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Ginus

Supply Chain Data

The impact in Supply Chain Performance

#1

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About Ginus

Over the past decade, there has been a noticeable trend towards the digitalization of supply chains, with a substantial majority of companies allocating significant resources to enhance and modernize their IT capabilities. Nevertheless, amidst this emphasis on systems, solutions, and digital services, the integrity and accuracy of supply chain data have often been overlooked, inadequately comprehended, or only partially grasped.

While many companies assert possession of data, showcasing their digital progression and achievements, the truth reveals a significant deficiency in data interpretation and integration with third-party entities and other partners within the supply chain.

The ramifications stemming from subpar supply chain and logistics data are directly correlated with diminished productivity, concealed but unrealized cost savings, and the ineffectiveness of supply chain risk management (SCRM).

Ginus has undertaken the challenge of addressing these issues with the ambition to become the OpenAI equivalent in the supply chain and logistics industry. This aspiration involves empowering partners to exchange data and intelligence within a collaborative framework. Essentially, Ginus is positioned to function as a personalized AI advisor for supply chain professionals, aiding in enhancing decision-making processes and delivering increased value to both their respective companies and supply chains.

ORGANIZATION AND MANAGEMENT

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1. Understanding Data Challenges

"Ah... data we have!"

Throughout nearly two decades of industry experience, aiding leading companies in optimizing warehouse operations, factory logistics, transportation, and supply chain network operations, a recurring trend has emerged encapsulated by the ubiquitous phrase, "Ah... data we have!"

Every company accumulates substantial volumes of operational data, converting these into information, reports, KPIs, and analyses that ultimately facilitate managerial decision-making processes. However, not all data should indiscriminately fuel reports and analyses. Consequently, external advisors and consultants are often summoned to lend support and pinpoint areas necessitating improvement.

Numerous factors contribute to data errors, yet the pivotal concern lies in the existence of a robust process to detect, rectify, or eradicate these errors.

38%

Up to 38% of data lines present issues that render them unsuitable for immediate utilization in an analysis without risking the distortion of results, consequently influencing suboptimal decision-making.

DATA ERRORS

1. **HUMAN INPUT**: Unless data input is automated by a machine or robot, typically, human intervention is required to enter data into various platforms such as forms, purchase orders, or new customer templates.

Moreover, within similar roles, individuals often exhibit variations in their approaches, resulting in diverse error patterns within the data. These discrepancies arise from the unique assumptions and methods employed by different individuals.

Merely 5 out of 100 optimization projects proceed without necessitating any data cleansing or manipulation before commencing analysis. In the remaining 95 projects, the incidence of errors within data ranges between 3% and 38%.

2. HUMAN OUTPUT: Every manager and professional, irrespective of their seniority, carries inherent biases shaped by their personality and professional experiences. Consequently, each individual develops distinct decision-making patterns.

When receiving information, each person interprets it differently, akin to the analogy of perceiving a glass as half-empty or half-full. Similarly, upon identifying errors in data, individuals may diverge in their approaches.

For instance, consider a scenario where 5% of data lines contain errors within a dataset. Some may opt to exclude these lines from an analysis or report, while others may choose to rectify them, aiming to reduce the error rate to e.g. 2%. The accuracy of these contrasting approaches and the subsequent impact on decision-making accuracy remain subjects of considerable debate.

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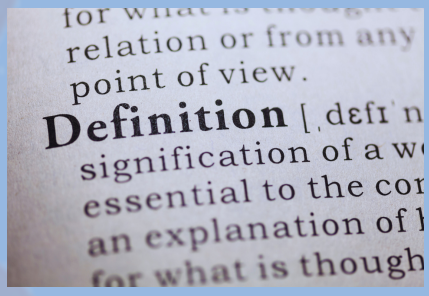
3. DEFINITIONS: The precise delineations of data groups, fields, or columns often lack clarity and comprehensive understanding across various management levels.



Often, these definitions were originally established by IT in collaboration with supply chain professionals several years ago. However, as time has progressed, the thorough comprehension of these definitions has gradually diminished. Consequently, during the creation of new reports, establishment of fresh Key Performance Indicators (KPIs), or data extraction for specific projects, newer managers and employees tend to operate under the assumption that they are utilizing the correct data, when in reality, they are not.

Engagements with Supply Chain VPs and Directors consistently anticipated a deficiency range of 6% to 7%. However, upon investigation, it has been consistently surprising to discover that the actual deficiency hovers between 15% to 20%.

