Applying Natural Language Understanding AI to

Complex Insurance Problems

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TABLE OF CONTENTS

Applying Natural Language Understanding Artificial Intelligence **to Complex Insurance Problems**

Insurance, with its high volume of data consumed by the underwriting, contracts, and claims processes, has the potential for tremendous benefit from artificial intelligence (AI) technologies that have emerged over the past decade. These technologies include among others image and voice recognition, robotics, and predictive analytics. Within the broad category of AI, a specific subset known as Natural Language Understanding (NLU) is most directly applicable to the complex tasks associated with corporate and commercial insurance.

Natural Language Understanding

AI NLU technology is a subset of AI specifically referring to computing systems that execute processes requiring comprehension usually handled by humans, such as reading unstructured (articles, post, emails) or semi-structured (invoices, order forms) documents and pattern recognition. For everyday situations found in insurance such as evaluating risk, investigating claims, examining contracts, or implementing corporate governance, NLU is the relevant AI discipline to consider. The closer the system can come to matching the decisions of a well trained human, the better.

> *"Artificial Intelligence is "The theory and capabilities that strive to mimic human intelligence through experience and learning."*
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Machine Learning and Rule Based Learning

Within NLU, approaches can be roughly classified into two main groups: symbolic "Rule Based Learning", and statistical "Machine Learning" (ML). Rule Based Learning is often referred to as "linguistic" or "semantic" technology, because it requires that the system understands language and extracts meaning in a way similar to how a human would. Linguistic rules based technologies can support most use cases. Rules and domain specific language knowledge must be programmed to give the system the ability to properly understand the content.

Statistics based ML technologies are a more recent addition to AI practice. Statistics based ML can be applied only if certain requirements are met. Pure ML systems are not programmed with rules or logic on how to understand language. ML samples input data in high volumes, and through statistical analysis, gradually is able to discern which are the good outcomes. Learning is a long and computationally intensive process. Importantly, ML systems are only as good as the breadth of learning data they consume.

Recent advances from academic research, combined with the computational advances of cloud computing have resulted in a proliferation of machine learning systems and attention. However, setting the wrong expectation for ML not only undermines its potential, it risks slowing down investment in a technology that shows great promise.

This paper identifies the specific requirements and insurance use-case considerations for success with NLU systems built on linguistic/semantic rule based learning, machine learning, or a hybrid of both.

Complexity & Sample Data

NLU technologies for unstructured information management have proven valuable across many industries for applications such as content enrichment, process automation, and conversational AI.

For the insurance industry, NLU technology is being applied most notably to processing unstructured documents to extract, organize and highlight important data. It is the ability of linguistic/semantic systems to mimic human understanding when reading unstructured information that makes them so valuable for insurance applications.

To identify the best technology or methodology to use in a typical application of NLU technologies on unstructured information, use cases must be classified on two dimensions: relative complexity and the availability of relevant sample documents or data.

> ### Complexity
> For classifying NLU applications, Complexity refers to how difficult and ambiguous a specific task is, even if a human was to do it. This could be measured, for example, by the the scope of questions a chatbot is required to answer, or how nested the knowledge to be extracted is and how much reasoning you need to apply to reach a conclusion from the analysis of documents in a claim automation project.

Completeness of Sample Documents

This second factor is a proxy for how applicable pure machine learning would be to a specific scenario. A ML system must be trained and its performance depends on two important factors necessary for supporting implementation:

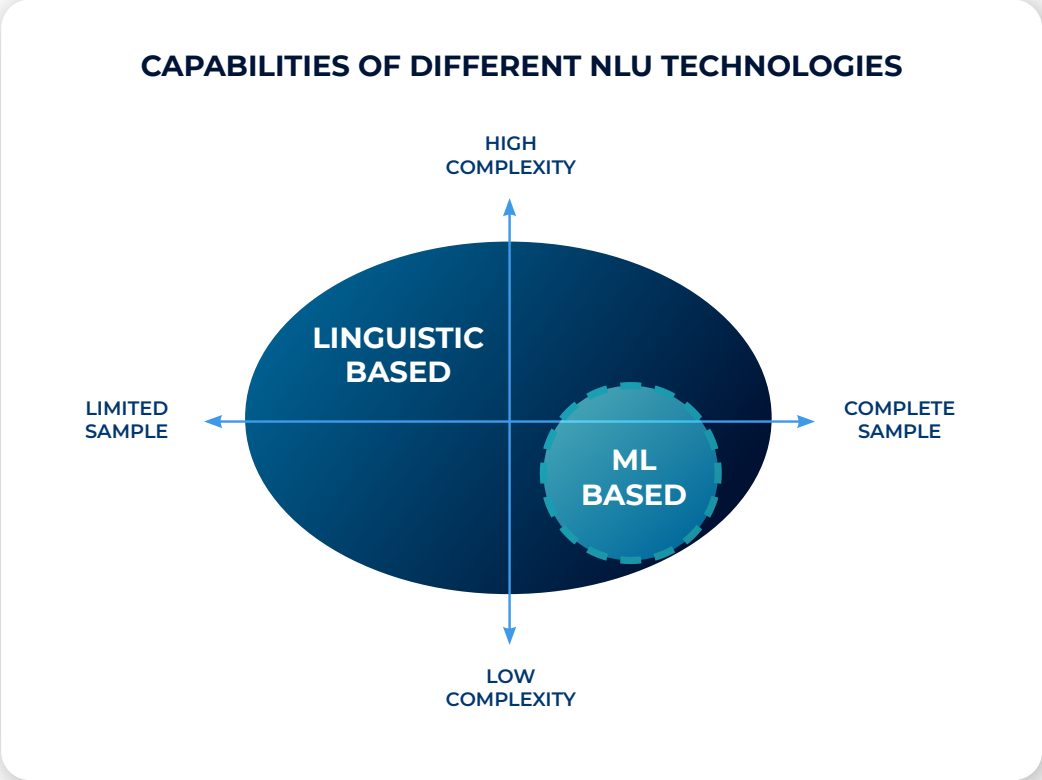
1. *Quantity of documents in the training set, and*
2. *Representativeness, or how representative the training data and documents are of the automation case of interest.*

Completeness of the ML training set is a measure of these two factors. The project that is a true candidate for pure machine learning will have both a large training set and a balanced coverage distribution across all the possible outputs.

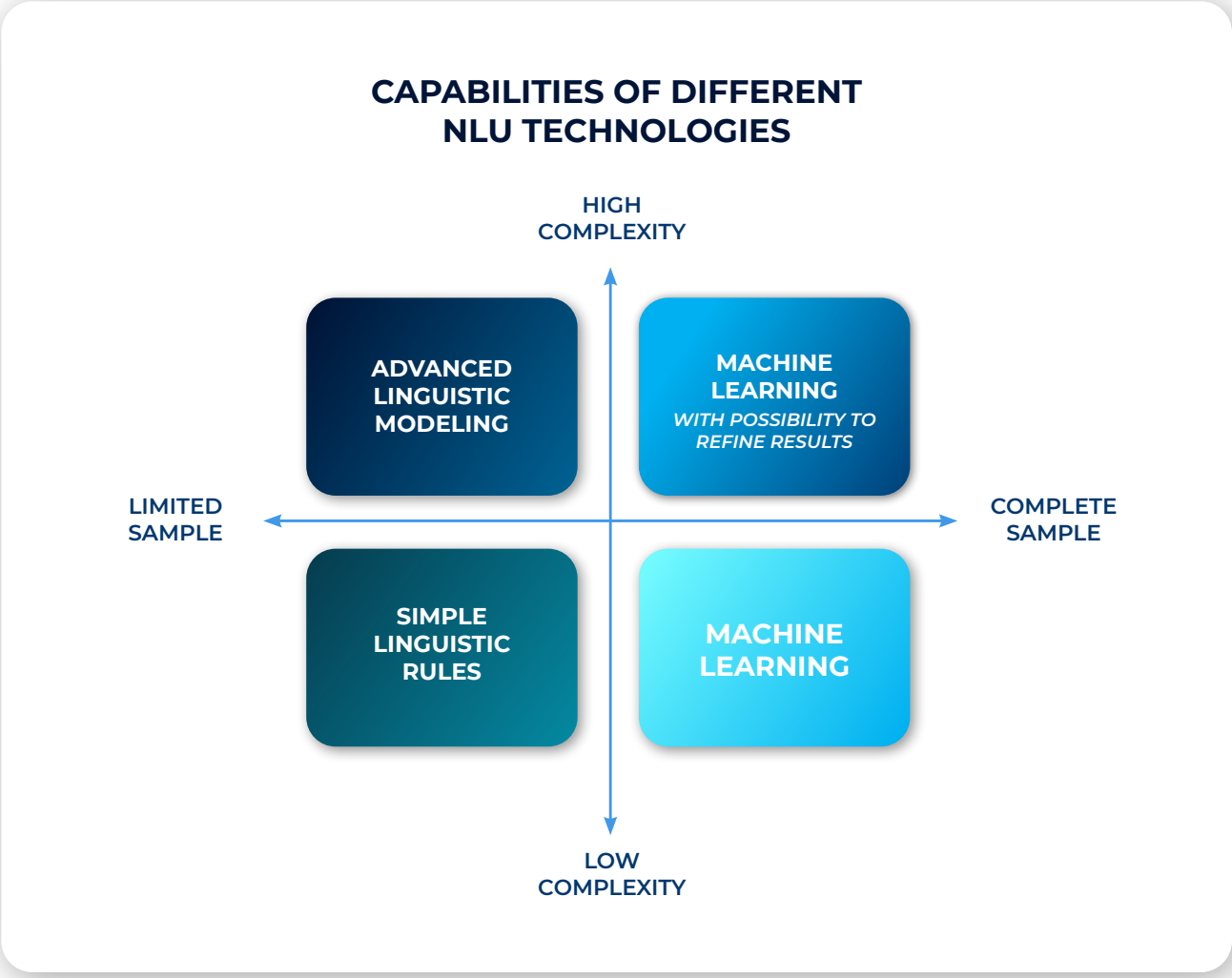
Typical Insurance Use Cases For **Natural Language Understanding**

