handling large and varied datasets in a flexible, cost-effective manner. Furthermore, these technologies significantly enhance autonomy, facilitating innovation and promoting reproducibility in the production of official statistics.

2.1 Limitations of traditional big data architectures

Over the last decade, the landscape of big data has dramatically transformed. Following the publication of Google’s seminal papers that introduced the MapReduce paradigm [13, 6], Hadoop-based systems rapidly became the reference architecture of the big data ecosystem, celebrated for their capability to manage extensive datasets

¹ As a preamble to this review, we should note that, although we did our best to ground our insights in the academic literature, a lot of it stems from informal knowledge gathered through diligent and ongoing technology watch. In the rapidly evolving data ecosystem, traditional research papers are increasingly giving way to blog posts as the primary references for cutting-edge developments. This shift is largely due to the swift pace at which big data technologies and methodologies are advancing, making the lengthy publication process of formal research often not the preferred way of disseminating timely insights and innovations.

through the use of distributed computing. The inception of Hadoop marked a revolutionary step, enabling organizations to process and analyze data at an unprecedented scale. Basically, Hadoop provided companies with all-rounded capabilities for big data analytics: tools for ingestion, data storage (HDFS), and computing capacities (Spark, among others) [9], thus explaining its rapid adoption across industries.

In the late 2010's, Hadoop-based architectures have experienced a clear decline in popularity. In traditional Hadoop environments, storage and compute were co-localized by design: if the source file is distributed across multiple servers (horizontal scaling), each section of the source file is directly processed on the machine hosting that section, so as to avoid network transitions between servers. In this paradigm, scaling the architecture often meant a linear increase in both compute and storage, regardless of the actual demand. In a recent article provocatively titled "Big Data is Dead"², Jordan Tigani, one of the founding engineers behind Google BigQuery, explains why this model doesn't fit the reality of most data-centric organizations anymore. First, because "in practice data sizes increase much faster than compute sizes". While the amount of data generated and thus needing to be stored may grow linearly over time, it is generally the case that we only need to query the most recent portions of it, or only some columns and/or groups of rows. Besides, Tigani points out that "the big data frontier keeps receding": advancements in server computing capabilities and declining hardware costs mean that the number of workloads that don't fit on a single machine — a simple yet effective definition of big data — has been continually decreasing. As a result, by properly separating storage and compute functions, even substantial data processing jobs may end up using "far less compute than anticipated [...] and might not even need to use distributed processing at all".

These insights strongly align with our own observations at Insee in recent years. As a use case of using big data infrastructures to improve statistical processes, an Insee team set up a Hadoop cluster as an alternative architecture to the one already in use to process sales receipt data in the context of computing the consumer price index. An acceleration of data processing operations by up to a factor of 10 was achieved, for operations that previously took several hours to perform [18]. Despite this increase in performance, this type of architectures were not reused later for several reasons. Mainly, the architecture proved to be expensive and complex to maintain, necessitating specialized technical expertise rarely found within NSOs [32]. But interestingly, subsequent projects involving large datasets didn't suffer much from this change, as their needs were actually very much in line with Tigani's observations. The bottleneck for these projects was generally on the side of computational needs rather than storage capacity. Furthermore, although these projects could still involve substantial data volumes, we observed that effective processing could be achieved using conventional software tools (R, Python) on single-node systems by leveraging recent promising tools from the data ecosystem. First, by using efficient formats to store the data such as Apache Parquet [11], which properties (columnar storage [1], optimisation for the "write once, read many" (WORM) paradigm, ability to partition data, etc.) make it particularly suited to analytical tasks such as those

² <https://motherduck.com/blog/big-data-is-dead/>

generally performed in official statistics [2]. Second, by performing computations using in-memory computation frameworks such as Apache Arrow [12] or DuckDB [26], that are also based on columnar representation — thus working in synergy with Parquet files — and implementing various optimizations (predicate pushdown, projections pushdown) to limit computations to data effectively needed, enabling much larger-than-memory data processing on usual, single-node machines.