4. PROCESS: The intricate process involved in capturing, processing, manipulating, aggregating, calculating, and ultimately summarizing data in reports and Key Performance Indicators (KPIs) frequently escapes thorough consideration.

Parallel to the issue of definitions, senior management typically anticipates and presumes the accuracy of data management procedures and resultant outcomes. However, the responsibility for data processing and analysis often rests with junior-level analysts who may lack the seasoned expertise and maturity necessary to discern gaps and errors within the processing workflow.

5. DATA SOURCES: Many companies and supply chain professionals often assume having appropriate data in their ERP, TMS, WMS, etc. means they can conduct any type of exercise, and analysis. WRONG!

The data typically available within these systems primarily pertains to the internal operations of the respective companies, often lacking crucial logistical and volumetric data associated with their third-party logistics providers (3PLs) in transportation and/or warehousing.

For instance, a company may possess information such as Orders, Advanced Shipment Numbers (ASNs), and quantities of units or weight, yet this alone is insufficient for optimizing their transportation or supply chain network. Critical details, such as the precise number of Full Truck Loads (FTLs) or Full Container Loads (FCLs) per specific transportation lane, remain unclear.

Consider that a single order may encompass multiple ASNs, while conversely, a single ASN may encompass numerous orders. Consequently, analysts or consultants are compelled to make assumptions, estimating metrics such as X tonnes per FCL or X units per FTL. These assumptions amplify the potential error percentage range and correspondingly diminish the accuracy of the final analytical results or reports.

SUMMARY

1. HUMAN INPUT

Errors from manual data input from internal or external stakeholders.

2. HUMAN OUTPUT

Errors from misinterpretation of data, due to personal bias.

3. DEFINITIONS

Data errors due to lack of knowledge, experience or due to inaccurate assumptions.

4. PROCESS

Errors from lack of or from inaccurate data manipulation prior to feeding reports, KPIs, or analysis.

5. DATA SOURCES

Errors from assumptions (averages, benchmarks) or from wrongly integrated external data sources.

2. Data Cleansing & Validation

"Garbage IN... garbage OUT."

What is Data Cleansing?

According to Wikipedia: **"Data cleansing or data cleaning is the process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table, or database and refers to identifying incomplete, incorrect, inaccurate or irrelevant parts of the data and then replacing, modifying, or deleting the dirty or coarse data."**

Why is it Important?

Data cleansing transcends merely rectifying typographical errors and other such mistakes. Drawing from extensive experience in cleansing diverse datasets from various renowned companies, I have unequivocally concluded that data cleansing stands as one of the pivotal tasks in ensuring the successful delivery of a project.

Our involvement spans across a wide spectrum within the realm of supply chain, encompassing projects ranging from Network Optimization & Re-design, Transport Optimization, Warehouse Optimization, Inventory Optimization, to Factory Logistics Reviews. Across all these diverse projects, the overarching objective consistently revolves around identifying avenues for cost reduction and performance enhancement.

Remarkably, in over 95% of these projects, the data cleansing process has been the compass directing us towards uncovering hidden opportunities for savings. The critical importance of data cleansing can be summarized with the points below:

- Establish confidence in the data set under analysis by implementing rigorous validation processes.
- Conduct a comprehensive critical evaluation to assess the severity and impact of identified errors within the dataset.
- Enhance comprehension of the operational intricacies and supply chain dynamics under investigation.
- Identify root causes attributing to the occurrence of errors within the dataset.
- Make informed decisions regarding the inclusion or exclusion of identified errors in the overarching study, based on their significance and influence.
- Acquire a precise understanding of the percentage accuracy of the study, Key Performance Indicators (KPIs), and generated reports through thorough analysis and evaluation.

Data Validation

According to Wikipedia, data validation is the process of ensuring data has undergone data cleansing to confirm they have data quality, that is, that they **are both correct and useful**. It uses routines, often called "validation rules", "validation constraints", or "check routines", that check for correctness, meaningfulness, and security of data that are input to the system.

In some companies, data maintenance falls under the responsibility of the IT department, while in other companies a “Master Data” team is taking after the task. Finally, in many companies each department is responsible for the maintenance of their own data.

However, supply chain data tend to be the poorest in quality amongst all other departments, mainly due to the vast number of external data sources, which are challenging to collect on a regular basis. In spite of the challenges, supply chain departments should dedicate resources to regularly make necessary updates, and ensure/validate the data quality, following the below approaches.

