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Whitepaper

Unleashing AI Potential in Insurance

HOW MODERN DATA SOLUTIONS ARE RESHAPING INDUSTRY STANDARDS

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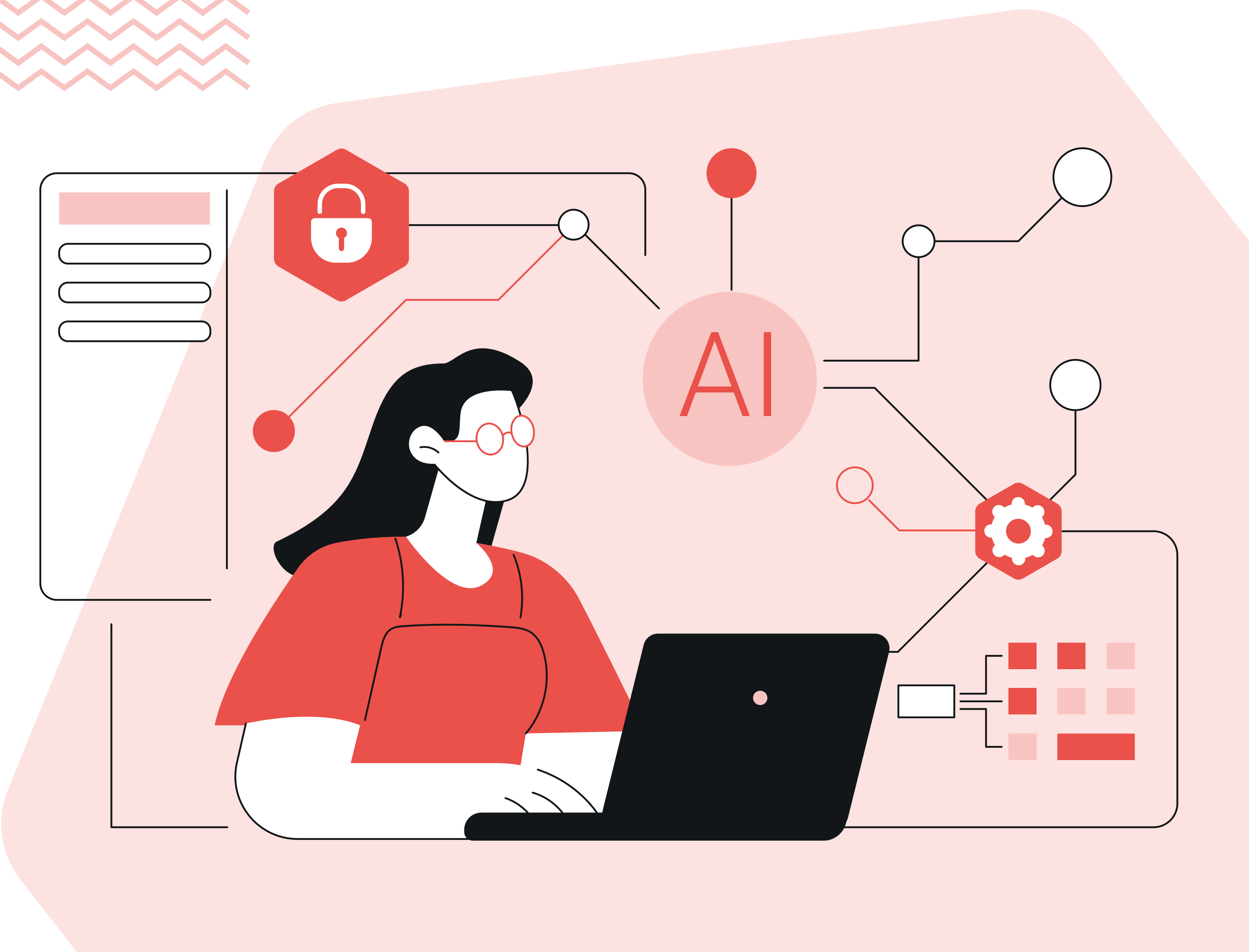

Table of Contents

Summary

Insurers need a significant amount of data to assess insurance risk and premium amounts. The amount of data collected, and the variety of information produced, are both increasing exponentially. Many data management platforms are inflexible and unable to combine various types of data to provide a single, integrated view of the data. Additionally, they are often unable to support artificial intelligence/machine learning (AI/ML) for new use cases to drive decision making. In this context, Insurers need a new approach with a modern data platform.

