Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 11, November 2024

Leveraging Large Language Models to Optimize Financial Services using Sales Force Eco System

Kamlakshya, Tikhnadhi
Citizens Financial Group, Inc.
Enterprise Transformation Specialist

Abstract

This technical journal is intended in discovering the integration of Large Language Models (LLMs) within the Salesforce platform to revolutionize financial services. In our analysis, we have identified ways which prove ways in which artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques can be harnessed to improve customer experience, streamline operations, and drive innovation in the financial sector. The paper presents an inclusive analysis of modern applications, potential use cases, and the technical challenges associated with implementing LLMs in Salesforce-based financial services solutions.

***Keywords*: Salesforce, LLM, Large Language Models, Financial Services, API, CRM, Multimodal**

1. INTRODUCTION

The financial services industry is evolving with a rapid digital transformation, accelerating growth by advancements by using AI and ML technologies driven solutions. Large Language Models, a subset of AI that focuses on natural language processing and generation, have appeared as a powerful tool for enhancing customer interactions, automating complex processes, and offering data-driven insights. This paper explores how LLMs can be utilized within the Salesforce ecosystem to address specific challenges and opportunities in the financial industries.

2. BACKGROUND

2.1 Large Language Models

Large Language Models (LLMs) are sophisticated deep learning algorithms designed to analyze, condense, translate, predict, and generate text, thereby emulating human-like ideas and concepts through extensive textual data. Notable examples include GPT and BERT, both demonstrating impressive skills in various NLP tasks.

2.2 Salesforce and Financial Services

Salesforce is a preeminent customer relationship management (CRM) platform that provides customized business solutions specifically tailored for the financial services sector. The Financial Services Cloud within Salesforce features a comprehensive array of tools aimed at facilitating the management of customer relationships, optimizing operational efficiency, and ensuring adherence to regulatory standards.

3. LLM APPLICATIONS IN FINANCIAL SERVICES ON SALESFORCE

3.1 Intelligent Customer Service

LLMs can be integrated into Salesforce's Service Cloud to provide advanced chatbots and virtual assistants capable of handling complex customer inquiries. These AI-powered agents can understand context, provide personalized responses, and even predict customer needs.

Python

Example: Implementing a basic LLM-powered chatbot in Salesforce

```python
import salesforce_ai_sdk
from transformers import AutoModelForCausalLM, AutoTokenizer
def initialize_llm_chatbot():
model = AutoModelForCausalLM.from_pretrained(
"financial-gpt-model")
    tokenizer = AutoTokenizer.from_pretrained
    ("financial-gpt-tokenizer")

return salesforce_ai_sdk.ChatBot(model, tokenizer)
    chatbot = initialize_llm_chatbot()
    response = chatbot.generate_response("What are the current
    interest rates for mortgages?")
```

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 11, November 2024

3.2 Automated Document Processing

Financial institutions manage extensive volume of documentation and data complexities which can be streamlined by incorporating LLMs to automate the extraction, classification, and analysis of financial documents within Salesforce, significantly reducing manual effort and ensuring accuracy.

3.3 Risk Assessment and Fraud Detection

Through the examination of patterns in textual data in conjunction with structured financial information, large language models (LLMs) can be augmented to implement risk assessment frameworks and enhance fraud detection functionalities within Salesforce's Financial Services Cloud.

4. TECHNICAL IMPLEMENTATION

4.1 Integration Architecture

To effectively integrate LLMs into Salesforce for financial services, a robust architecture is vital to optimize AI innovation and meet evolving financial sector needs.

The subsequent diagram aims to provide a comprehensive overview of the proposed integration framework:

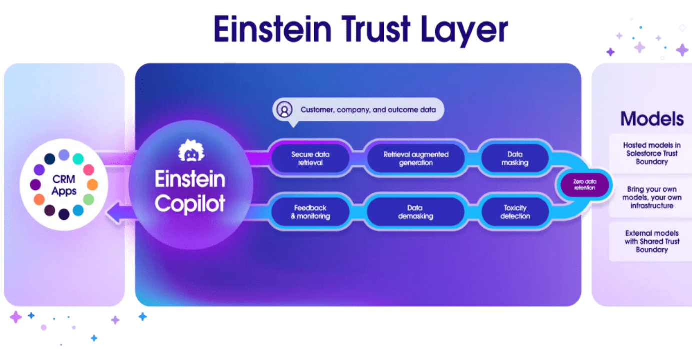
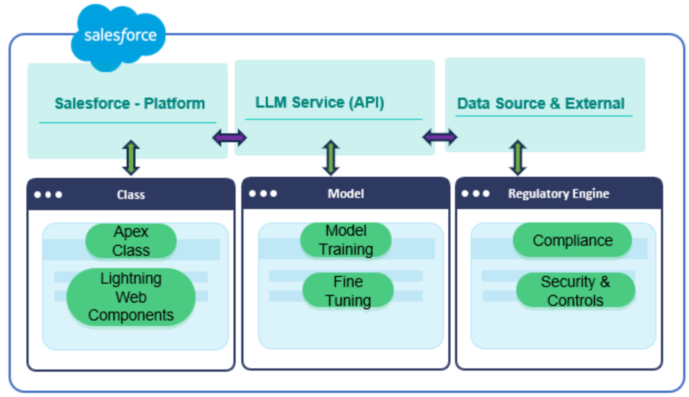


Diagram: Large Language Model Integration Architecture for Financial Services within Salesforce



LLM Integration Architecture for Financial Services

The implementation of a standardized JSON format for application programming interfaces (APIs), function calls, and generator outputs offers multiple advantages. Firstly, it establishes a systematic approach to verify the completeness of the generator’s output by ensuring the inclusion of all requisite fields, whereby outputs that do not adhere to these criteria are systematically excluded. Furthermore, the JSON structure facilitates effective verification of function calls to ensure correct parsing and the validity of arguments; calls that contain arguments not present in the API library or those that invoke fictitious functions are similarly rejected, thereby enhancing the overall integrity of the dataset. Additionally, this standardized format promotes scalability. By adopting this uniform structure, APIGen can seamlessly integrate data from various sources—including Python functions, REST APIs, and others—through the development of format converters that transform this diverse data into essential JSON components, all while preserving the integrity of other fundamental elements, such as the prompting library. This characteristic significantly contributes to the framework’s adaptability and extensibility.

4.2 Model Training and Fine-tuning

To attain the requisite performance standards in financial services functions, pre-trained large language models (LLMs) may be incorporated and subsequently tailored using domain-specific datasets. This procedure entails several critical stages, which are as follows:

1. Data collection and preparation
2. Model selection (e.g., GPT-3, BERT)
3. Fine-tuning on financial services datasets
4. Evaluation and iteration

The fine-tuning process can be represented mathematically as:

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 11, November 2024

```
$$\theta_{new} = \theta_{pretrained} - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_{financial})$$
Where:
- $$\theta_{new}$$ is the updated model parameters
- $$\theta_{pretrained}$$ is the initial pre-trained model parameters
- $$\alpha$$ is the learning rate
- $$\mathcal{L}$$ is the loss function
- $$\mathcal{D}_{financial}$$ is the financial services dataset
```

4.3 API Integration
The seamless integration of LLMs into Salesforce is dependent on a a robust API layer and this layer must handle:
- Authentication and authorization
- Request/response formatting
- Rate limiting and error handling