2.2 Embracing cloud-native technologies

In light of this evolution of the big data ecosystem, there has been a notable shift in recent years within the industry towards more flexible and loosely coupled architectures. The advent of cloud technologies has been instrumental in facilitating this shift. Unlike the era where Hadoop was prominent, network latency has become much less of a concern, making the traditional model of on-premise and co-located storage and compute solutions less relevant. In terms of the nature of the data that need to be processed, we are observing an evolution that some have described as moving "from big data to flexible data": modern data infrastructures are required not only to process large volumes but also to be adaptable in multiple dimensions: accommodating various data structures (ranging from structured, tabular formats to unstructured formats like text and images), ensuring data portability across multi-cloud and hybrid cloud environments, and supporting a diverse range of computational workloads (from parallel computations to deep learning models necessitating GPUs, as well as the deployment and management of applications) [20]. In recent years, two technologies have emerged in the data ecosystem as foundational technologies for achieving such flexibility in cloud-based environments: containerization and object storage.

In a cloud environment, the computer of the user becomes a simple access point to perform computations on a central infrastructure. This enables both ubiquitous access to and scalability of the services, as it is easier to scale a central infrastructure — usually horizontally, i.e. by adding more servers. However, such centralized infrastructures have two well-identified limitations that need to be dealt with: the competition between users in access to physical resources and the need to properly isolate deployed applications. The choice of containerization is fundamental as it tackles these two issues [4]. Fundamentally, a container is a logical grouping of resources that makes it possible to encapsulate an application, its libraries and other system dependencies, in a single package. By creating “bubbles” specific to each service, containers thus guarantee application isolation while remaining lightweight, as they share the support operating system with the host machine — contrary to virtual machines (see. graph X). In order to manage multiple containerized applications in a systematic way, containerized infrastructures generally rely on an orchestrator software — the most prominent one being Kubernetes, an open-source project initially developed by Google to manage its numerous containerized workloads in production [33]. Orchestrators automate the process of deploying, scaling, and managing containerized applications, coordinating their execution across various servers. In-

terestingly, this property makes it possible to handle very large volumes of data in a distributed way: containers break down big data processing operations into a multitude of small tasks, organized by the orchestrator, thus minimizing the required resources while providing more flexibility than hadoop-based architectures [34].

The other fundamental choice in a data architecture is the nature of data storage. In the cloud ecosystem, so-called "object storage" has become the de-facto reference [31]³. In this paradigm, files are stored as "objects" consisting of data, an identifier and metadata. This type of storage is optimized for scalability, as objects are not limited in size and the underlying technology enables cost-effective storage of (potentially very) large files. It is also instrumental in building a decoupled infrastructure such as discussed before: the data repositories — referred to as "buckets" — are directly searchable using standard HTTP requests through a standardized REST API. In a world where network latency is not the main bottleneck anymore, this means that storage and compute don't have to be on the same machines or even in the same location, and can thus scale independently according to specific organization demands. Finally, object storage is a natural complement to architectures based on containerised environments for which it provides a persistence layer — containers being stateless by design — and easy connectivity without compromising security, or even with strengthened security compared with a traditional storage system [24].

2.3 Leveraging cloud technologies to increase autonomy and foster reproducibility

Understanding how the technological choices described in the technical discussion above are relevant in the context of official statistics require an in-depth review of statisticians' professional practices in their use of computing environments. At the end of the 2000s, with micro-computing at its peak, many of the technical resources used by statisticians at Insee were local: the code and processing software were located on individual computers, while data was accessed through a file-sharing system. Because of the the limited scalability of personal computers, this setup greatly limited the ability of statisticians to experiment with big data sources or computationally intensive statistical methods, and involved security risks because of the widespread data dissemination within the organization. In order to overcome these limitations, a transition was made towards centralised IT infrastructures, concentrating all — and thus overall much more — resources on central servers. Such infrastructures, made available to statisticians through a shared, virtual desktop environment for ease of use, remains the dominant method for conducting statistical computations at Insee at the time of writing this article.

Through our observations and discussions with fellow statisticians, it became evident that although the current IT infrastructure adequately supported the core activities of statistical production, it noticeably restricted statisticians' capacity to

³ Mainly because of Amazon's "S3" (Simple Storage Service) implementation.

experiment freely and innovate. The primary bottleneck in this organization is the dependency of statistical projects on centralized IT decision-making, such as the allocation of computing resources, access to shared data storage, the use of pre-configured programming languages and packaging environments, etc. Besides, such dependencies often lead to a well-known phenomenon within the software development community that lies at the heart of the DevOps approach, where the priorities of developers — iterate rapidly to improve functionality in a continuous manner — often clash with IT's focus on security and process stability. On the contrary, it is our understanding that modern data science practices reflect an increased involvement of statisticians in the IT development and orchestration of their data processing operations, beyond merely the design or validation phases. New data science infrastructures must take this expanded role of their users into account, giving them more autonomy than conventional infrastructures.