As explained before, NLU technologies for the automatic management of unstructured information can be roughly classified into two main groups: linguistic/semantic rule based and statistic/machine learning (ML) based.

Linguistic rule based technologies can support any of the different use cases independently from the complexity and availability of a relevant set of sample documents. Statistic and ML based technologies are instead applicable only for use cases in which you meet the requirements of high quantity of documents and complete coverage of the problem space. Even so, for a given quantity and coverage of learning, the performance of ML systems tends to degrade as complexity is increased.



Based on this balance between complexity and completeness, organizations should evaluate which NLU approach provides the highest possible business value. To identify the ideal set of features and functionalities for high performance, we can use the diagram located on the next page.



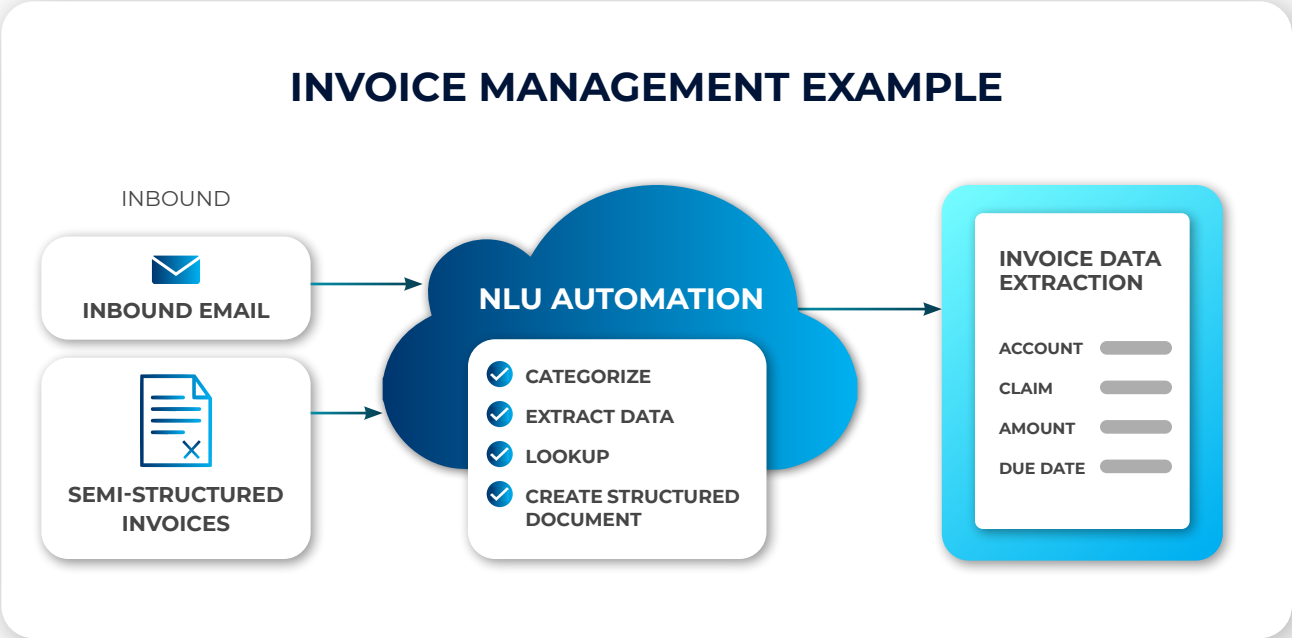
LOWER RIGHT QUADRANT:

Best Fit for Machine Learning

The combination of low complexity and a highly complete sample marks the business cases that are the best fit for pure machine learning techniques.

For insurance, an example for this scenario is the management of supplier invoices by the purchasing department. Usually the process consists of extracting data (name, dates, quantities, payment terms) from documents that, even if different from one supplier to the other, are semi-structured, they contain the same data and the difference in the format is minimum. In this case, we have a significant number of sample documents. In addition, there is a relatively small number of data elements to be extracted and the differences in the format are limited. These factors—large number of sample documents and low complexity—make it the ideal scenario for pure ML.

In this scenario we can select a big enough sample to perfectly represent each type of invoice. In addition, the abundance of samples ensures that if the results of a single iteration are unsatisfactory, the sample size is large enough to retrain the system until you reach the point of best possible results.



UPPER RIGHT QUADRANT:

Machine Learning with The Possibility to Refine Results

Moving to the top right of the diagram, we still have a large number of well-distributed sample documents but the subject matter is much more complex. This use case is for projects that deal, for example, with a rich and variable set of questions for a question answering system or a rich and deep taxonomy, or system used to classify documents, for an automatic categorization task. The higher complexity means that it is more difficult to identify samples that uniquely represent each node of the taxonomy or desired outcome of the automation task. The training data sample may have the quantity, but the nature of the task makes complete coverage impractical. This makes the pure ML model much more difficult, or practically impossible, to train to the level of performance required.

Insurance examples would include unstructured medical reports for accident claims. While there are standard terms and patterns that can be specifically identified, the documents from outside sources are unstructured and content varies widely. Achieving the required level of accuracy here requires additional rules based learning beyond the range of pure ML training on the input sample.

The practical implication of this is a requirement to essentially give the ML process some knowledge that it could not attain purely by analyzing the samples. In the example, injury codes, critical dates, tests and results are detected by ML analysis, even from an unstructured input document with an unknown format. More subtle signals such as fraud indications and expert opinions depend on rules based logic to augment the ML data sample.

MEDICAL RISK ASSESSMENT

Machine Learning is a Black Box

This case highlights an important aspect of pure ML systems that is less advertised or understood: ML systems are black boxes. This means that you cannot apply your "human" understanding of the phenomena that you are trying to automate to improve the results. For machine learning systems, there is no tool with which to refine the algorithm. With pure ML, the only option you have is to feed more training examples to the system, and depend on the algorithm to adjust results statistically over time. Unfortunately, this doesn't always guarantee that you'll improve the results or reach the level of accuracy required.

Ideally the use cases in this quadrant could still leverage the advantages of ML.... if only you could adjust the model.

Maintenance

To provide a complete picture of the different AI techniques and approaches, it is important to emphasize that these systems cannot be configured and then just left without any further attention. Once the level of accuracy and performance required is reached and the solution is implemented, different factors can contribute to the deterioration of its performance. Thus, it is important to regularly monitor the results and to plan for maintenance activities.

Different approaches must be taken when maintaining the semantic/linguistics technique vs the pure ML technique. The semantics/linguistics approach generally allows for incremental changes to the rule set that, in most situations, are sufficient in repristinating the original performances. Instead, the ML approach usually calls for a retraining based on a training set that is representative of the changed scenario.

It is not the objective of this paper to provide an analysis of the advantages or disadvantages of one technique versus the other, but it is important to note and understand that these maintenance activities should be considered when looking at the total cost of ownership of these systems.