Apex Class

```
Apex Class
// Example: Apex class for LLM API integration
public class LLMIntegration
{
@future(callout=true)
    public static void callLLMAPI(String input, String
    recordId)
    {
        HttpRequest req = new HttpRequest();
        req.setEndpoint('https://llm-api.example.com/generate'
        );
        req.setMethod(' POST ') ;
        req.setHeader('Content-Type', 'application /json');
        req.setBody(JSON.serialize(new Map<String, Object>{
        'input' => input,
        'max_tokens' => 100
        }));

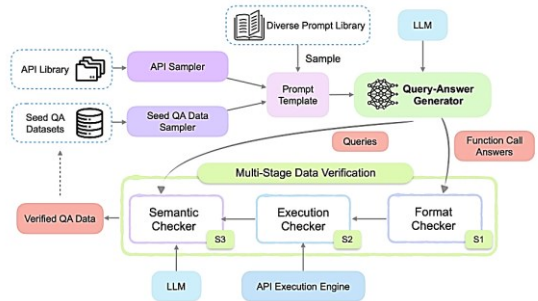
        Http http = new Http( );
        HttpResponse res = http.send( req );

        if ( res.getStatusCode() == 200 ) {
        String.generatedText = (String)JSON.deserializeUntyped
        (res.getBody()).get('generated_text');
        updateRecord(recordId, generatedText);
        }
        }

private static void updateRecord ( String recordId, String
generatedText ) {
// Update the Salesforce system record with generated text
value.
}
```

```

APIGen Framework
This section presents a comprehensive overview of the design of APIGen, an Automated Pipeline for Generating verifiable and diverse function-calling datasets. The framework has been meticulously crafted with three primary objectives: ensuring data quality, promoting data diversity, and facilitating scalable collection. These objectives are achieved through several core modules: a multi-stage data verification process that upholds data integrity, a seed question-answer (QA) data sampler, an API sampler, and various prompt templates that collectively contribute to the diversity of the datasets. Additionally, our structured modular design, which adheres to a unified format, allows the system to effectively scale across a variety of API sources, including but not limited to Python functions and Representational State Transfer (REST) APIs.

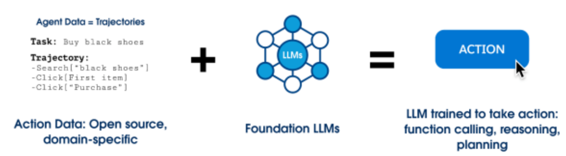



5. CHALLENGES AND CONSIDERATIONS

5.1 Data Privacy and Security
Implementing LLMs in financial services does requires strict adherence to data protection regulations such as GDPR and CCPA. Techniques such as federated learning and differential privacy can be utilized to enhance data privacy while simultaneously improving the efficacy of large language models (LLMs).

5.2 Explainability and Transparency
The opaque characteristics inherent to large language models (LLMs) present significant obstacles regarding their interpretability, an aspect that is particularly vital within the financial services sector Local Interpretable Model-agnostic Explanations and SHapley Additive exPlanations may be utilized to illuminate the decision-making mechanisms inherent in these models.

5.3 Bias Mitigation
LLMs can inadvertently perpetuate biases which is multifaceted issue rooted in the data used for present in training. Implementing bias detection and mitigation strategies are needed to ensure a more sustainable and inclusive use of LLMs demonstrating remarkable computational power and linguistic capabilities.




6. FUTURE DIRECTIONS

6.1 Multimodal LLMs
Future research could revolutionize the integration of multimodal LLMs that can process and analyze both text and numerical data, enabling more comprehensive financial analysis and decision-making support within Salesforce.
```

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 11, November 2024

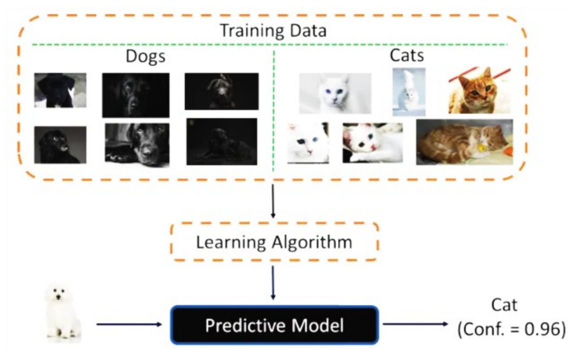
6.2 Quantum-Enhanced LLMs
As quantum computing advances, exploring quantum-enhanced LLMs could potentially lead to breakthroughs in processing speed and complexity handling for financial services applications it possess the ability to handle massive datasets and perform complex calculations at a lightning speed.

7. CONCLUSION

The incorporation of Large Language Models (LLMs) into the financial services ecosystem of Salesforce offers a significant opportunity for transformative advancements within the industry. By harnessing the capabilities of artificial intelligence (AI), machine learning (ML), and deep learning (DL), financial institutions can enrich customer experiences, optimize operational efficiency, and derive critical insights. Nevertheless, meticulous consideration of technical challenges, ethical concerns, and regulatory frameworks is essential for effective implementation.
As the technology underpinning LLMs continues to advance, the spectrum of potential applications within the financial services sector is likely to broaden, ushering in a new era characterized by enhanced productivity and connectivity. Future research endeavors should prioritize addressing existing limitations and investigating innovative applications to fully capitalize on the capabilities of LLMs within the Salesforce financial services framework.