Cloud technologies stand out as a powerful solution to grant statisticians this much-needed autonomy in their daily work, enabling a culture of innovation. Through object storage, users gain control over the storage layer, allowing them to experiment with diverse datasets without being constrained by the limited storage spaces typically allocated by IT departments. Containerization empowers users to customize their working environments to their specific needs — be it programming languages, system libraries, or package versions — while also providing the flexibility to scale their applications according to the required computing power and storage capacities. By design, containers also foster the development of portable applications, which enables smoother transitions between environments (development, qualification, production), ensuring that applications can be moved seamlessly without the hurdles of environmental inconsistencies. Finally, with orchestration tools like Kubernetes, statisticians can more readily deploy applications and APIs and automatize the whole building process, sidestepping complexities associated with inconsistent or complex deployment environments. This capability aligns with the DevOps approach, enabling quicker iteration and building minimal prototypes as proofs of concept (POCs) rather than building the optimal (but time-consuming) solution for a pre-defined objective [19].

Besides scalability and autonomy, these architectural choices also foster reproducibility of statistical computations. The concept of reproducibility — namely the ability to reproduce the result of an experiment by applying the same methodology to the same data — is a fundamental criterion of scientific validity [23]. It is also highly relevant in official statistics, as it serves as a foundation for transparency, which in turn is crucial for building and maintaining the public's trust. Fostering reproducibility in statistical production involves devising processing solutions that can produce reproducible statistics on the one hand, and that can be shared with peers on the other hand [22]. Traditional IT infrastructures — either a personal computer or a shared infrastructure with remote desktop access — fall short in this regard, as building a project or just computing a statistical indicator there generally involves a series of manual steps (installing system libraries, the programming language binary, projects packages, dealing with potentially conflicting versions, etc.) that can not be fully reproduced across projects. In comparison, containers are reproducible by de-

sign, as their build process involves defining precisely all the needed resources as a set of processing operations in a standardized manner, from the "bare machine" to the running application [25]. Furthermore, these reproducible environments can be easily shared to peers as they can be readily published on open registries (for example, a container registry such as DockerHub) along to the source code of the application (for example, on a public software forge like GitHub or GitLab). This approach significantly enhances the reusability of code projects, fostering a community-driven model of development and innovation.

3 Onyxia: an open source project to build cloud-native data science platforms

The Onyxia project, initiated by the French Public Service and available at onyxia.sh, is an open source project aimed at creating self-sufficient data science environments in the cloud or on-premises. This project can be seen as a "Platform as a Package" (PaaS) solution for organisations wishing to create a data science environment based on cloud technologies.

3.1 Making cloud-technologies accessible to statisticians

Our technology watch and literature review highlighted cloud-native technologies, in particular containerization and object storage, as instrumental in building a data science platform that is both scalable and flexible. Building on these insights, we established our initial on-premise Kubernetes cluster in 2020, integrating it with MinIO, an open-source object storage system designed to work seamlessly with Kubernetes. Yet, our first experiments highlighted a significant barrier to their widespread adoption: the complexity of their integration. This is an important consideration when building data architectures that prioritize modularity — an essential feature for the flexibility we aim to achieve. For instance, due to MinIO's compatibility with the Amazon S3 API, the storage source could easily be switched without requiring substantial modifications to one managed by a public cloud provider. However, modularity of the architecture components also entails that any data application launched on the cluster must be configured so as to communicate with all the components. For instance, in a big data setup, configuring Spark to operate on Kubernetes while interacting with datasets stored in MinIO requires an intricate set of configurations (specifying endpoints, access tokens, etc.), a skill set that typically lies beyond the expertise of statisticians.

This very insight is really the base of the Onyxia project : choosing technologies that foster autonomy won't actually foster autonomy if their complexity acts as a deterrent from widespread adoption in the structure. In recent years, statisticians at Insee already need to adapt to a changing environment in terms of their every-

day tools : transitioning from proprietary software (SAS) to open-source ones (R, Python), acculturating to technologies that improve reproducibility (version control with Git), consuming and developing APIs, etc. These changes, that make their activity more and more akin to the one of software developers, already imply significant training and changes in the modalities of work everyday. In this regard, adoption of cloud-technologies was utterly dependent on making them readily accessible.