This paper explores three key data challenges inherent to applying AI/ML in the insurance sector with a traditional data management approach and explains how a modern data platform can help eliminate them.

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Introduction

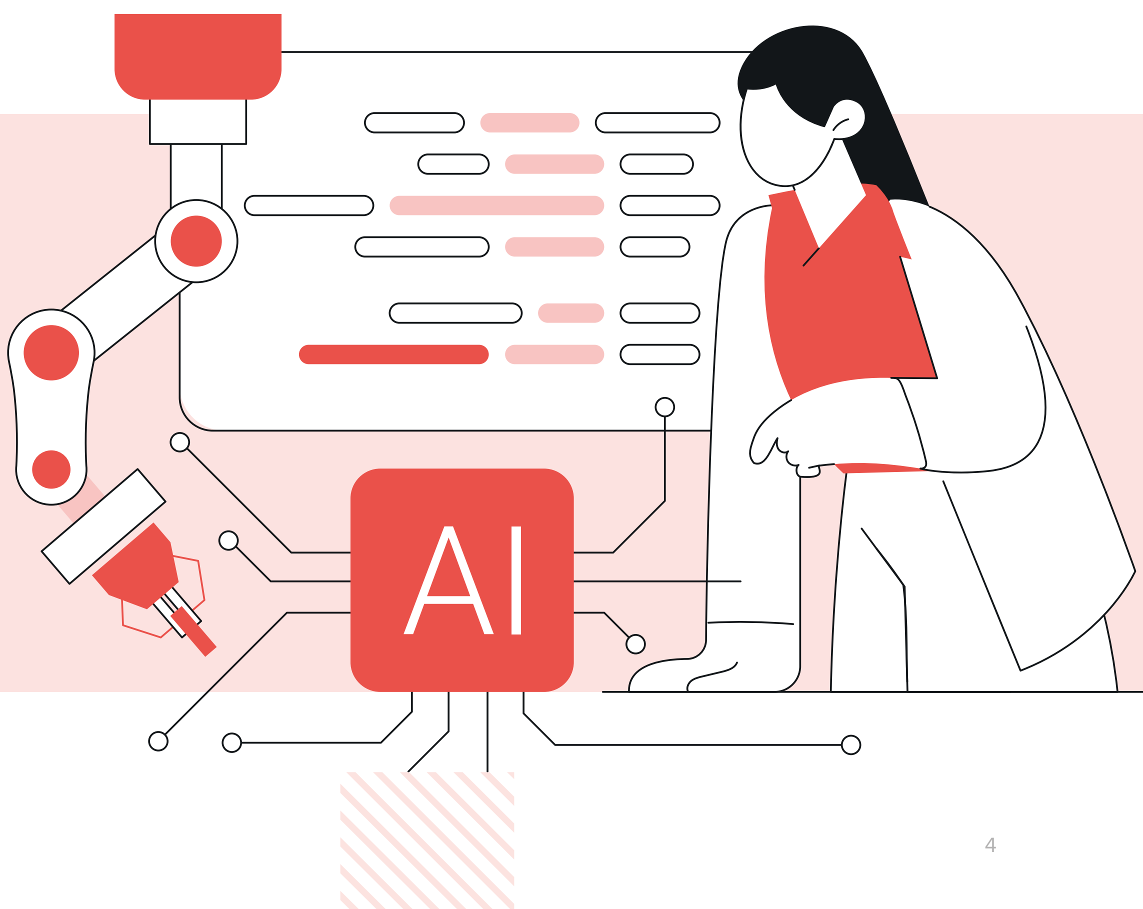
AI is a game changer across all business sectors, and some companies are leveraging it to innovate new methodologies to improve decision-making through predictive modeling.

Despite its great potential, AI has not yet fulfilled its promises. ML, which can be seen as a branch of AI, is based on two fundamental pillars: on the one hand, the data, which are the examples from which the algorithm will learn; on the other hand, the learning algorithm, which is the procedure that is run on this data to produce a model. These two pillars are equally important. No learning algorithm will be able to create a good model from irrelevant data. In addition, most AI technologies perform best when supplied with a high volume of data from a variety of sources.

In many cases, companies have enough data, but they cannot deal with a heterogeneous, polyglot enterprise data landscape, in which data is often siloed and not integrated.

This paper focuses on the data challenges that affect AI adoption in an insurance setting. It places a special emphasis on ML, which is one of the main ways in which AI is being applied, leveraging algorithms that can learn from examples and can improve performance with more data over time. We will explore how your organization can address the data challenges of AI/ML with a logical data management approach.

