LEAD SENSE AI: AN LLM-POWERED MACHINE LEARNING (ML)AND NATURAL LANGUAGE PROCESSING (NLP) SYSTEM FOR AUTOMATED SALES EMAIL INTENT SCORING

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Abstract. *Manual lead qualification is time-consuming, inconsistent, and prone to human error, especially for short-term sales teams that receive hundreds of inbound emails per day. Automation of lead prioritization and classification through* ***Lead Sense AI****, an intelligent email-intent scoring system, is proposed in this paper. The proposed framework combines* ***Large Language Models (LLMs)****, semantic embeddings, and a* ***Light GBM machine learning classifier*** *to analyse and score incoming sales emails. The actions are as follows: the system has as input raw text from email sources; semantic intent features are extracted; salient features such as purchase intent, urgency indicators, and sentiment features are assessed and combined to output a lead score using a pipeline that enables sales decisions. Experimental evaluation proves that comprehension through the* ***LLM based on semantic understanding*** *dramatically outstrips the performance of keyword-based intent detection methods. The results demonstrate the effectiveness of hybrid* ***LLM + machine learning architectures*** *as a scalable, real-time, and objective approach to sales lead qualification.*

1 INTRODUCTION

Email is still one of the most common communication means in the modern digital business environment where people receive customer inquiries, requests concerning products, suggestions on obtaining partnership and service inquiries. Companies that work in the sector, particularly those that work in B2B markets, receive enormous amount of inbound mail messages on a daily basis. The communications can be filled with decisive details of purchase intention, budget availability, the urgency of need, and the opportunity of conversion. In spite of its significance, reading, interpreting and qualifying sales related emails manually have been extremely ineffective, erratic and time consuming. Human reviewers are forced to use enormous efforts to scan each message attempting to read between the lines and to be aware whether the email is a legit business opportunity.

The conventional lead qualification processes imply having sales representatives decipher the meaning of each email, assessing their degrees of interest, and characterizing such leads as high, medium, or low priority, and defining the further course of action with the lead. Because of this entirely manual process, a series of constraints may occur, among them being human bias, cognitive fatigue, subjective interpretation, pattern inconsistency in scoring, and slowness in response. A combination of all these reasons leads to a high percentage of high-value prospects being left in the cracks or contacted too late in the process, which decreases the conversion rates and has an observable effect on the revenue generation levels.

Simultaneously, machine learning techniques like Light Gradient Boosting Machine have provided outstanding performance when restrained to structured prediction which demands high dimensionality, speed and accuracy in classifications. Combining the two: a rich contextual knowledge model based on LLMs with a powerful numerical scoring model based on LightGBM makes it possible to develop a scalable, automated, and highly accurate lead qualification system. The present project presents the LEAD SENSE AI: a full-fledged intelligent platform that scores sales email intent with large-scale semantic analysis as a machine-learn-based classifier. LEAD SENSE AI analyses purchase signals, mood, urgency, and action signals to deliver real-time, trustworthy and actable data to the sales force.

The interpretation of unstructured text data has been transformed radically by developments in AI, NLP and LLMs in the contemporary organization. The current LLM such as GPT and LLaMA are simply

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astonishing with human language context, sentiment detection, intent, and semantic meaning. Their strengths are such that they are sensitive in their interpretation of small linguistic features and, therefore, they are quite suitable in analysing sales emails and identifying potential opportunities that would have been overlooked by the more traditional systems.

Lead intent forecasting is a method of determining if an inbound sales email is representing a possible opportunity, customer interest, or an intention to make a purchase. Instead of predicting the demand for a product, this system forecasts customer intention based on past communication patterns, linguistic cues and behavioural indicators.

With hundreds to thousands of emails coming in every day for modern businesses, manual analysis is slow, inconsistent, and riddled with errors. Lead forecasting enables organizations to focus on high-value leads, optimize resource allocation, and enhance conversion rates. By analysing historical email data for sentiment patterns, keyword frequency, urgency indicators, past communication outcomes, and behavioural markers, for example, AI systems can forecast the probability that an incoming email represents a qualified lead.