To bridge this gap, we developed Onyxia, an application that essentially acts as interface between the modular components that compose the architecture. The main entrypoint of the user is a user-friendly web application⁴ that enables users to launch services from a data science catalog (see section 3.2) as running containers on the underlying Kubernetes cluster. The interface between the UI and Kubernetes is done by a lightweight custom API⁵, that essentially transforms the application request of the user into a set of manifests to deploy Kubernetes resources. For a given application, these resources are packaged under the form of Helm charts, a popular way of packaging potentially complex applications on Kubernetes [15]. Although users can configure a service to tailor it to their needs, they will most of the time just launch a service out-of-the-box and be able to start developing. This point really illustrates the added value of Onyxia in facilitating the adoption of cloud technologies. By injecting authentication information and configuration into the containers at the initialization, we ensure that users can launch and manage data science services in which they can interact seamlessly with the data from their bucket on MinIO, their sensitive information (tokens, passwords) stored in Vault, etc. This automatic injection, coupled with the pre-configuration of data science environments in Onyxia's catalogs of images⁶ and associated helm-charts⁷, make it possible for users to execute potentially complex workloads - such as running distributed computations with Spark on Kubernetes using data stored in S3, or training deep-learning models using a GPU - without getting bogged down by the technicalities of configuration.

3.2 Architectural choices aimed at fostering autonomy and reproducibility

- no vendor-lockin (enfermement de la structure → coût (licences) et des pratiques → fige les compétences)

In contrast to many commercial or proprietary solutions also based on cloud technologies, the use of Onyxia is not restrictive: it was designed not to make statisticians dependent on it. When an organization chooses to use it, it chooses the underlying technologies - containerization and object storage - but not the solution.

⁴ <https://github.com/InseeFrLab/onyxia-ui>

⁵ <https://github.com/InseeFrLab/onyxia-api>

⁶ <https://github.com/InseeFrLab/images-datascience>

⁷ <https://github.com/InseeFrLab/helm-charts-interactive-services>

In a sense, Onyxia aspires to be removable; we want to enhance users' familiarity and comfort with the underlying cloud technologies rather than act as a permanent fixture in their workflow. An illustrative example of this philosophy is the platform's approach to user actions: for tasks performed through the UI, such as launching a service or managing data, Onyxia provides users with the equivalent terminal commands, promoting a deeper understanding of what actually happens on the infrastructure when triggering something.

In lines with the previous principle, Onyxia fundamentally aims at giving statisticians more autonomy. This can take multiple forms depending on their needs and familiarity with IT skills. Statisticians that just want to have access to computational resources to experiment with new data sources or statistical methods will have access in a few clicks to easy-to-use, pre-configured data science environments in which they can directly start to work and prototype their solution. However, many users want to go deeper and build actual prototypes of production applications for their projects: configuring initialization scripts to tailor the environments to their needs, deploying an interactive app that delivers data visualisation to users of their choice, deploying other services than those available in our catalogs, etc. For these advanced users to continue to push the boundaries of innovation, Onyxia gives them access to the underlying Kubernetes cluster. This means that users can freely open a terminal on an interactive service and interacts with the cluster - within the boundaries of their namespace - in order to apply custom resources and deploy custom applications or services.

- cloud-native : onyxia n'est pas le choix fondamental, le parti pris est sur le choix sous-jacent : conteneurisation + stockage objet - users have access to the underlying Kubernetes cluster -> full autonomy to launch services tailored to their needs - Acculturation aux bonnes pratiques par l'usage

3.3 An extensive catalogue of services to cover the entire lifecycle of data science projects

Axe : principes - A catalog of services which covers the entire lifecycle of a data science project - production-ready : outils d'automatisation (-> autonomie)

3.4 Building commons : an open-source project and an open-innovation platform

- Utilisation de communs : briques open-source - Orientation plateforme : instance vivante d'Onyxia, ouverte, collaborative, sandbox (cf. ref papier SSP Cloud sur l'aspect plateforme) - Innovation ouverte → littérature - Open-data - Instance de partage : formations reproductibles + utilisation dans les écoles de stats + hackathons (organisation annuelle du funathon cf. one-stop-shop)

4 Case-study : deploying a machine learning model into production following MLOps principles

This chapter aims, through a concrete example, to illustrate how INSEE managed to deploy its first machine learning model into production. It will delve into the MLOps approach that this project strived to adhere to as much as possible, focusing on the various technologies and infrastructures that were employed. This initial production deployment, while successful, faced various challenges, whether technical or organizational, and we will endeavor to discuss them and propose solutions wherever possible. The idea is to illustrate the development of this project as transparently as possible, without claiming it to be the definitive approach. The entire project is available in open source⁸ and remains under active development.