We will start with an introduction of insurance as one of the most data-intensive industries, and then highlight a few key use cases for AI in insurance. A greater use of AI results in a broad range of benefits for both consumers and insurers, affecting underwriting, claims, customer service, and fraud prevention. We will investigate the data challenges in this context with practical examples. Then we will show how logical data management addresses these issues in a more efficient, agile way.



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The Case of Insurance Companies

Data has always been the backbone of insurance companies. They possess a large volume of data, which continues to grow. The data covers a wide variety of elements, including information about customers' histories and individual transactions, and this data is often fragmented and siloed across multiple data sources, waiting to be analyzed. The use of AI/ML offers opportunities to acquire additional data, to engage in such activities as determining insurance risk or introducing programs to generate revenue or increase profit.

This data includes both personal and non-personal information coming from internal or external sources as well as information that might be structured or unstructured. There are hundreds of applications and tools designed for managing the insurance lifecycle, to address such areas as underwriting systems, policy administration, and customer relationship management. In this respect, AI/ML can help insurers in multiple ways. For example, the policy pricing is normally updated regularly based on profitability, new claims data, and the competitive landscape. AI/ML enables more flexible pricing, for a significant improvement over the classic policy-pricing process.

ML deals with the design of algorithms and computer resources to learn from the data to create insights that improve performance or inform predictions. Today, ML models are used not only to analyze client behaviors and trends and for personalizing the customer experience, but also to identify suspicious activities and prevent fraud.

ML requires data science tools to first clean, prepare, and analyze unstructured data. Data and models are both evaluated and refined through numerous iterations. These iterations can range from initial training to deployment in production. Each iteration retrains and refines the model and improves the predictions. AI/ML can improve insurance industry processes by interpreting the data more efficiently.

USE CASE EXAMPLES

ML is already widely in use across the insurance industry. Following is a list of some of these use cases that augment existing capabilities, rather than replace human activity. They all provide benefits such as better decision-making and a better customer experience.

Pricing prediction - pricing, through detailed risk classification, is the mechanism through which insurance companies can compete and reduce the cost of contracts. The goal is to charge different premiums to different customers, based on their profiles, to reflect the level of risk insured.

Overpricing means fewer customers, and underpricing means potential losses, so insurance companies need a more accurate assessment of risk. Insurance companies leverage a variety of data sources to gather risk data on customers, which is used as a basis of price.

Price prediction with ML determines the insurance price based on the customers' personal information such as age, gender, region, whether they smoke, the number of children, etc.

Fraud prediction - insurance fraud is a growing problem that negatively affects the insurance industry and its customers. Insurance companies' fraud detection systems attempt to identify suspicious activity as it passes through the backend system. However, traditional fraud detection methods, such as rule-based systems, are not an option in insurance today. That is because traditionally, detecting insurance fraud has depended on manually inspecting claims, which is expensive and inefficient.

Moreover, fraudulent behavior is dynamic and cannot be relied upon to identify fixed characteristics. For these reasons, ML has enabled more effective fraud prediction.

Next-best-offer prediction - insurance companies often have a wide range of product offerings and a large pool of customers. But they have limited interactions with their customers. These interactions often take place during the initial purchase of an insurance policy, the processing of a claim, and the renewal of a policy. Being able to present consumers with the right offer at the right time is a critical part of personalized marketing.

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Analyzing customer data can help insurance companies to increase revenue by predicting the most relevant products or services and upsell opportunities. An ML model can be used to help predict the next best offer and estimate when a transaction will take place. But precise predictions require a mountain of data about consumer behavior, as well as the ability to analyze all that information.

Churn reduction - since it is more profitable for insurance companies to keep existing customers than to attract new ones, it makes sense to try to predict when a customer is likely to leave and to try to prevent them from doing so or decreasing their purchasing activity. Using ML models, insurance companies can better assess when a customer could be at risk of leaving and why.

Using ML models to help predict churn has become increasingly popular as the volumes of data are continually increasing. It enables insurance companies to adjust more effectively to changing conditions.

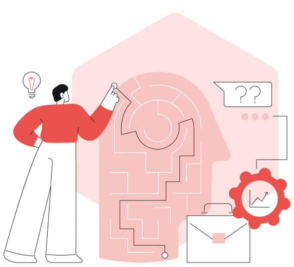
These use cases all require the combination of data from a variety of source systems, including both structured and unstructured data and based on a variety of different storage technologies. ML models need to be trained on the data, which needs to be collected and prepared for this use. However, the current landscape of data that is increasingly distributed, which includes data warehouses, NoSQL, and streaming data sources, significantly compounds the complexity of developing an enterprise-wide view of data sets for AI/ML applications.