1. Manual

Exporting into spreadsheets and performing analysis and data quality checks.

vs

2. Automated

Automated tasks with the use of internal or external systems and tools.

3. Asynchronous/Periodic

Whether manual or automated, these checks take place every week/month/quarter etc.

vs

4. Synchronous/Dynamic

Automated processes that operate real time via API, RPA or other approaches.

BENEFITS:

- Improved Data Quality
- Increased accuracy of decisions
- Identification of NEW opportunities for savings
- Improved operational performance
- Lower response lead times to unforeseen events
- Stronger personal and team confidence
- Better customer experience & service
- More competitive supply chain

3. Data Standardization

"Apples with Apples"

What is Data Standardization?

Data standardization refers to the process of establishing and implementing a uniform set of rules, formats, structures, and definitions for data within an organization or across multiple systems. It aims to ensure consistency, accuracy, and comparability of data across different databases, applications, or departments.

Key Aspects:

- Format Consistency: Standardizing the format of data elements (such as date formats, units of measurement, or naming conventions) to ensure uniformity and ease of understanding.
- Normalization: Organizing and structuring data in a standardized manner to eliminate redundancies, inconsistencies, or anomalies, thereby improving data quality and integrity.
- Common Vocabulary: Establishing a common vocabulary or data dictionary to define terms, variables, and their meanings, ensuring clear communication and interpretation across various systems or teams.
- Interoperability: Enabling different systems or databases to seamlessly exchange and use data by adhering to standardized formats, making integration and data sharing more efficient.
- Compliance and Governance: Adhering to regulatory standards and industry best practices to ensure data compliance, governance, and security.

BENEFITS:

- An enabler to enhance supply chain visibility with 3rd parties, customers, suppliers or even with different internal BUs globally.
- An enabler for dynamic supply chain modeling
- Dynamic "what if" scenarios modeling
- Improved decision-making

4. Passive Data Integration

"Supply Chain Visibility"

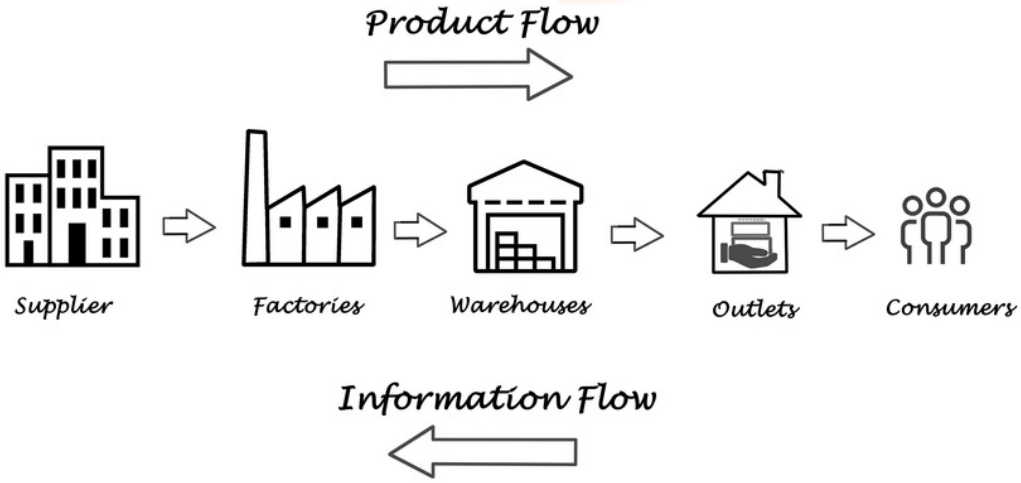
What is Passive Data Integration?

Passive data integration refers to a method or approach of combining and consolidating various sources of data without actively interacting with the data sources in real-time or modifying the original data structures. In this context, "passive" implies that the integration process does not involve continuous or immediate interaction with the data streams or databases.

Key aspects of passive data integration include:

- **Data Aggregation:** Passive integration involves the aggregation of data from multiple sources, such as databases, applications, files, or systems, without modifying the original sources or interrupting ongoing operations.
- **Batch Processing:** Data is typically gathered periodically or in batches from different sources rather than being continuously streamed or collected in real-time.
- **Data Consolidation:** Once collected, the data is consolidated or merged into a unified repository or data store where it can be processed, analyzed, or used for various purposes.
- **Synchronization:** Passive integration might involve synchronization processes to ensure that data from diverse sources is aligned, standardized, and updated regularly to maintain consistency.
- **Offline Processing:** After the data is collected and integrated passively, further analysis, reporting, or manipulation might occur offline or at predetermined intervals, rather than in real-time.