4.1 Context and motivations

Coding tasks are common operations for all national statistical institutes and can sometimes be challenging due to the size of certain nomenclature. At INSEE, a highly sophisticated coding tool called Sicore was developed in the 1990s to perform various classifications. Sicore uses a reference file that can be considered as a training file, which serves as examples of codings. The label to be coded is compared to the labels contained in the training file, and when the label is recognized, the associated code is assigned. When the label is not recognized, it must be manually classified by an INSEE agent. Two main reasons drove the experimentation of new coding methods. Firstly, there was an internal change with the redesign of the Sirene registry, which lists all companies in France and assigns them a unique identifier, the Siren number, for use by public institutions, notably to improve the daily management of the registry for INSEE agents and to reduce waiting times for companies. Additionally, at the national level, the government launched a one-stop shop for business formalities, allowing more flexibility for business owners in describing their main activities.

The initial testing exercises revealed that Sicore was no longer the suitable tool for performing NACE classification, as only 30% of tasks were being automatically coded. The teams working on the Sirene registry were already overwhelmed with numerous changes, making it unrealistic to further increase their workload with manual reclassification, which is both time-consuming and unstimulating. Therefore, in May 2022, the decision was made to experiment with new methods for performing this classification task, with the aim of using this method in production by January 1, 2023, the launch date of the new Sirene registry, if successful.

This choice of innovation was not initially a voluntary decision but rather a necessity, given that the current state of the process could not remain unchanged. Therefore, all decisions made during this project were taken considering these temporal and organizational constraints. The aim is to present these various strategic

⁸ <https://github.com/orgs/InseeFrLab/teams/codification-ape/repositories>

choices that we made at INSEE while bearing in mind that they may not be applicable or advisable in all organizations.

Three stakeholders were involved in this project: the business team responsible for managing the Sirene registry, the IT team developing software related to the registry's operation, and the *"innovation"* team tasked with implementing the new coding tool. The latter team is the INSEE Lab, which was created in 2017 with the objective of providing support to other teams on innovation topics to streamline their various projects.

4.2 Démarrage du projet comme les projets expérimental et prise en compte des contraintes

The project we aim to implement is a standard natural language classification problem. Indeed, starting from a textual description, we want to predict the class associated with it in the NACE Rev. 2 nomenclature. This nomenclature has the particularity of being hierarchical and containing 5 different levels⁹: section, division, group, class, and subclass. In total, 732 subclasses exist, which is the level at which we aim to perform our classification. Table 1 summarizes this hierarchical structure with an example.

Level	NACE	Title	Size
Section	H	Transportation and storage	21
Division	52	Warehousing and support activities for transportation	88
Group	522	Support activities for transportation	272
Class	5224	Cargo handling	615
Subclass	5224A	Harbour handling	732

Table 1 NACE Nomenclature

With the establishment of the one-stop shop, business owners can now freely draft their activity descriptions. As a result, the labels received by INSEE are very different from the harmonized labels that were previously received. Therefore, it was decided to work with machine learning models that have proven their effectiveness in the literature. This represents a significant paradigm shift from INSEE's perspective, as no machine learning model has ever been deployed into production. In fact, the initial years of the INSEE Lab were characterized by a multitude of experiments on various subjects without ever transitioning to production. Nevertheless, all these experiments were valuable and accelerated the project through the gained experience. This project thus marked the first instance where the challenges of production deployment were considered from the outset, guiding numerous methodological and technical choices. As such, several points had to be agreed upon to facilitate coordination among the various stakeholders, and several strategic choices had to be made from the outset,

⁹ Actually, there are 5 different levels in France but only 4 at the European level.

including the working infrastructure, work methods, and the type of model to be used for such a project. The goal was to accommodate the constraints of each team and reconcile their needs.