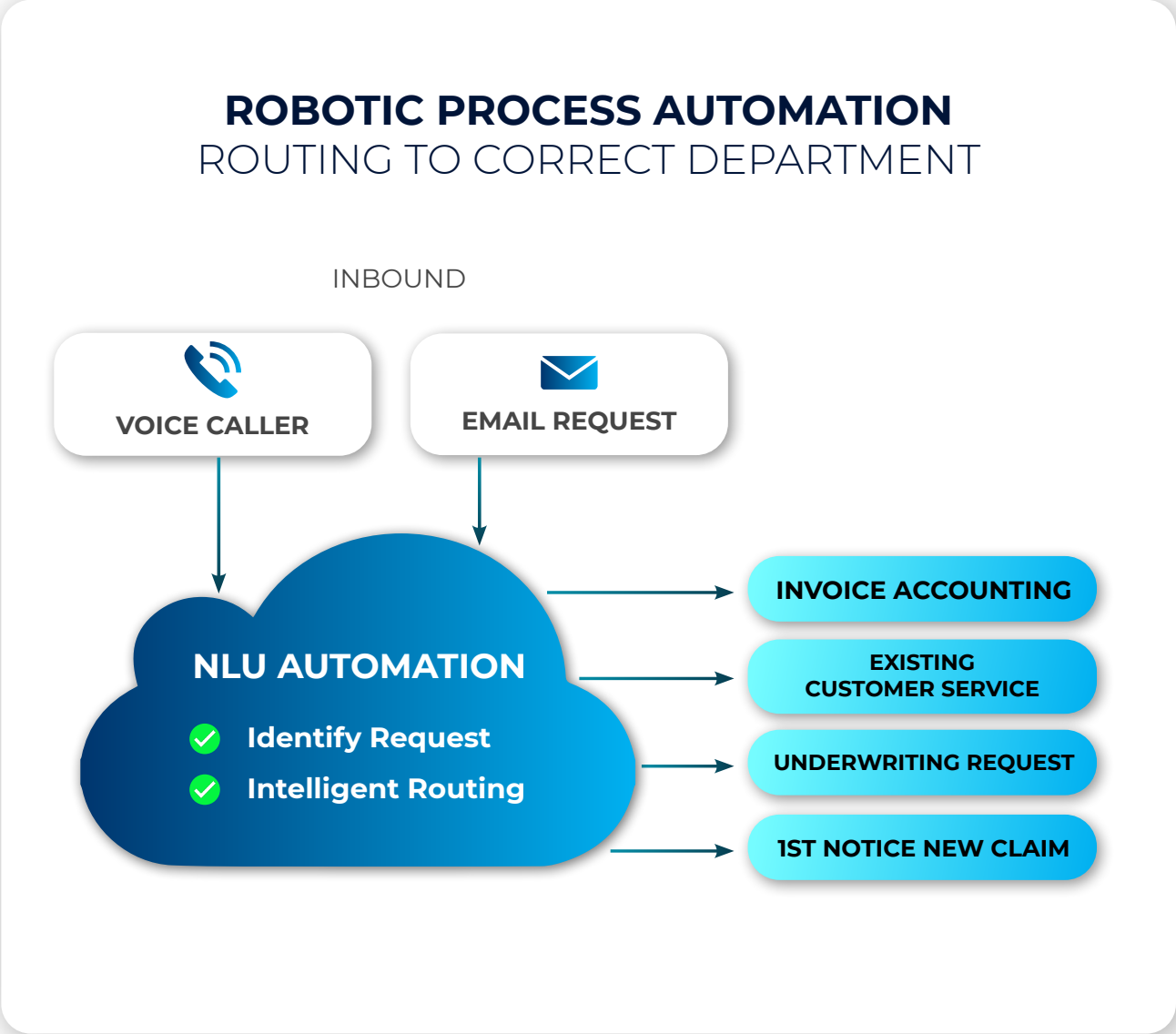
Linguistic Model Based Only Use Cases

The left side of the graphic above includes business use cases that can be addressed only via linguistic based systems. In these use cases, the training set is simply insufficient to use ML. Let's take a closer look at each.