Passive data integration is often employed in scenarios where real-time data interactions are not necessary or feasible, and where periodic or batched processing of data from multiple sources is sufficient for the intended purposes, such as analytics, reporting, or historical analysis.



5. Leveraging Ginus

Data Cleansing

- Dynamic real-time cleansing via API or batch data cleansing via excel uploads... in a few minutes.
- Improves the accuracy of KPIs, and optimizations studies.
- Identify data errors once off or periodically with Ginus.
- Feed your modelling tools with cleansed data.
- Boost and optimize by >5% your routes, transport, and network models.

Geocoding & Data Enrichment

Use the advanced robotic process automations (RPAs) of Ginus to increase the accuracy of batch geocoding, and/or correct the coordinates of your existing network, suppliers, customers, etc. Moreover, Ginus enriches your data sets by performing of specific functions that allows mixed data sets to get standardized and ready for analysis, as well as enabling to integrate them.

Data Validation & Standardization

Simplify and standardize your data maintenance processes across different BUs, and employees easily, with only 1 hour onboarding training. This way you can roll out and train your employees across geographies easily, and avoid utilizing expensive consultants and other external parties.

Passive Data Integration

Use Ginus as your supply chain cloud integrator with your third parties, warehouses, production facilities, distribution centers, suppliers and customers. Ginus acts as a blockchain alternative with the difference that no other party can share or view your company’s data. Ginus can achieve data synchronization, while maintaining data security & privacy!

- Expand your supply chain visibility
- Improve your supply chain performance, while reducing costs
- Enable a more effective supply chain risk management (SCRM)

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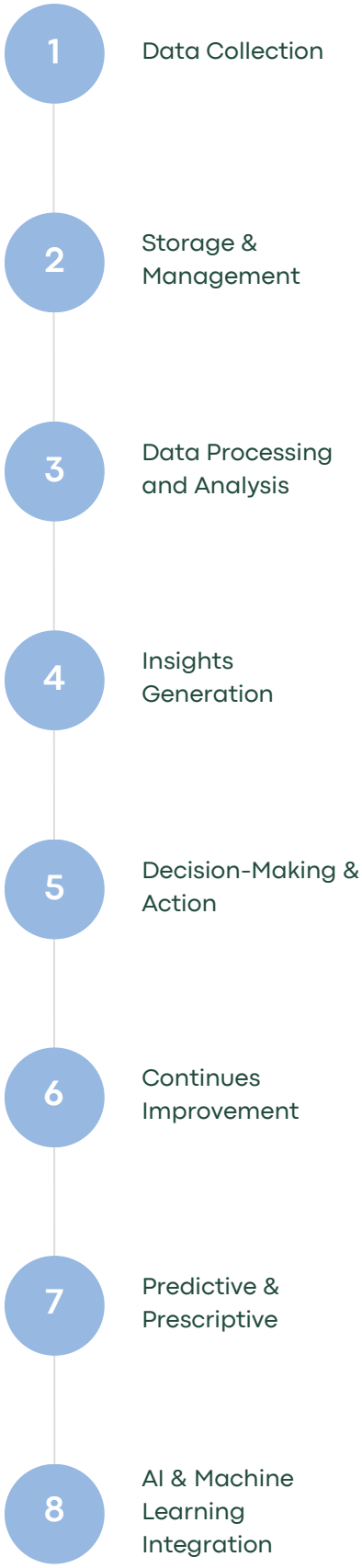
Click here

Conclusion

Stages of Data Evolution

The evolution of data can be understood through several stages that highlight the progression, development, and utilization of data within various contexts. Here are common stages in the data evolution process:

- **Data Collection:** This initial stage involves gathering raw information from different sources, which can include traditional databases, sensors, IoT devices, social media, web interactions, and more. The data collected might be structured, semi-structured, or unstructured.
- **Storage and Management:** Once collected, data needs to be stored and managed effectively. This stage involves choosing appropriate storage systems, databases, data lakes, or warehouses to accommodate the collected data. Managing data includes organizing, categorizing, and indexing it for easy retrieval and analysis.
- **Data Processing and Analysis:** After storage, data goes through processing and analysis. This stage involves cleaning the data (removing errors or inconsistencies), transforming it into a usable format, and analyzing it to extract valuable insights using various tools and techniques such as data mining, statistical analysis, machine learning, etc.
- **Insights Generation:** The processed data leads to the generation of insights and actionable information. This stage involves interpreting the analyzed data to derive patterns, trends, correlations, and other valuable information that can drive decision-making, strategy formulation, or problem-solving.
- **Decision-Making and Action:** Insights derived from data analysis inform decision-making processes. Organizations or individuals use these insights to make informed choices, develop strategies, improve products/services, optimize operations, or address specific issues.