4.2.1 Infrastructure de travail

In a machine learning project, the choice of development infrastructure is central. Working on a modular infrastructure is crucial in machine learning projects due to the diversity of tasks to be performed, such as data collection, preprocessing, modeling, evaluation, inference, monitoring, among others. This allows for easy replacement or updating of components without disrupting the entire workflow pipeline. As elucidated in the preceding chapter, traditional Big Data infrastructures often prove too rigid and specialized, failing to adequately cater to the diverse demands of various projects. Therefore, we decided to use a more modular infrastructure that better addresses the needs of machine learning projects by leveraging the most appropriate technologies for each stage of our pipeline. This primarily allows us to take advantage of the latest technological advancements without being limited by a predefined architecture, as innovations in machine learning progress rapidly. We exclusively utilized open-source cloud technologies available in the SSP Cloud catalog, an instance of the Onyxia software developed by INSEE. This platform, based on Kubernetes, offers flexible and scalable container management, enabling easy scaling of services as needed. As we will see in the following sections of this chapter, we used various tools for each stage of our pipeline: MinIO, Vault, MLflow, ArgoCD, Argo Workflows, Label Studio, Vscod, etc. The decision to opt for the SSP Cloud was also motivated by the ongoing implementation of a private instance of Onyxia on the production servers at INSEE. This initiative is poised to streamline the connection between production and development environments in the long run.

While the utilization of SSP Cloud has proven to be the right solution for us, it does come with its set of considerations. Working on SSP Cloud implies operating in ephemeral environments, thus ensuring the proper backup of code and data is imperative. Thankfully, SSP Cloud provides a file storage solution through the use of MinIO, which addresses this requirement. Although Onyxia simplifies initial setup and usage, it may require a bit of a learning curve for new users. However, given the widespread adoption of Amazon's S3 storage system in cloud computing, investing time in understanding it proves beneficial for any data scientist. Furthermore, comprehensive documentation is available at the following address: <https://inseefrlab.github.io/docs.sspcloud.fr/docs/en/storage.html>. Similarly, regular versioning of code is essential. We've opted for Git and Github for source code management, enabling seamless collaboration among our teams. While Git may require some initial learning, it's a crucial tool for anyone working on data science projects. To facilitate its adoption within INSEE, the innovation teams developed an internal training session on Git usage. For specific documentation related to SSP Cloud, it can be found here.

As for data privacy, while SSP Cloud is secure, it doesn't guarantee complete confidentiality. However, since we solely deal with open data, this hasn't posed any issues for us. At the time, the internal Onyxia instance at INSEE was not available yet.

4.2.2 Méthodes de travail

As mentioned earlier, our working infrastructure essentially required us to use Git to version our code. However, regardless of your setup, knowledge and usage of Git are essential prerequisites for any machine learning project. Another significant choice was made at the project's outset: the programming language to use. Currently, INSEE is undertaking a large-scale project to migrate all SAS code to the open-source R language. While we could have followed suit to align our projects with other INSEE initiatives, we opted for Python. Without getting into the futile debate over the superiority between R and Python, it's generally accepted that the majority of the machine learning ecosystem leans towards Python. That's why we chose this language. However, this decision wasn't made lightly, as it means our three stakeholders primarily work with three different programming languages: Java for IT teams, R for business teams, and Python for innovation teams. This diversity can pose a significant challenge to collaboration among the three teams, and we'll explain how we've attempted to overcome this hurdle.

In this project, we deliberately favored the use of scripts over notebooks, even though we're accustomed to using the latter in other projects. With a focus on production deployment, where our main goal was to ensure code scalability and efficient maintenance, notebooks present several significant limitations, including:

1. Defining and making all objects (functions, classes, and data) available in the same file, thereby complicating long-term code maintenance.
2. Limited potential for automating ML pipelines.
3. Notebooks' tendency to encourage code duplication and marginal modifications rather than using functions, making the code less modular and harder to maintain.
4. Lack of extensions to implement best practices, such as linters, making it challenging to apply code quality standards.
5. The costly transition to production with notebooks, whereas well-structured scripts are easier to deploy.
6. Major versioning challenges with Git, as notebooks are essentially large JSON files, making it difficult to identify code changes and thus collaborate among team members.