Types of Bias to Examine:
Bias can manifest in various forms, often arising from systematic errors or social prejudices, with the distinction between the two occasionally being ambiguous. Recognizing these two sources of bias is crucial as we analyze how bias can infiltrate an artificial intelligence system.

Measurement Bias
Measurement bias happens when data is misclassified, improperly grouped, or overly simplified, leading to inaccuracies. This type of bias can be introduced through human error in labeling or through computational inaccuracies. Consequently, certain characteristics, factors, or groups may be either overrepresented or underrepresented in a dataset.
For instance, consider a benign illustration of an image recognition system designed to differentiate between cats and dogs. The training dataset appears straightforward — comprising images of cats and dogs. However, if the dataset exclusively contains pictures of black dogs alongside either white or brown cats, the AI may misclassify a photograph of a white dog as a cat. Although real-world training datasets are seldom as simplistic, the potential for substantial inaccuracies remains, with significant repercussions.



Training data illustration with photos of six black dogs, four white cats, and two brown cats fed into a learning algorithm for a predictive model. The model classifies the white canine as a "cat," assigning it a confidence score of 0.96.

Type 1 and Type 2 Errors

Consider a financial institution utilizing artificial intelligence to assess the likelihood of a loan applicant's repayment capability. If the algorithm forecasts that an applicant is likely to fulfill their repayment obligation, yet the applicant defaults, this scenario is classified as a false positive, or Type 1 error. Financial institutions aim to extend credit to individuals whom they believe possess the capacity to meet their repayment obligations. To mitigate risk, their predictive models are generally calibrated to avoid Type 2 errors. Nevertheless, the occurrence of false negatives adversely affects applicants who are mistakenly assessed as incapable of repayment.

Association Bias

Association bias is evident in the classification of data in accordance with dominant societal stereotypes. For instance, an inquiry into "toys for girls" on numerous e-commerce websites generally produces a wide assortment of culinary sets, dolls, princess-oriented products, and items predominantly featuring pink hues.

Confirmation Bias

Confirmation bias influences the categorization of data based on pre-existing beliefs. The personalized recommendations presented to consumers during online shopping are reflective of their purchasing behaviors; however, these behaviors are, in turn, shaped by the data that initially informed their choices. This phenomenon demonstrates the capacity of recommendation systems to reinforce stereotypes. Specifically, if superhero toys are not included on a webpage categorized as "toys for girls," it becomes improbable that consumers will encounter these items in other areas of the website, consequently reducing the probability of their acquisition.

Automation Bias

Automation bias manifests when the intrinsic values embedded within a system are inadvertently imposed upon users. A relevant illustration of this phenomenon occurred during a beauty contest judged by an artificial intelligence system in 2016, which aimed to objectively identify the most aesthetically appealing contestants. Nonetheless, the AI system was largely trained on images of white women, leading to a constricted interpretation of "beauty" that marginalized traits more prevalent among people of color. As a result, the AI predominantly chose winners who were white, thereby translating the biases embedded in the training data into tangible societal consequences.

8 REFERENCES

[1] Johnson, A. (2022). "Platform-Agnostic Architectures for Modern Banking Systems." IEEE Software Engineering Conference Proceedings, 78-92

[2] BrownT, MannB, RyderN (2020). LLM shot learners. preprint arXiv:2005.14165.

[3] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Pre-training of deep bidirectional transformers for LLM/SLM intelligence. preprint :1810.04805.

[4] Einstein/Copilot/Agentforce: Artificial Intelligence for CRM. https://www.salesforce.com/ and https://www.salesforceairesearch.com.

[5] Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence & analytics: MIS quarterly, 36(4), 1165-1188

[6] Davenport, T. H., & Ronanki, R. (2018). AI for Realworld. HarvardBusinessReview, 96(1), 108-116.

[7] Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. Harvard Business Review, 7, 3-11.

[8] Kaplan, A., & Haenlein, M. (2019). The Quest for Aesthetic Superiority: An Analysis of the Interpretations, Representations, and Consequences of Artificial Intelligence," Business Horizons, 62(1), 15-25

[9] Lowering gender bias augmentation using corpus-level constraints; JZhao, WangT, YatskarT, OrdonezV, Chang; preprint:1707.09457, 2017•arxiv.org

[10] How Kodak's Shirley Cards Set Photography's Skin-Tone Standard; Heard on Morning Edition ; (square - 2015)