- **Continuous Improvement:** Data evolution is a cyclical process. Organizations continuously collect feedback, refine their data collection methods, improve data quality, and enhance analytical models to ensure ongoing improvement in decision-making and operational efficiency.

- **Predictive and Prescriptive Analytics:** Advanced stages of data evolution involve predictive and prescriptive analytics. Predictive analytics uses historical data and statistical algorithms to forecast future outcomes, while prescriptive analytics suggests actions to optimize or improve future results based on predictive models.

- **AI and Machine Learning Integration:** With further advancements, organizations integrate artificial intelligence (AI) and machine learning (ML) to automate processes, derive deeper insights, and enhance decision-making by leveraging algorithms that can learn from data and improve over time.

Ginus is an exceptionally versatile tool designed to provide comprehensive support across every phase of the data evolution journey. Its capabilities are tailored to augment your existing workflows significantly, leading to a substantial enhancement in the quality of your supply chain data.

Irrespective of your current position in the data maturity continuum, we invite you to explore the capabilities of GINUS. Embrace the challenge of leveraging GINUS to quantify the depth and breadth of supply chain insights it can unveil.

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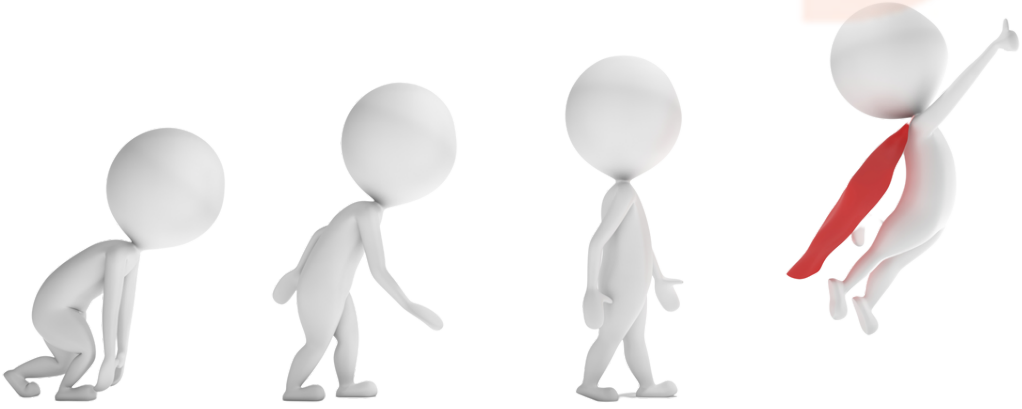
1. Get ahead of your competition by unlocking value & savings in your supply chain.

2. Be more responsive & more accurate in your decisions to supply chain volatility.

3. Speed, Quality, Efficiency & Flexibility... All in 1.



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Useful Sources & References

- Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. Journal of management information systems, 32(4), 4-39.
- Chopra, S., & Meindl, P. (2016). Supply Chain Management: Strategy, Planning, and Operation. (6th ed). Pearson Education.
- Christopher, M. (2022). Logistics and supply chain management. Pearson Uk.
- Green, K. W., Whitten, D., & Inman, R. A. (2008). The impact of logistics performance on organizational performance in a supply chain context. Supply chain management: An International journal, 13(4), 317-327.
- Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2018). Back in business: Operations research in support of big data analytics for operations and supply chain management. Annals of Operations Research, 270, 201-211.
- Kamble, S. S., & Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation. International journal of production research, 58(1), 65-86.
- Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. International Journal of Production Research, 59(6), 1875-1900.
- Mursidah, S., & Fauzi, A. M. (2022, July). Sustainable sugarcane supply chain performance assessment: A review and research agenda. In IOP Conference Series: Earth and Environmental Science (Vol. 1063, No. 1, p. 012039). IOP Publishing.