Moreover, by open-sourcing all our code, we've committed to following community standards by documenting our code and using formatters such as Ruff (<https://github.com/astral-sh/ruff>).

4.2.3 Méthodologie retenue

The model chosen after various trials is the fastText model [16], for several reasons:

1. The innovation team had gained experience in using this model through several previous experiments.
2. The performance obtained was very good.
3. The model is very simple methodologically and quick to train.
4. There is a Java wrapper available that allows reading fastText models. (share github ?)
5. Once trained, the model is lightweight enough to be deployed on our production servers.

rappeler les nouveaux enjeux pour les projets de ML (model versionning, logging parameters) L'utilisation du ssp cloud permet d'accéder à plusieurs logiciels tous interconnectés pour favoriser le développement de projet de machine learning favorisant une approche MLOps Objectif d'appliquer cette approche durant ce projet.

4.3 MLflow as the cornerstone of the project

Logiciel qui permet de suivre cette approche = MLflow et c'est dispo sur ssp cloud

- Why Mlflow ?
- Projects
- Models
- Tracking server
- Model registry

4.4 Embracing the power of Onyxia from training to deployment

- Distributing trainings with Argo workflows
- Deployment on the kubernetes cluster (freed from DSI) with fastAPI → conteneurisation Docker
- Automatiser les déploiements avec argoCD

Environnement dev et production très proche → passage en prod facilité

- Transmission d'une image
- Transmission d'une API

4.5 Monitoring of the model

- Enjeu du monitoring => indispensable
- data drift/ concept drift
- Pour APE : Création d'un dashboard (faire un super graphs qui récap tout)
- encore on utilise les trucs du datalab (argocd pour le déploiement, argoworkflow pour les cronjob quotidien)

4.6 Annotation en continue

- Evaluer la performance en créant un fichier test golden standard -> intégré au dashboard
- Amélioration du jeu d'entraînement en corrigeant les erreurs
- passage en NAF2025 très bientôt gros enjeu
- tout ca réalisé sur le datalab avec LabelStudio
- Rappeler les problèmes rencontrés (faire comprendre aux équipes métiers que c'est ultra important pour améliorer la performance, nécessite ressources humaines importantes..)

4.7 Gouvernance d'un projet de ML/ challenges

dire que pour contrecarrer probleme de langage on a recruté un data scientist + les informaticien doivent se mettre à python

5 Discussion

5.1 Future

- Onyxia, un bien commun opensource largement réutilisé (Insee, SSB) → faciliter les contributions pour la postérité du projet open-source, qui dépasse l'Insee
- One-stop-shop : SSP Cloud comme plateforme de référence pour les projets de ML → croissance de l'offre de formation (+ traduction)
- Accompagner les réinstanciations (datafid, POCs dans le secteur privé)
- Multiplication des projets qui passent en prod (applications de dataviz, modèles de ML avec MLOps, webscraping : Jocas/WINs)

5.2 Discussion

- Cout d'entrée important pour l'organisation : stockage objet, cluster kube/conteneurisation
 - Choix fondamental d'archi → limite à la diffusion d'onxyia
 - Assumer le choix : compétences, organisation ...
 - Mais globalement : tendance favorable car beaucoup d'orga et INS font ce choix
- Cout d'entrée important pour le statisticien :
 - Non-persistence de l'environnement → git + stockage objet
 - Travail dans un conteneur → perte de repères sur l'environnement
 - Mais formation : bonnes pratiques + écoles de formation Insee + accompagnements
- SSP Cloud :
 - Instance ouverte → absence de données sensibles → grosse limitation des cas d'usage réalisables + frustrations → en résumé, difficile de maximiser à la fois innovation et sécurité (pb sur-contraint)
 - → résolution via le choix de l'innovation max car sujet des échanges inter-administration de données complexe + le SSP Cloud a pavé la voie à des instances internes, plus fermées → stratégie assumée "platform-as-a-package" : projet open-source packagé → facilité ++ de réinstanciation
 - Pas une plateforme de diffusion de données → pas de stratégie globale de gouvernance → le sujet de la méta-donnée n'est pas abordé.
- Gouvernance :
 - Quelle organisation ? Equipe DS centralisée qui vient en appui ou data scientists dans les orgas métiers ? Collaboration avec les équipes infos ? (cf. graphique orga/compétences de Romain)

Appendix

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