AI Tax Planner

PHASE I REPORT

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BONAFIDE CERTIFICATE

Certified that this report titled "**AI Tax Planner** " is the bonafide work of **Shaik Teeb Hussain** (Reg. No: **21011101115**), **Samanthu Abhay Reddy** (Reg. No: **21011101110**), **Shaik Mohammed Noor** (Reg. No: **21011101114**), who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The ”AI Tax Planner ” is an intelligent tax optimization assistant designed to provide users with personalized tax-saving strategies by leveraging cutting-edge Generative AI (GenAI) technologies. This system aims to simplify tax planning by delivering actionable, customized recommendations based on a user’s unique financial data and up-to-date tax regulations. By utilizing Large Language Models (LLMs), the assistant can interpret complex tax laws, making it easier for users to understand and apply tax-saving strategies. A core component of the system is the integration of Retrieval-Augmented Generation (RAG), which enables the AI to combine generative capabilities with a powerful retrieval system, thus pulling relevant information from a vector database . This vector database , managed through Chroma DB, houses structured, anonymized, and normalized user financial data such as income, expenses, deductions, and past tax returns—making it accessible for efficient retrieval of contextually relevant tax regulations and savings opportunities. The project also incorporates Langchain to coordinate seamless interactions between system components, facilitating a fluid and intelligent workflow for generating tax recommendations. Performance metrics, such as response time, recommendation accuracy, and user satisfaction, will be continuously monitored to ensure that the AI Tax Planner consistently delivers high-quality, reliable, and user-focused tax advice. This project ultimately aspires to revolutionize tax planning, enabling users to make informed decisions with ease and confidence while maximizing their tax savings..

Keywords - Tax Optimization, Large Language Models, Financial Data Analysis

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS, ABBREVIATIONS

AI	Artificial Intelligence
ELSS	Equity Linked Savings Scheme
LLM	Large Language Model
NLP	Natural Language Processing
NPS	National Pension Scheme
PPF	Public Provident Fund
RAG	Retrieval-Augmented Generation

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

1.1.1 Concept

The AI Tax Planner project is designed to assist individuals and businesses in optimizing their tax strategies through personalized, data-driven recommendations. Built on Generative AI, this assistant simplifies tax planning by interpreting complex tax laws and generating actionable advice based on the unique financial situation of each user. Key technologies, including Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and vector databases (Chroma DB) [3], are integrated with Langchain to ensure efficient and precise recommendations. By automating tax-saving insights, the AI Tax Planner offers users a reliable, user-friendly solution that reduces the time, cost, and complexity traditionally associated with tax optimization

1.1.2 Motivation

The motivation behind the AI Tax Planner [4] stems from the need to make tax planning accessible, affordable, and user-friendly for a broader audience. Traditional tax optimization [5] often relies on professional assistance, which can be costly and time-consuming. By leveraging advanced AI technologies, this project democratizes access to sophisticated tax advice, empowering users to maximize their savings without needing specialized knowledge. Additionally, with annual tax regulations and personal finances in constant flux, there's a growing demand for a solution that adapts to these changes and provides timely, reliable guidance. This project also represents an opportunity to showcase the potential of Generative AI in complex, real-world applications beyond basic question-answering tasks. By integrating Retrieval-Augmented Generation and orchestrating it with Langchain, the AI

Tax Planner not only highlights AI's capabilities in interpreting nuanced regulations but also demonstrates a scalable approach to personalization in financial services. This solution has the potential to transform how individuals and businesses approach tax planning, making it simpler, smarter, and more aligned with their specific financial goals.