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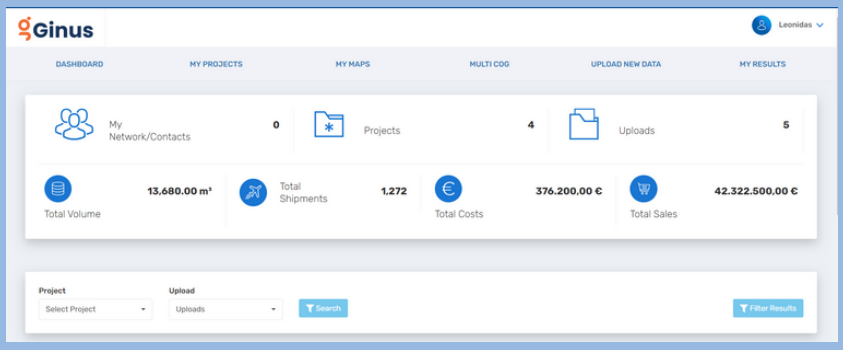

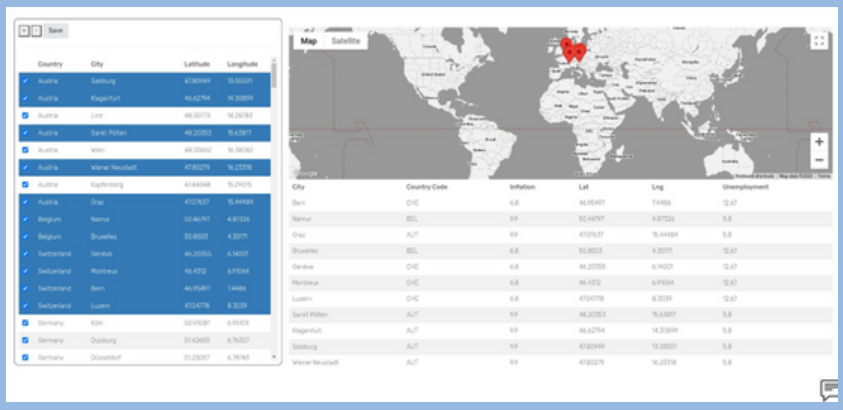

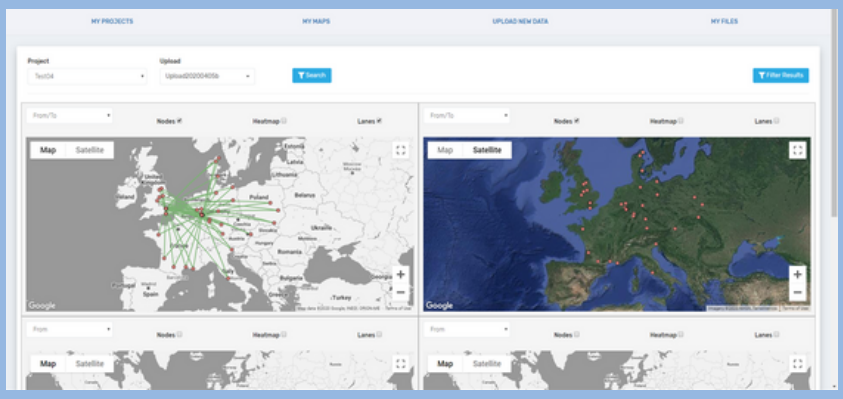

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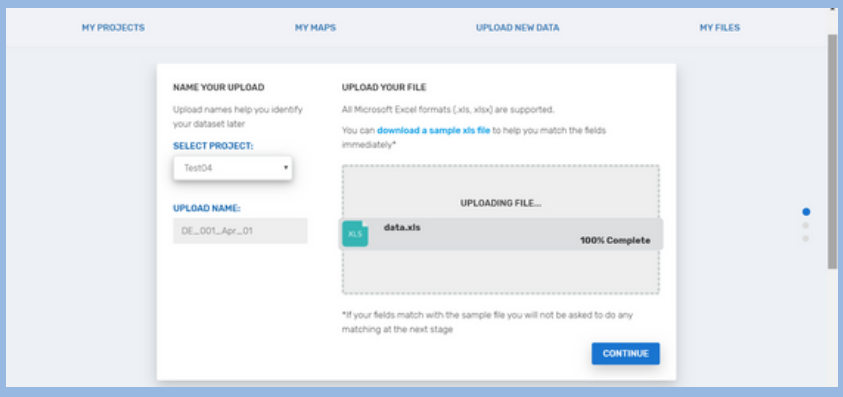

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