LOWER LEFT QUADRANT:

Simple Linguistic Rules

This scenario doesn't require very sophisticated linguistic engines. Shallow linguistic systems or even simple 'bag of words' classification tools are enough to reach a reasonable quality. The relative simplicity of the taxonomies or extraction objectives allows you to configure the rules, usually with good results. Robotic Process Automation is the most commonly applied application of this scenario. These scenarios are less interesting for business and commercial insurance today, because due to their simplicity, the automation value has already been achieved.



UPPER LEFT QUADRANT:

Advanced Linguistic Modeling

Moving to the top left corner, we have scenarios that involve a small and not uniformly distributed set of samples and high complexity. For these use cases, you need a linguistic engine that is sophisticated enough to ensure a deep understanding of the content and a set of tools that are powerful enough to ensure the development and effective application of advanced linguistic rules. Because of the complexity here (i.e. the similarities between the documents to be classified or data to be extracted are so close) simple keywords and boolean operators, etc. would be completely ineffective in distinguishing the differences between very similar concepts.

Risk analysis reports are a typical example of this high complexity / low volume scenario. Engineering analysis of risk factors in an industrial or large public venue, or the comparison of policies and contracts to a standard are common situations for commercial and corporate insurance underwriting. In most cases, a human underwriter must spend many hours, even days, reading, comparing and evaluating these complex documents. A rules based system, embedding specific industry and company knowledge, can automate this analysis. However the variety of risks to consider, sensitivity to language differences across documents, and the sparse coverage of possible outcomes in each sample make this a poor candidate for ML.

Another example of a high complexity low volume scenario is the one related to policy review. Insurance carriers are often requested to review and analyze non standard policies, especially at the time of negotiation or renewal, to evaluate unexpected exposure. By automatically using pre-defined checklists to effectively identify implicit and explicit coverages and exclusions NLU based systems allows insurances to streamline this usually manual slow and error prone process. The complexity of these documents and the relative limited number of examples make it a good case for the top left quadrant of our diagram.

POLICY REVIEW
RISK IDENTIFICATION

Master Policy

Local Policy

COVERAGE A
Um, quost, qui qui aut eveleni hictota diciam ut volorep udandan digniam ipsam, con eaquia autati rem dus apicia alicim aut que eos et rendae omnisciamus pre net ratiis ilignih el ipsusda quam, sae nam harupta perem eaquiaspid et haruntinum fugiate voluptio. Ebis modis mosantus et omnis eos debis sunt faci quuntio et et doluptat et optatur, consectota corestrum aut et quosam harchicae. Xerspie ndandandel ma cusae nia cus asi in nonserescid estrum ut que nullent omnis minum isciunt voluptatem qui nonsequi veni.

Loss Prevention Expenses

COVERAGE A
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COVERAGE B
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Property Damage

COVERAGE B
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COVERAGE C
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Pollution Enviornmental Damages

COVERAGE C
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COVERAGE D
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Personal Injury

COVERAGE D
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RISK ASSEMENT

POLICY OVERVIEW
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INSURANCE RECOMMENDATIONS FOR **NATURAL LANGUAGE UNDERSTANDING AI**

The differences in these use cases alone makes it clear that there isn't a single AI technique that can ensure high performance for every insurance situation. Commercial and Business insurance, with the high value and risk associated with each policy and the unique conditions to consider, generally fall above the horizontal line in the high complexity range.

For those complex insurance cases, machine learning offers great efficiencies for business cases that fall under the scenarios on the right side of the diagram (large training set), provided there is a way to steer the ML training appropriately. A solid semantic NLU technology integrated with machine learning capabilities is the ideal way to address insurance needs and acheive desired results from NLU computing Investments.

Advanced semantic understanding systems built specifically for the insurance industry already have the native flexibility to address all of the diverse use cases in each area of the matrix. So, why not apply ML functionalities selectively where it will add the most value? The desired combination is a technology stack that provides a combination of rule based NLU technology capabilities and ML based algorithms to address the most common use cases for unstructured information.