The Machine Learning Workflow

Building ML models is hard but putting them into production is harder. This requires a continuous approach based on workflow, along with tracking capabilities that enable data scientists and engineers to compare and reproduce results.

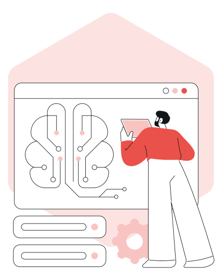
ML projects involve data processing, model training, and model deployment. These changes make the ML lifecycle more challenging than traditional software development lifecycle (SDLC) management. The process of applied ML consists of a sequence of steps that provide structure to the ML project. The sequence is not linear, and iterations are very common.

The typical workflow consists of four main phases:

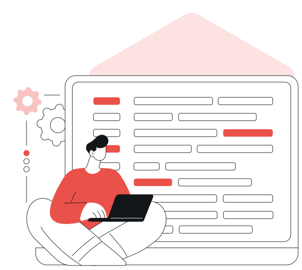


1 Requirements-gathering for solving the business problem

2 Data engineering (data acquisition and data preparation)



3 ML model engineering (training and serving)



4 Code engineering (integrating the ML model into the final product)

The model may become obsolete as data increases, so it is essential to monitor and maintain it regularly to keep the algorithm working.

Data preparation is an expensive step in end-to-end ML. Collecting data, cleaning it, and making it suitable for ML training takes 45% or even 80% of the time.

Data Challenges

Insurers can acquire data from a variety of sources. They can acquire not only general statistics and data related to the risks insured, but also data collected through insurance claims.

The AI/ML workflow involves a series of choices and practices, from model definition to user interfaces used upon deployment. Each stage involves decisions that can lead to undesirable effects. While data collection and data quality issues (such as detecting and fixing dirty data) are important for machine learning, there are other critical data challenges. AI/ML poses new challenges to data access.

Insurance companies will face three key challenges in pursuit of their AI/ML strategies:

1. Data acquisition and preparation,
2. Data democratization,
3. And data security and privacy.

DATA ACQUISITION AND PREPARATION CHALLENGES

After setting AI/ML research goals, data needs to be collected. Some organizations collect huge amounts of data without knowing whether it is useful or not. Additionally, the abundance of data sources makes it difficult to find the right data.
Data acquisition and preparation may be the most important and time-consuming part of an AI/ML project. It's the act of transforming raw data into a form that is appropriate for modeling. Data preparation requires an iterative process that can be performed manually, automatically, or in some combination of both, to discover what works best.

Challenges:

- Insurance companies cannot evaluate an ML algorithm on raw data, they first need to transform the data to meet the model requirements. Even more, they need a representation of the data that enables them to obtain the best possible predictions.
- Data needs to be extracted from external and/or internal sources and cleaned prior to the model-building phase. Data can be acquired from several different sources including legacy data stores, data warehouses, relational data sources, NoSQL, CSV, JSON, and big data sources. Internal data sources that are already stored in the company's database management system, e.g., transactional data regarding policy changes or existing policyholder information, are generally easier to access.
- In real-world systems, data is rarely of the required quality. Usually, there are some missing values, duplication, inconsistencies, etc. In addition, data collection sometimes does not gather certain information due to various reasons like legal restrictions.
- Descriptive metadata is essential for data scientists. Incorrect interpretations of data create confusion and misunderstanding, and it can lead to incorrect ML models and ultimately poor business decisions.

DATA DEMOCRATIZATION CHALLENGES

Insurance companies generate data in large quantities across all business functions. But data often remains solely in the hands of experts, without benefiting anyone else internally or externally. Today, companies want to decentralize control and decision-making to create an interactive approach to business, ensuring better decision making without delay for individuals across the organization.

Breaking down the silos and making data more accessible enables insurers to make more profitable investments, unlocking the true power of data for everyone's benefit. When data is siloed in different enterprise applications, data warehouses, and data lakes, it is nearly impossible for a user to know where to find the data they need to do their job. This dramatically slows down and limits data sourcing and sharing for AI/ML.