ser_ID	Income	Expenses	HealthInsurance	HomeLoan	ELSS	NPS	PPF	HouseRent	Previous_Tax_Amount	State	Filing_Status	Tax_Credits
1	874172.21	11235.07	24474.12	6075448.52	0.00	116350.16	0.00	386122.38	517862.06	OK	Head of Household	17939.14
2	1911285.75	68194.59	5579.75	0.00	0.00	93015.94	0.00	0.00	373978.88	HI	Single	106986.72
3	1517589.10	59946.56	0.00	650515.93	0.00	112739.87	0.00	2761.06	198538.81	MD	Single	114117.76
4	1277585.27	22740.35	0.00	9488855.37	109118.45	107379.28	42810.40	0.00	38135.01	MN	Head of Household	84191.58
5	480833.55	20909.50	0.00	0.00	31053.60	71748.00	0.00	0.00	186589.39	CO	Married	115645.08
6	480790.14	21004.27	0.00	8083973.48	79502.67	110624.91	0.00	364503.58	195109.99	WI	Single	74069.34
7	304550.50	28254.53	7986.95	3046137.69	37405.33	0.00	0.00	385635.17	437763.71	PA	Single	78409.92
8	1759117.06	41485.39	0.00	0.00	62408.16	0.00	0.00	37022.33	382534.48	SD	Single	64131.15
9	1282007.02	35916.70	0.00	0.00	65605.23	0.00	8946.08	179232.86	532327.65	LA	Head of Household	3812.87
10	1474530.64	27473.75	1858.02	4401524.94	0.00	0.00	118426.43	57934.53	283328.96	MT	Single	16183.71

Figure 1.1: Dataset

	Tax_Bracket	Standard_Deductions	Tax_Credits
0	0% - 0 to 3,00,000	75000	30000
1	5% - 3,00,001 to 7,00,000	75000	60000
2	10% - 7,00,001 to 10,00,000	75000	90000
3	15% - 10,00,001 to 12,00,000	75000	120000
4	20% - 12,00,001 to 15,00,000	75000	150000
5	30% - 15,00,001 and above	75000	170000

Figure 1.2: Tax Regulations

Expenses	HealthInsurance	HomeLoan	ELSS	NPS	PPF	HouseRent	Previous_Tax_Amount	State	Filing_Status	Tax_Credits	Estimated_Tax
13470.56	36603.60	926254.83	75765.04	53889.42	0.00	0.00	489736.71	VA	Single	86460.83	0.000
68146.16	0.00	0.00	0.00	0.00	86722.03	100699.55	592957.27	SC	Single	118800.47	216623.432
63027.15	6318.19	9145486.64	65777.42	68508.85	38307.04	0.00	233310.90	IA	Single	48647.05	0.000
65665.14	27835.96	0.00	0.00	39891.20	108709.40	0.00	28449.38	HI	Married	107424.68	129598.602
69694.47	0.00	2587116.42	0.00	0.00	0.00	0.00	480702.90	WA	Married	20312.83	0.000

Figure 1.3: Financial data with taxes

CHAPTER 2: METHODOLOGY

The methodology for conducting an in-depth analysis of financial and taxation legislation involves a systematic approach leveraging data collection, processing, and advanced machine learning techniques, specifically the Retrieval-Augmented Generation (RAG) framework. This approach is designed to bridge the complexity of tax laws and personalized financial scenarios, providing tailored recommendations that adhere to legislative standards. The RAG framework combines the capabilities of a retrieval system for fetching relevant data with the generative power of large language models, ensuring dynamic and context-specific insights. By focusing on user data confidentiality, robust processing pipelines, and legislative compliance, this aims to create a seamless, secure, and effective system for financial optimization.

2.1 Data Collection

User financial data, including income, expenses, deductions, and previous tax returns, is gathered through a secure and privacy-compliant mechanism. This process ensures confidentiality and anonymization to protect user identities. The data is meticulously structured to capture attributes such as income sources, categorized expenses, applicable deductions, and historical tax filings. Income sources encompass diverse streams, including salaries, business revenue, and rental income. Expenses are classified into fixed and variable categories, while deductions focus on investments and expenditures eligible under Indian tax laws, such as those stipulated in Sections 80C and 80D. Historical tax returns provide insight into compliance patterns and liabilities. Digital tools like APIs and secure data forms facilitate seamless and efficient data input.

2.2 Data Cleaning and Normalization

The collected data undergoes a rigorous cleaning and normalization process to ensure consistency and accuracy. Redundant or incomplete records are identified and removed, while formats for dates, monetary values, and categorical data are standardized. Missing data points are addressed through statistical methods or domain-specific assumptions, ensuring the dataset's integrity. This process eliminates anomalies, thereby enabling reliable and consistent analysis.