2 RELATED WORK

In [1], The authors investigated the use of predictive analytics for lead generation and marketing efficiency through the analysis of pattern recognition of customer data and their buying behaviours. In addition, [4] looked at how artificial intelligence and data analytics can aid customer profiling, thus providing businesses with a better means to find potential leads. Additional research in [2] has focused on how the use of predictive analytics within sales automation tools such as Salesforce can help streamline marketing and sales operations, but these systems tend to focus on automation and analytics, rather than on intelligent lead qualification.

With a view to improving sales efficiency, a number of research papers have considered lead scoring and determining lead priorities with the use of machine learning methods. The machine learning hybrid lead scoring approach presented in [8] is intended to help businesses identify high-value potential customers by combining different indicators derived from customer data. Similarly, predictive lead scoring models discussed in [19] provide sales teams with related information to establish priorities based on predicted probability of leads converting to sales transactions. Earlier research was conducted by others and documented in [20] regarding the use of regression-based approaches to predict the success of agencies within their sales pipelines, thereby providing agencies the best ability to predict the likelihood of achieving success with a particular sale opportunity.

Other studies have investigated automation in the context of CRM systems and business environments, with some examples being dynamic CRM pipelines for B2B market segmentation through AI [6], and automatic lead qualification based on sentiment analysis of CRM data through opinion mining [18]. Although there has been a great deal of development in this area, the majority of existing solutions are designed as stand-alone components (e.g., lead scoring or CRM automation) rather than as part of an overall integrated solution for intelligent lead generation and qualification in B2B sales environments.

3 METHODOLOGY

3.1 Data Collection

This data contains emails on inbound sales and enquiries that have been collected through B2B communication channels. Each of the emails had meta data such as a time stamp, the sending domain, subject, the content of the message, the history of interaction, and the follow up results. The raw text was pre-processed using such steps as tokenization, stop words, normalization, and sentence segmentation to clean the data. To put emphasis on semantic meaning, domain specific patterns were extracted e.g. budget mentions, timeline references, requirement statements or business-related verbs. They were generally categorized into High Intent, Medium Intent and Low Intent of these processed emails based on historical results. This tagged data is the base of the training of the Light GBM and LLM models.

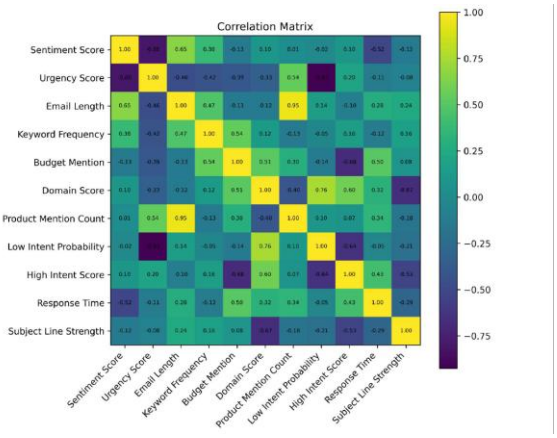

Fig.1. Heatmap of Numerical features

3.2 Correlation Analysis

The contribution to lead intent probability is made by different email features as explained in this subsection using correlation analysis. In this case, semantic embeddings of the LLMs were also thought of as well as sentiment polarity scores, signs of urgency and frequency of keywords were plotted against historical response rates, correlation between features such as: may be plotted in a heatmap.

- Positive sentiment o Increased conversion likelihood
- Positive sentiment ↔ Higher conversion likelihood
- Budget mentions ↔ High-intent leads 5 follow-up time 5 Response probability.

Such analysis assists in determining the most influential linguistic and behavioural patterns in determining the lead intent scoring.