Challenges:

- Democratizing data in this context means enabling insurance employees and individuals to access reliable data at any time, without needing specialist skills. The challenge is to make data fully accessible and

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understandable, to facilitate its reuse, to offer everyone a simplified data experience, ultimately to deploy AI/ML use cases to enable rapid access to valuable insights for decision making. To do this successfully, insurers need to remove bottlenecks to data access and provide an easy way for everyone to understand and manipulate the right data.
- Some data owners are reluctant to engage in a data democratization process for security reasons. They often worry about the misuse of data, especially sensitive personal data of customers or employees.
- The successful implementation of a data democratization strategy involves the evolution of enterprise data security and governance policies, but it also requires having a proven tool, to enable smarter usage and data sharing.

DATA SECURITY AND PRIVACY CHALLENGES

Gathering data and using it for AI/ML presents challenges to the security and privacy of individuals and organizations. Security and privacy preservation in AI/ML projects aims to bridge the gap between preserving security and privacy and reaping the benefits of AI/ML. Within the data ecosystem, information is constantly flowing in many directions. A very important pillar of data governance is data privacy.

Challenges:
- A critical issue is the protection of personally identifiable information (PII), that is, data that can be used to identify a given person. For insurance companies, information including a name (first and last), birthdate, social security number, bank account number, health insurance ID numbers, policy numbers, and more, can also be considered PII. A set of users might allow the use of their personal health records for medical research, but not for marketing purposes.
- In addition to cryptographic techniques to keep data private, data privacy requires the need to ensure that data analytics techniques are applied effectively on data sets without revealing personal information. It's possible to enhance ML with masking and encryption techniques, which enable organizations to use data sets without exposing the real data, safeguarding data privacy. Data anonymization aims to protect the privacy of an individual within a given data set.
- Besides protecting PII from potential leakage, data managed by a distributed insurance company infrastructure may have different origins and provenance and be subject to divergent regulatory requirements (such as the General Data Protection Regulation (GDPR) in Europe). Such regulations define what the organizations are allowed to do with their data, and for which purposes it may be used. Compliance with these regulations can be complex without effective data governance and the appropriate data management platform in place.
- Before using ML models, we need to ensure that all parties involved are comfortable with the solution, including data owners, customers, and regulators. Therefore, data governance is of primary importance in the insurance industry.

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Logical Data Management and AI/ML

Traditional data management solutions alone cannot address all the challenges that data scientists face in building AI/ML models. Without manually intensive transformation efforts, such solutions do not semantically unify the available data before it is delivered to the models. Additionally, these traditional data management solutions rely on batch-oriented extract, transform, and load (ETL) processes for data integration, which can introduce latency into the process.

Logical data management solutions, in contrast, provide real-time connections to data across many different systems, in real time. This enables insurance companies to establish a unified semantic layer that can securely deliver data to AI/ML models in readily usable formats, at the speed that the business demands. This is made possible by a technology called “data virtualization.”

Data virtualization abstracts users from the complexity of the underlying data sources (heterogeneous sources, data lakes, etc.) and builds a virtual layer between data consumers and the variety of data sources that are distributed across different locations or reside in the cloud. To data scientists, it feels as if the required data is stored in a single integrated system, in the format they need. Any request for the data is executed against these virtual views, which in turn transform the request into a series of queries needed to access data. This ensures that users adhere to data governance policies and increases their ability to access real-time data.

This section describes how the Denodo Platform, a logical data management platform powered by data virtualization, can help overcome the challenges described in the previous section.

DATA ACQUISITION AND PREPARATION

The Denodo Platform offers unified access to all data available in the company, decreases the costs (e.g., time) of data acquisition and data preparation, and guarantees the freshness of data. Data virtualization not only saves time, but it also shifts the way that people interact with data. It fetches data in real time from underlying source systems. Data sources are integrated into the virtual layer, regardless of protocol and format, and this simplifies tasks related to identifying the right data and understanding the relationship between different data entities. A data source of interest to data scientists – but not yet present in the virtual layer – can be added quickly and easily.

The Denodo Design Studio - the Denodo Design Studio is used to build virtual models (create connections to databases, web services, and views; publish web services…). Having to integrate data into heterogeneous data stores often results in a semantic integration problem where the same business entity may have a different meaning in a different semantic context. In the Denodo Design Studio, data can be correlated based on filtering, joins, or aggregation. It can apply all the needed table-level transformations and operate at the field-level, thanks to a rich, extensible functions library. The Design Studio can help with data cleansing, which ensures that the quality, accuracy, completeness, consistency, and uniformity of the data is preserved. It enables filtering for incorrect rows/values after applying data validation logic, so the data consumer only receives rows with correct data. Denodo provides a vast library of transformation, filter, and matching functions, and quality rules for validating, cleansing, enriching, standardizing, matching, and merging data.