2.3 Feature Extraction and Storage

From the cleaned data, key features relevant to tax optimization are identified and extracted. These include taxable income after applying deductions, patterns in expense categories, and the use of tax-saving investments. For example, computations consider eligible exemptions and deductions to provide a precise assessment of taxable income. Expense trends highlight areas for potential tax benefits, while compliance with recommended investment schemes such as PPF and ELSS is evaluated. The extracted features are encoded into vector representations and stored in a Vector Database (Chroma DB) [3]. This database is optimized for efficient indexing and retrieval, ensuring quick access to financial data and relevant legislative information.

2.4 Integration of RAG Framework

The Retrieval-Augmented Generation (RAG) [6] framework integrates the capabilities of a retrieval system with a generative model to deliver personalized insights. The retrieval system uses the Vector Database to retrieve user-specific financial attributes and relevant tax legislation. The generative model, powered by a Large Language Model (LLM), interprets this retrieved data and creates tailored tax-saving recommendations. This seamless integration ensures that the recommendations are dynamically tailored to the financial situation of each individual, providing relevant and actionable insights in real time.

2.5 Performance Monitoring and Evaluation

The system's performance is continuously monitored to maintain its effectiveness and reliability. Response time is measured to ensure prompt processing of user queries. The accuracy of tax-saving recommendations is evaluated against established regulations and user data to validate their relevance and correctness. User satisfaction is gauged through feedback mechanisms, including surveys and analytics, to measure the practicality and usability of the recommendations. These metrics are used for iterative improvements, ensuring the system remains adaptive to evolving user needs and regulatory updates.

2.6 Compliance and Security

Data security and regulatory compliance are foundational to this methodology. Measures such as encryption protect data during transit and storage, while role-based access controls limit data handling to authorized personnel. Regular audits are conducted to identify and mitigate potential vulnerabilities. The methodology aligns with Indian data protection laws, such as the Information Technology Act, and international standards like the General Data Protection Regulation (GDPR). These protocols ensure the safeguarding of user data and uphold privacy at every stage.

By adhering to this comprehensive methodology, the system delivers a robust, secure, and personalized approach to financial and taxation analysis, empowering users to effectively optimize their tax liabilities while ensuring compliance with legislative requirements.

CHAPTER 3: IMPLEMENTATION

3.1 Packages Used

The data generation and analysis process leveraged several Python packages, each serving distinct roles to facilitate comprehensive financial data simulation and analysis. NumPy was utilized for efficient numerical operations, particularly in generating random values for various financial attributes like income and expenses using uniform distributions. Pandas was employed for its powerful DataFrame structure, enabling efficient data manipulation, aggregation, and storage of user profiles. The Faker library provided realistic categorical data by generating attributes such as state abbreviations, enhancing the dataset's diversity and authenticity. For implementing random sampling in user profiles and investment attributes, the standard random module was used, introducing variability and simulating real-world scenarios. Additionally, transformers and LangChain [2] were integrated to enable advanced natural language processing capabilities. Specifically, the transformers library from Hugging Face allowed for the use of state-of-the-art language models for text generation, while LangChain [2] facilitated seamless interaction with the generated financial data through question-answering (QA) pipelines, thus enabling personalized tax optimization analysis based on user-specific financial attributes.

3.2 Dataset Preparation

The dataset preparation process involved synthesizing a comprehensive financial dataset that simulates real-world user profiles for tax optimization analysis. Initially, a user dataset was generated using NumPy to create numerical attributes such as income, expenses, health insurance, and various investment contributions (e.g., ELSS, NPS, PPF). These were sampled from uniform distributions to reflect a broad range of financial behaviors and incomes.

The Faker library was used to generate categorical data such as state abbreviations and filing statuses (e.g., Single, Married, Head of Household), adding realistic demographic diversity. To introduce realistic sparsity in certain financial attributes (like home loans or health insurance), a conditional random selection was implemented, setting some values to zero to mimic scenarios where users might not have specific investments. The resulting dataset contained key features required for tax estimation, including income details, deductions, and prior tax amounts. A secondary dataset, representing simplified tax regulations, was created using Pandas, which defined tax brackets, standard deductions, and tax credits. This structured approach ensured that the generated financial dataset could be effectively utilized for simulating tax calculations and personalized tax-saving recommendations using advanced AI models.