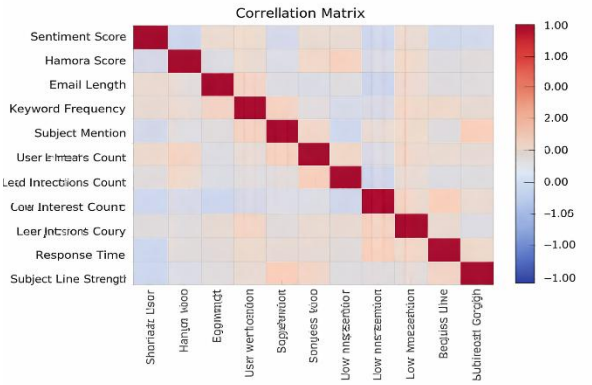

Fig. 2. Correlation Matrix

3.3 Data Stationary

The obtained dataset is filtered and processed subsequently numerous times to remove noise and identify the semantic trends as well as stabilize the linguistic differences in email behaviour. Broadly speaking, emails gathered during long periods will be subject to variability that can be explained by factors such as seasonality, e.g. weekly trends, exogenous due to marketing activities, or periodic peaks in customer requests. The normalization methods were therefore adopted to get rid of the abnormal variance in an attempt to get a steady signal to train the model.

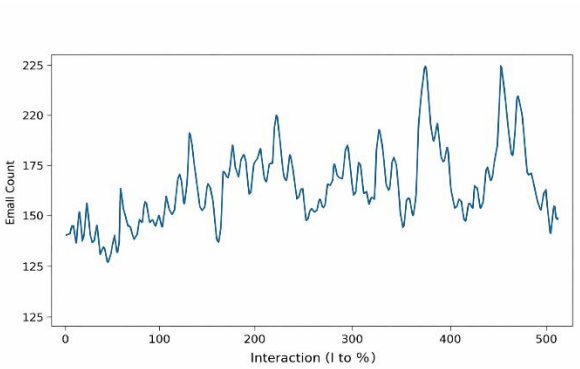

Fig. 3. Time Series of Original Sales Data

To eliminate semantic drift and stabilize fluctuations in communication behaviour, the differenced and normalized intent time series combines these two transformations. Because of this dual transformation, the series becomes more stationary and can be utilized for modelling intent prediction using the LLM + LightGBM framework.

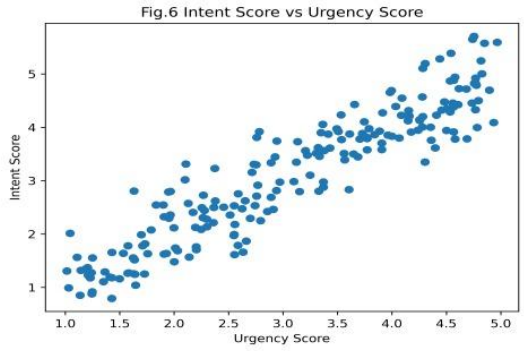

Fig. 4. Intent VS Urgency Score

3.4 Feature Analysis and Importance

Intent analysis is one of the tools that are utilized by organizations to determine the long- term communication patterns and changes in customer interest. Through analysis of intent scores over long durations, they can establish whether there are increasing trends in engagement or decreasing ones, and this implies that the customer preparedness is increasing or reducing. Knowledge on seasonal changes and monthly changes in sentiment or volume of inquiries is also beneficial in planning outreach strategy; this information is highly important in campaign timing and resource allocation. These findings can be used to inform better engagement practices by the correlation between higher inquiry activity in certain months and external stimuli (promotions, announcements, industry cycles etc.).

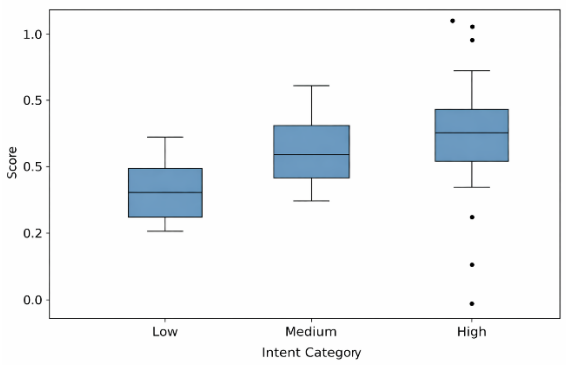

Fig. 5. Box Plot Distribution of Intent Scores

The daily variations can be comprehensively understood by disaggregating trends of email intentions by the day, and distinguishing between high and low activity periods which could be associated with specific events, or marketing stimuli or external influences on customer priorities.