The Denodo Data Catalog - the Denodo Data Catalog provides a user-friendly interface that enables data consumers to search, find, and explore data assets. It provides a single source of truth about a company’s data sources. It enables business users and data scientists to access, query, instantly evaluate, and find associations between all the data assets defined in the virtual layer. These assets can be classified using tags and categories, and queries can be created graphically, saved, and then shared with peers for collaboration. The Denodo Data Catalog promotes self-service and discovery capabilities for data scientists, enabling them to explore both data and metadata in a single Web front-end tool. With this tool, the data scientist can access a graphical representation of the business entities and relationships, as well as data lineage and tree-view information. It stays within the security boundaries defined by the data virtualization layer in the data model, so administrators can determine exactly what data each user can see through the self-service interface.

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Extending the Data Lake - the volume and variety of data sources pose serious problems of access and integration. Data lake systems, which store raw data in their original formats and provide a common access interface, have been proposed to overcome these problems. Data scientists and business analysts often leverage data lakes to create and apply analysis models. As part of its abstraction layer, the Denodo Platform incorporates a massively parallel processing (MPP) engine, based on Presto, which provides efficient access and processing capabilities and intelligently extends a data lake. The Denodo Platform's MPP engine provides a flexible, universal, and technology-independent model that goes beyond the data lake with inexpensive, ubiquitous data lake storage in the cloud. In the spirit of Denodo's philosophy of "bringing the processing to the source," the Denodo Platform's MPP engine brings parallel data processing power to object storage, without sacrificing technology-agnostic virtualization. It also gives data scientists access to a playground in which they can test their methods without impacting other sources.

Generic Connectivity with Python - Python is one of the most widely used programming languages in the data science community. The Denodo Platform can be seamlessly integrated into the data scientist's workflow as a powerful data preparation and data governance tool, one that provides the most optimized and broadest access to internal and external data sources. The Denodo Platform provides native connectivity with Python, enabling data scientists to access the Denodo Platform with their preferred development environment, so as to be able to run their ML pipeline fetching training data directly from the Denodo Platform. There are several Python libraries available with which to establish the connection between Python and the Denodo Platform. To all these libraries, the Denodo Platform is exposed as a standard relational database. Data scientists will be able to import the data from the Denodo Platform to Python and transform it into Pandas DataFrames, the data structure that represents the starting point of data exploration, analysis, visualization, and training of ML algorithms.

DATA DEMOCRATIZATION

For many insurance companies, providing data that can be used to address new business needs can take a significant amount of time. In this context, it is not possible to develop a data culture when data is not available to meet new needs. The Denodo platform makes accessing and integrating data as simple as possible for everyone in an organization. By doing this, it puts the appropriate controls in place to ensure data security and provides a data catalog to help users find what they are looking for while ensuring a certain level of quality. The goal is also to provide more data to analyze for decision-making, because part of the organization's data often remains inaccessible to decision-makers. To do this, the Denodo Platform enables insurance companies to create new uses for:

Self Service - the Denodo Platform promotes self service, which provides organizations with much lower costs of extracting information from their systems. The Denodo Data Catalog provides centralized access to data and makes information understandable to those who lack technical expertise. It combines both traditional catalog metadata capabilities with a full-blown data delivery layer in a single platform, so that search and data exploration are a combination of both. This will not only help data consumers to discover, catalog, and locate available data sets, its metadata, and its lineage, but it will also enable quick integration of all the enterprise data sources. It enables users to become more autonomous and less dependent on the IT organization. It provides easier access to data for reporting, analysis, or data discovery for AI/ML, and collaborative end-user interfaces.

Data Services Marketplace - the Denodo Platform is a flexible, modern data integration and data management solution that can serve as the foundation for an effective data services marketplace. For example, an organization can use the Denodo Platform to deliver data from a myriad of sources and establish a data services marketplace for business users, data scientists, and business analysts. Data scientists can quickly discover interesting data sets, by browsing over datasets classified in business categories and by searching the metadata as well as the contents of the datasets. They can view column descriptions, tags, business categories of the datasets, data lineage information, and information about how other users and applications are using those datasets. In addition, the Denodo Platform promotes an innovative way to manage data as a reusable, shareable business resource. For example, a company can create a set of certified reusable datasets, a dataset created for a ML project used for another, and other use cases.