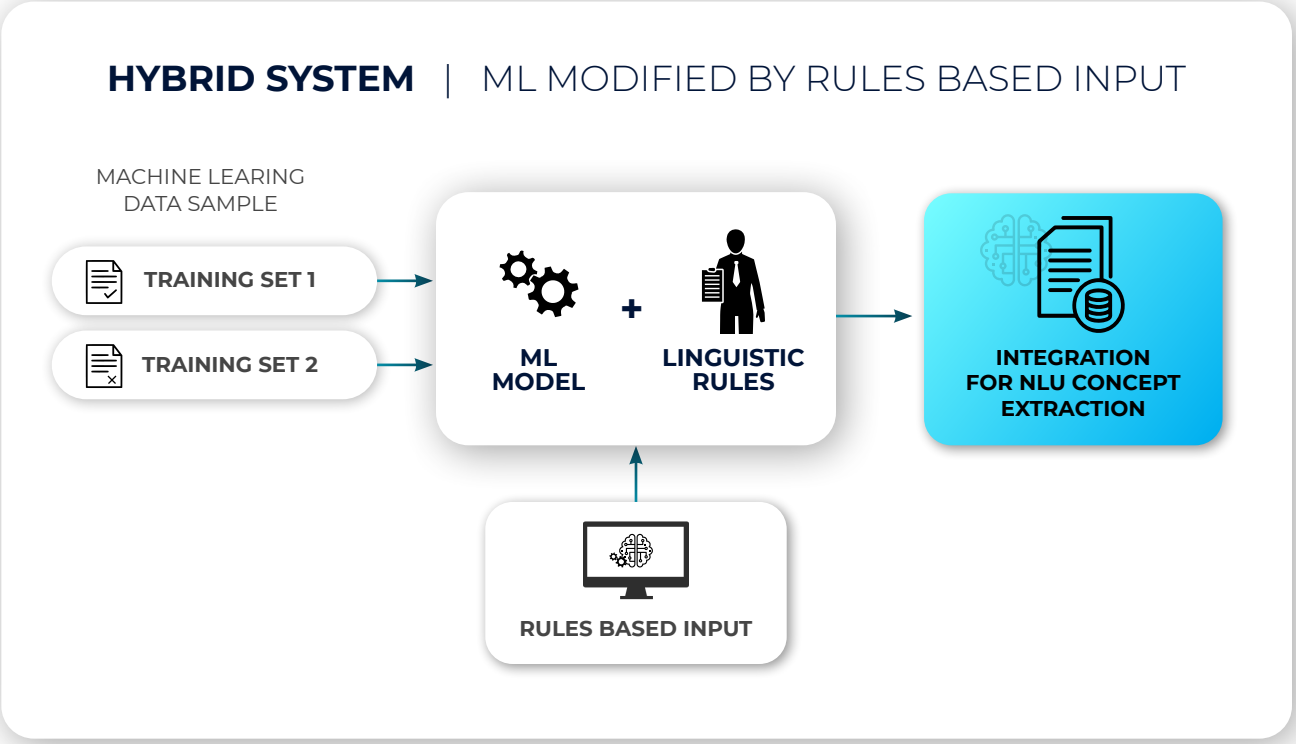
ESSENTIAL ELEMENTS TO COMBINE INCLUDE:

- Statistic based Machine Learning environment as a starting point
- Deep, human-like understanding of written text
- Insurance specific knowledge graph based on industry experience and use cases
- Visibility of the rules created through ML algorithms to make results explainable, eliminating the ML "Black Box"
- Ability to use rules based algorithms to add precision to the learning algorithms directly, rather than only by adjusting sample data

NLU AI & INSURANCE **CONCLUSION**

Natural Language Understanding, with its ability to mimic human understanding, has the potential to significantly improve decisions in insurance underwriting, contracts and claims. While pure machine learning (ML) systems are proving value for consumer facing and simple automation efforts, rules based systems with deep "linguistic" understanding of unstructured information are required for addressing the risk and complexity of corporate and commercial insurance.

A better alternative is to deploy a hybrid system that can adapt to the variations of coverage and complexity present across a corporate and commercial insurance environment. Rather than employ a separate technology for each application, build all applications on a system that can combine rules based and ML properties when needed.



The ideal NLU solution is one that combines the automated learning and breadth of an ML system with the human precision and industry knowledge of a rules based one. This hybrid system requires the ability to explicitly change the rules based on organizational knowledge, rather than depend on the system to learn only from examples.

When establishing an AI foundation for applications including risk reduction, contract management, claims leakage, insurance carriers will need the flexibility to adjust the approach in each situation. Insurers should evaluate systems combining firm foundations in both rules based and machine learning techniques, and with the ability to selectively combine them for each situation.

Get **Started**

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