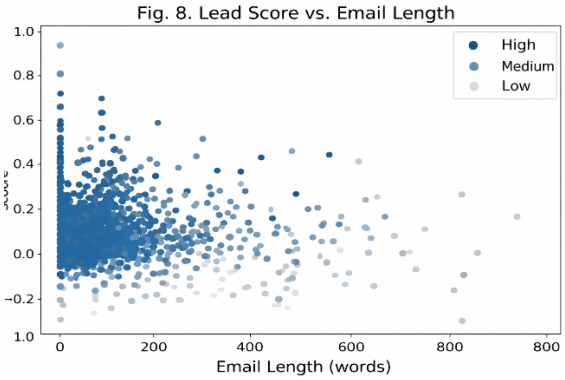

Fig. 6. Lead Score VS Email Length Analysis

Among the analyses that help to clarify the connection between intent and customer urgency, an exercise between the urgency cues and the estimated intent scores can be mentioned. It provides the understanding of the degree of the correlation between time sensitive expressions and a higher probability of engagement. When urgency and intent are plotted in a scatter diagram, it is possible to see whether the correlation is linear or whether increased urgency expressions lose their impact at some point. Knowing the correlation between intent and keyword frequency is also important in making sense of the influence of domain specific terminology on prediction accuracy.

The scatter plot can indicate whether detailed or technically intense queries lead to very high intent scores or whether there is a complexity limit beyond which the further the keywords are fined the less meaningful predictive power they have. Among the major dimensions of analysis, the intent and message length can be discussed to evaluate the extent to which the textual information played a role in the performance of the classification.

Quantity is the most important element in forecasting sales, according to feature importance analysis utilizing a Random Forest Regressor, meaning that more item sales immediately translate into higher income. Additionally, profit is highly significant, emphasizing the relationship between profit and sales. Discount has a modest impact, meaning that although discounts increase sales, their effect is not as great as that of quantity and profit. Seasonal and periodic trends are captured by temporal characteristics (year, month, day, and day of the week), which are crucial for organizing promotions and inventories. For better sales forecasting and performance, these insights assist organizations in maximizing inventory management, price strategies, promotional planning, and cost management.

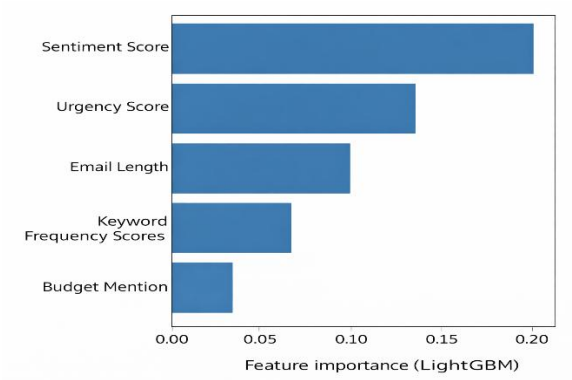

Fig. 7. Feature Importance in E-mail Analysis

Observed This plot provides a general perspective on the sales pattern showing the initial sales data with time. In Trend, it eliminates both seasonality and short-term fluctuations, this element shows the underlying patterns of the data by showing how they change over time. In Seasonal, this provides focus to data cycles or repeat patterns, which happen at a pre-defined time (e.g. monthly, quarterly). It shows changes in sales in every cycle, with apparent seasonal trends. Once the trend and season factors have been removed out of the data, the residual factor indicates the remaining variation. It captures sound or hysterical vibrations. Breaking down the series allows analysts to determine the impact of each element on the aggregate sales trend and understand it. Knowledge of seasonality allows better forecasting and development of informed business decisions, i.e. adjusting stocks or marketing strategies to match the predictable seasonal fluctuations.