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DATA SECURITY AND PRIVACY

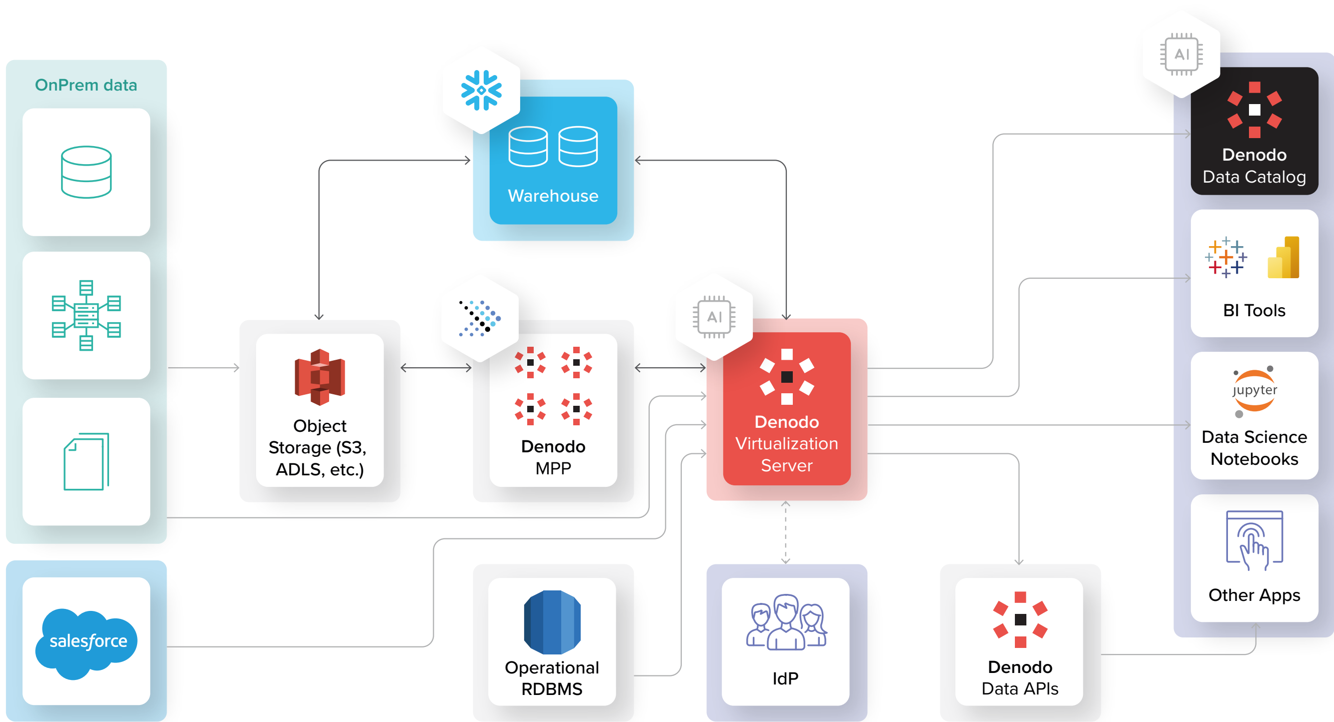
ML workloads often push companies to collect data aggressively, with lax data access policies. This puts a lot of sensitive user information at risk if the company is hacked. To overcome these risks, the Denodo Platform establishes a centralized access point for all information and metadata across the enterprise, enabling effective security management and data governance. It is very important to define security policies in the data virtualization layer that enables semantic security rules to be implemented on the data, independent of the technologies used:

- The Denodo Platform offers role-based access control (RBAC), an approach to data security that allows or restricts system access based on an individual's role within the organization. Roles are assigned to a user with a scope. This establishes the person as being responsible for performing the tasks of the role, within the assigned scope.
- Attribute Based Access Control (ABAC) is one of the access control models that can be used to restrict access to users based on their connected session. With ABAC, administrators can control data access on a global scale through global security policies (GSPs), minimizing the need to create multiple roles with specific restrictions for each user.
- GSPs enable the definition of security restrictions that apply to all or some views that verify certain conditions. GSPs are often used together with tags that can be assigned to views and their columns.

Modern Data Architecture

Traditional data architectures are being overtaken by data growth, new processing needs, and a growing interest in supporting new use cases. One of the biggest challenges many insurances companies face is leveraging their existing enterprise data architectures. Most of these data architectures rely on a monolithic design that does not meet the constraints of highly distributed environments and future needs.

Modern data architecture seems suitable for insurance companies to be able to support AI/ML use cases. A modern data architecture must not only meet current demands but must be designed to adapt to future needs.