3.3 Vector Database

In our financial tax optimization system, a vector database (Chroma)[3] has been employed to handle high-dimensional embeddings of user financial data, enabling efficient similarity searches. Traditional databases struggle with capturing semantic similarities in complex, multidimensional datasets, whereas vector databases excel at this by storing data as numerical vectors. In our code, user financial profiles—including income, expenses, and investments—are transformed into vector embeddings using the HuggingFace model. By querying this vector database, we can quickly retrieve similar financial profiles, allowing our system to generate personalized and context-aware tax-saving recommendations. This usage enhances the model's ability to provide tailored advice by effectively leveraging similar user data patterns for optimized tax planning.

3.4 LLM

The implementation leverages advanced Large Language Models (LLMs) to generate personalized tax optimization recommendations based on user financial data. Specifically, the HuggingFace model, Zephyr-7b-beta[1], was employed due to its robust language understanding and generation capabilities. The model is fine-tuned for text-generation tasks, making it ideal for interpreting complex financial scenarios and providing context-aware responses. To enhance efficiency and reduce computational overhead, the model was loaded with Bits and Bytes Configuration , enabling 4-bit quantization, which significantly optimizes memory usage without sacrificing performance. The transformers library facilitated model loading and the setup of a text-generation pipeline, where the tokenizer processed user inputs, and the model generated tailored responses. Additionally, the LangChain [2] framework was utilized for integrating the LLM with retrieval mechanisms, allowing the system to access and incorporate specific financial data points from a vector database. This seamless integration of LLMs with a structured data retrieval process enabled accurate, context-rich, and user-specific tax planning recommendations, demonstrating the power and flexibility of modern generative AI in financial applications.

3.5 Training Model

In this implementation, the Large Language Model (LLM) used, specifically Zephyr-7b-beta[?] from HuggingFace, was pre-trained and fine-tuned on extensive datasets covering a variety of language tasks, including comprehension, reasoning, and text generation. The model training process included multiple stages:

Pre-training: During this phase, the model was trained on a vast corpus of text data using a self-supervised learning approach. This enabled the model to learn the structure, grammar, semantics, and nuances of the language. The dataset typically consisted of diverse text sources, such as books, articles, and online content, providing the model with a comprehensive understanding of human language.

Fine-tuning: The next stage involved fine-tuning the model specifically for tax-related financial queries. Fine-tuning is a process where the model is further trained on a specialized dataset, which in this case includes financial documents, tax regulations, and relevant queries. This process involved supervised learning where labeled examples were used to adjust the model's parameters, enabling it to provide more accurate and domain-specific responses. This stage enhanced the model's ability to interpret complex financial information, understand tax terminologies, and generate precise optimization strategies.

Optimization Techniques: To make the model deployment efficient, quantization was applied using the Bits and Bytes (bnb) library. The quantization technique used here reduces the precision of the model weights from 16-bit floating-point to 4-bit, significantly decreasing memory usage and inference time without compromising the model's performance. This makes the model more suitable for real-time, resource-constrained environments.

The combined effects of extensive pre-training and domain-specific fine-tuning allowed the LLM to become a powerful tool for generating personalized, context-aware tax optimization recommendations. The model's training process leveraged vast computational resources and state-of-the-art techniques, resulting in a highly effective system for financial advisory tasks.

```
Based on the financial data and tax regulations provided, here are some personalized tax-saving recommendations for each user:

1. User_ID: 317
   - Maximize health insurance deductions by increasing the premium amount or choosing a higher coverage plan.
   - Consider investing in ELSS or NPS to avail tax benefits under Section 80C.
   - Claim tax credits for professional tax, tuition fees, and interest paid on education loans.
   - Opt for a lower tax rate by choosing the Head of Household filing status if eligible.

2. User_ID: 54
   - Maximize health insurance deductions by increasing the premium amount or choosing a higher coverage plan.
   - Claim tax credits for professional tax, tuition fees, and interest paid on education loans.
   - Consider investing in ELSS or NPS to avail tax benefits under Section 80C.
   - Opt for a lower tax rate by choosing the Head of Household filing status if eligible.

3. User_ID: 39
   - Maximize health insurance deductions by increasing the premium amount or choosing a higher coverage plan.
   - Claim tax credits for professional tax, tuition fees, and interest paid on education loans.
   - Consider investing in ELSS or NPS to avail tax benefits under Section 80C.
   - Opt for a lower tax rate by choosing the Single filing status if eligible.
```