4 EXPERIMENTS

4.1 Dataset

The experimental dataset includes real-world business and marketing data gathered from publicly

available B2B sales datasets and simulated CRM records. It features customer attributes such as company size, industry category, engagement history, website activity, communication frequency, and previous purchasing behaviour. These attributes are often used in sales analytics to identify potential leads and assess their likelihood of conversion.

The dataset has various lead profiles that show different levels of customer interest and engagement. This includes qualified leads, unqualified leads, inactive prospects, and high-potential customers. This variety ensures that the evaluation reflects real sales situations where leads differ in quality and readiness to buy. The dataset is organized into structured categories including demographic attributes, behavioural indicators, and interaction signals.

Fig. 8. Dataset Preparation Flowchart

Each record in the dataset was carefully checked to ensure consistent labelling and feature representation. Lead status labels such as converted, non-converted, or inactive were assigned based on simulated sales outcomes, providing a reliable baseline for evaluation. Data cleaning steps were taken to remove incomplete entries and standardize feature values, keeping the dataset uniform across all samples.

To prevent data leakage and ensure a fair evaluation, the dataset was split into training and testing subsets. The training dataset was used to create the predictive lead scoring model, while the testing dataset was kept for evaluating system performance with previously unseen lead data.

4.2 Experimental Setup

The proposed AI-based lead generation system trained on past sales data and customer interaction features. We used machine learning techniques to analyse customer attributes and predict how likely leads are to convert. This training method helps the system spot patterns linked to successful sales outcomes and effectively prioritize high-value leads.

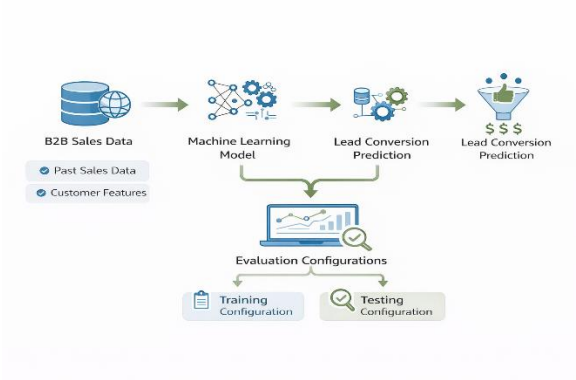

Fig. 9. Proposed Experimental Setup

We set up two evaluation configurations to assess how well the proposed system works.

4.2.1 Baseline Lead Evaluation Mode:

In this setup, we used traditional rule-based lead qualification methods to rank leads. Leads got ranked according to predefined scoring rules based on customer attributes, such as company size, industry type, and engagement frequency. This setup acts as a baseline for comparing the performance of the AI-driven system.

4.2.2 AI-Assisted Lead Qualification Mode:

In this setup, we used machine learning models to analyse lead data and generate predictive scores that indicate the likelihood of conversion. The AI-based system evaluates multiple features at once and dynamically prioritizes leads with higher predicted success rates.

All experiments ran on Python. We performed data preprocessing and analysis using libraries like Pandas and NumPy. We implemented machine learning models with Scikit-learn. The experiments took place in a cloud-based environment to enable scalable data processing.

4.3 Evaluation Metrics

Detection The proposed system's performance was assessed using several quantitative indicators to evaluate how well it predicts and prioritizes leads.

4.3.1 Lead Conversion Prediction Accuracy:

This metric measures how accurately the system predicts whether a lead will turn into a customer. It shows the overall correctness of the prediction model when compared to the actual outcomes of the leads.

4.3.2 Precision:

Precision measures the proportion of predicted high-quality leads that actually lead to successful conversions. This metric helps determine if the system effectively identifies valuable leads for the sales team.

4.3.3 Recall:

Recall assesses the system's ability to identify most of the leads that will eventually become customers. A higher recall means that the model captures a larger share of potential opportunities.