Modern data architecture is not a simple evolution of computer processing power, the replacement of a tool, or even the migration of data to the cloud. It must:

- Support the distribution of data in multiple locations or systems (on-premises, hybrid, multi-cloud) and must be managed with consistency.
- Use a logical data strategy to manage it and enable data consumers to access data through a centralized semantic model, decoupled from data location, following security and governance requirements.

Data virtualization, the underpinning of the Denodo Platform's logical approach to data management, is a modern data integration technology that reduces the complexity of traditional data integration solutions and provides a single, consolidated, integrated view of the data. The figure below is a high-level overview of a data architecture in which the Denodo Platform forms the heart.

- On-premises data from applications, databases, files, and other sources is virtualized by the Denodo engine, providing a unified, secure access point.
- The Denodo Platform provides a semantic layer that centralizes access to all data, including other databases and data still on-premises.
- Modern data lakes and data warehouses have become key elements of a modern data strategy but do not meet all the requirements of modern data strategy. However, it can be combined with the Denodo Platform for more widespread agility, better governance, data democratization, and self-service data access.
- All connected data sources are combined, secured, and exposed as virtual data sets consumed by analytical applications, data science tools, the Denodo Data Catalog, and all real-time applications.
- The Denodo Platform applies access control policies on its semantic models. It can enforce access control using ABAC and RBAC policies that can even leverage metadata like PII or other tags.
- Snowflake is a component of the analytics stack, providing storage and processing power for all analytics workloads. Some specialized processes may have direct access to Snowflake.
- The Denodo Data Catalog provides a great tool for end users and data scientists to explore, browse, and document data.

Users can virtually connect to a variety of data sources and aggregate and combine the data to form virtual views that can then be exposed as data services or APIs to support multiple formats such as SQL.

This architecture enables organizations to democratize access to data with an intelligent data catalog, one that leverages AI/ML techniques for recommending different views based on users' data manipulation experiences.

The Denodo Platform goes beyond traditional data virtualization scenarios to better support new types of users and new types of use cases, such as data science and ML initiatives. It can help organizations to solve all the data challenges exposed in this document, by providing:

- A unified semantic layer, in which users can define business entities that represent a common definition across the enterprise, exposing them as data services that any application or user can consume, avoiding elimination inconsistencies and improving the overall quality of information.

- A data catalog, which provides data preparation wizards for querying and customizing the data, enabling users to connect to the data with their favorite data visualization tools and enabling data scientists to better manage their time, devoting most of it to the creation and evaluation of AI/ML models, rather than data ingestion and preparation.

- A single-entry point for enforcing governance and security policies in the data delivery stage, across all systems. It establishes security controls over the entire infrastructure from a single point, enabling companies to comply with regulations quickly and easily like GDPR.

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Conclusion

Many insurers maintain large volumes of data in data warehouses and a multitude of analytical applications. However, most fail to meet the demands of today's ever-changing business climate and the potential of AI/ML. Today, AI/ML has the potential to generate solutions superior to what insurance companies would expect. This revolution has led to the emergence of tools and techniques to exploit data at this new scale.

Data challenges are one of the primary influencers of organizations' data strategies. Therefore, many organizations investigate the latest data architectures, technologies, and practices to address these challenges. The approach presented in this paper has been used successfully by several Denodo customers in insurance and finance, for their AI/ML initiatives.

DNB is Norway's largest insurance provider. The company offers a wide range of personal and business insurance products with significant market share., The company uses the Denodo Platform to leverage all its data sources, including multiple data warehouses, transactional databases, cloud data lake, etc., and to simplify its architecture to support its data science initiatives. DNB leveraged the Denodo Platform to create a logical data structure to connect disparate data sources. This logical data structure also acts as a data marketplace for the data science team, enabling data scientists to build their models using tools like Visual Studio Code and RStudio.

The insurance sector should therefore try to take advantage of this revolution by implementing a data strategy with a modern data architecture, as the traditional methods will be unable to cope with the exponential increase in data sources and types. According to the Forrester Total Economic Impact of Data Virtualization Report 2021, data virtualization delivered an 83% reduction in time-to-revenue and a 65% decrease in delivery times over ETL processes.

The Denodo Platform offers solutions to the challenges covered in this paper by handling today's constantly changing data requirements. It helps data scientists face these challenges by reducing the number of tedious data preparation tasks, enabling anyone in the organization to access data through data democratization, and facilitating the management of emerging regulations to protect data privacy.

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