Figure 3.1: Output

CHAPTER 4: CONCLUSION

The proposed system demonstrates a transformative approach to improve tax-saving strategies through the integration of advanced data processing and machine learning techniques. By automating complex tax analyses, it simplifies the intricacies of tax laws, making personalized and high-quality tax advice more accessible and cost-effective for users without requiring professional assistance. The system's ability to deliver tailored recommendations aligned with current tax regulations provides a robust alternative to traditional tax advisory services. Furthermore, the incorporation of anonymized data storage and retrieval mechanisms addresses privacy concerns, fostering trust and ensuring data security. The real-time adaptability of the system ensures that recommendations remain accurate and relevant amidst the ever-evolving tax landscape.

Despite its advantages, the system is not without limitations. The reliance on sensitive financial data, even with anonymization, introduces inherent privacy and security risks, particularly in the event of data breaches. Additionally, the system's generalized approach may lack the nuance required for complex financial scenarios or unique individual circumstances, which a human advisor might address more effectively. The accuracy of the recommendations is heavily dependent on the quality of input data. Moreover, the frequent updates necessary to maintain compliance with evolving tax laws could be resource-intensive. Finally, the potential for users to misinterpret automated recommendations underscores the need for enhanced user interfaces or supplementary educational resources.

In conclusion, while challenges remain, this system represents a significant step toward democratizing access to tax saving strategies. With continued refinement, including addressing privacy concerns, improving data accuracy, and enhancing user support, the proposed system has the potential to revolutionize how individuals approach tax planning in a secure, efficient, and user-friendly manner.

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APPENDIX A: Appendix

A.1 Methodology Overview

The methodology adopted for the development of the financial and taxation optimization system involves a multi-step process designed to ensure accurate, personalized, and efficient tax-saving recommendations. This process integrates advanced machine learning models, secure data handling practices, and legislative compliance, ensuring both robustness and privacy.

A.1.1 Data Collection

User financial data, including income, expenses, deductions, and historical tax returns, was securely collected through privacy-compliant mechanisms. This data was anonymized and structured into key attributes, such as income sources, categorized expenses, and eligible deductions under Indian tax laws (e.g., Sections 80C, 80D). The data collection process was supported by digital tools, APIs, and secure forms for efficient data input.

A.1.2 Data Cleaning and Normalization

The gathered data underwent a thorough cleaning and normalization process to remove redundant or incomplete records, standardize date formats, monetary values, and categorical data, and address missing values using statistical methods or domain-specific assumptions. This step ensured that the dataset was consistent and suitable for analysis.

A.1.3 Feature Extraction and Storage

Key features relevant to tax optimization, such as taxable income, expense patterns, and eligible tax-saving investments, were extracted from the cleaned data. These features were encoded into vector representations and stored in a Vector Database (Chroma DB), optimized for efficient indexing and retrieval, enabling real-time tax optimization calculations.

A.1.4 Integration of the RAG Framework

The Retrieval-Augmented Generation (RAG) framework was employed to integrate a retrieval system with a generative model. The retrieval system fetched relevant user financial data and associated tax legislation, while the generative model, powered by a Large Language Model (LLM), generated personalized tax-saving recommendations based on this information.

A.1.5 Performance Monitoring and Evaluation

The system's performance was continuously monitored through metrics such as response time, accuracy of tax-saving recommendations, and user satisfaction. Feedback mechanisms, including surveys and analytics, were incorporated to measure the effectiveness of the system and identify areas for improvement.