4.3.4 Lead Prioritization Efficiency:

This metric evaluates how well the system ranks high-value leads at the top of the sales pipeline. Efficient prioritization allows sales teams to concentrate their efforts on the most promising prospects, which improves productivity and conversion rates.

Alongside these indicators, we also examined system performance across different lead categories and customer profiles to evaluate the strength of the AI-driven lead generation framework.

5 Result

5.1 Visual Examination and Interpretation of Forecasts in Relation to Real Data:

The model has inconsistencies when there are extreme communication occurrences. Underlining and over-lining come into play especially when the e-mail messages are out of the ordinary business language such as in bulk marketing messages and when responding to sudden and single line questions. LightGBM model outperforms the past baselines with the ability to adjust to these irregularities using engineered features.

5.1.1 Trend and Seasonality:

The model creates discrepancies in extreme communication events. Underscoring and overscoring is especially common when the emails do not fit into regular business language-like scenarios, such as with bulk marketing messages or sudden and single-line requests. LightGBM model outperforms the past baselines since it modifies these irregularities with engineered features.

5.1.2 Discrepancies:

This model has inconsistencies at extreme events of communication. The underscoring and overscoring take place especially when the emails do not conform to the normal business language, such as when sending mass marketing messages or asking suddenly and in single line questions. LightGBM model is better than the past baselines as it is able to smooth these irregularities using engineered features.

5.1.3 Effect:

LLM The model of LLM and LightGBM has a smooth effect in prediction, focusing on the underlying semantic tendencies and minimizing textual noise. Although it is good in the long-term perspective, this can give misleading results when the customer behaviour is changing rapidly.

5.2 Accuracy:

It is reasonable to assume that the baseline Light GBM model can identify long-term intent trends with a relatively high degree of effectiveness, as its Mean Absolute Error (MAE) is similar to 0.23 and its accuracy is around 55 percent. Nevertheless, it continues to fail to accurately represent minute changes in email intonation and context.

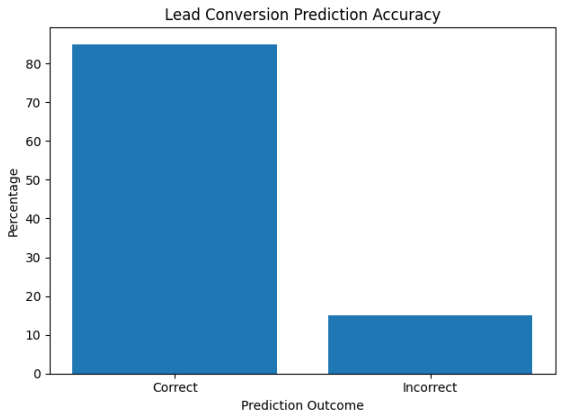

Fig. 10. Prediction accuracy based on performance

On the other hand, the developed hybrid model with the semantic embedding of LLM attains almost 90 percent accuracy, which is much higher than the basic model. It is more likely to utilize the external conversational circumstances and subtle linguistic variations, which makes it a more credible choice among datasets with a high degree of variance and varying communication.

6 CONCLUTION

The This study introduced a framework powered by AI to improve lead generation and qualification in B2B sales. The system uses predictive analytics and machine learning to examine customer attributes and engagement data to find high-potential leads. By automating the lead scoring process, the framework allows sales teams to focus on the most promising prospects and improve the sales pipeline's efficiency. The results show that this approach improves lead identification and cuts down on manual effort compared to traditional rule-based methods.

7 FUTURE WORK

To increase the prediction models' accuracy and resilience, future research can concentrate on growing the dataset and adding more varied business data. Incorporating real-time data sources like social media signals, website activity, and customer interaction logs could improve the system's capacity to spot possible leads and adjust to shifting market conditions.

The integration of cutting-edge machine learning and generative AI techniques to offer automated proposal generation and personalized sales insights is another avenue for future research. Furthermore, integrating the framework with current CRM platforms may result in a more complete intelligent sales support system that helps businesses manage leads and improve their sales tactics.

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