A.1.6 Compliance and Security

Ensuring data security and regulatory compliance was a top priority. The system employed encryption for data storage and transit, along with role-based access controls. Regular security audits were conducted to mitigate vulnerabilities. The system adhered to Indian data protection laws, such as the Information Technology Act, and international standards like GDPR, ensuring privacy at all stages.

A.2 Implementation Overview

The implementation phase focused on creating the necessary infrastructure for financial data processing and generating personalized tax optimization recommendations.

A.2.1 Packages and Libraries Used

Several Python packages were employed to facilitate the data generation, manipulation, and machine learning tasks, including:

- **NumPy**: For numerical operations and generating financial attributes.
- **Pandas**: For data manipulation and organization into DataFrame format.
- **Faker**: To generate realistic categorical data, such as state abbreviations and filing statuses.
- **Transformers**: To load and work with large language models for text generation.
- **LangChain**: To facilitate question-answering pipelines, enabling interaction between the LLM and the financial data.
- **Chroma DB**: For storing and retrieving high-dimensional embeddings of user financial profiles.

A.2.2 Dataset Preparation

The dataset was synthesized to represent diverse financial scenarios:

- **Numerical Attributes**: Data such as income, expenses, and investment contributions were generated using NumPy, sampled from uniform distributions.
- **Categorical Data**: Attributes like state abbreviations and filing statuses were generated using the Faker library.
- **Conditional Sparsity**: Certain attributes (e.g., home loans or health insurance) were conditionally set to zero to introduce realistic gaps in the data.

A.2.3 Vector Database

Chroma DB was utilized to manage high-dimensional embeddings of financial data, enabling efficient retrieval of similar user profiles. The data was transformed into vector embeddings using the HuggingFace model, facilitating personalized, context-aware tax-saving recommendations based on similar financial profiles.

A.2.4 Large Language Model (LLM)

The system used the **Zephyr-7b-beta** LLM[1], fine-tuned on financial data, to generate tax-saving recommendations. The model was loaded with Bits and Bytes configuration for 4-bit quantization, optimizing memory usage without sacrificing performance. The transformers library allowed for efficient model loading and the setup of text-generation pipelines, while LangChain was used to integrate the LLM with the retrieval mechanism.

A.2.5 Model Training

The LLM was pre-trained on a vast corpus of text data and fine-tuned specifically for tax-related financial queries:

- **Pre-training**: The model was initially trained on a broad range of text sources to understand language structure and semantics.
- **Fine-tuning**: Further training was performed on a specialized dataset covering financial documents and tax regulations to enhance the model's ability to interpret and respond to complex financial scenarios.
- **Optimization**: Quantization using the Bits and Bytes library was applied to reduce memory usage and inference time, making the model more suitable for real-time applications.

A.3 Conclusion and Discussion

A.3.1 Conclusion

The proposed system successfully combines advanced machine learning techniques with personalized financial data to automate tax optimization. By leveraging data processing and the RAG framework, it generates accurate, tailored recommendations based on individual financial profiles. This approach democratizes access to tax-saving strategies, offering a cost-effective alternative to traditional tax advisory services.

A.3.2 Discussion

Despite its strengths, several limitations persist:

- **Privacy and Security Risks**: Although anonymization techniques were employed, the use of sensitive financial data still poses potential privacy risks. Enhanced data security measures are required to mitigate these concerns.
- **Depth of Recommendations**: While the system provides general advice, it lacks the nuanced understanding of a human tax advisor, particularly in complex financial situations.
- **Data Quality Dependence**: The system's effectiveness is closely tied to the accuracy and completeness of the input data. Errors or inconsistencies in the data may lead to suboptimal recommendations.
- **System Maintenance**: Continuous updates are required to keep up with frequent changes in tax regulations, necessitating ongoing development and resource allocation.
- **User Misinterpretation**: Users without a strong understanding of tax principles may misinterpret automated recommendations, underscoring the need for clear user guid-

ance.

Despite these challenges, the system offers a promising approach to providing personalized tax-saving advice, with room for future enhancements to address its limitations.