

Automated Personalized Investment Advisory Platform

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Abstract

The goal of this proposal is to transform the personal financial industry by introducing the idea of an automated personalized investment advisory platform. The platform's primary objective is to offer personalized investing recommendations to individuals by utilizing artificial intelligence and machine learning in personal finance domain. It considers the individual's risk tolerance, financial objectives, and current market conditions. The system provides a user-friendly interface, thorough market analysis, and customized investment methods to address current issues with managing personal finances. The Automated Personalized Investment Advisory Platform aims to enable people to make educated financial decisions, contributing to their long-term financial success, by democratizing access to expert investment advice.

Problem Statement:

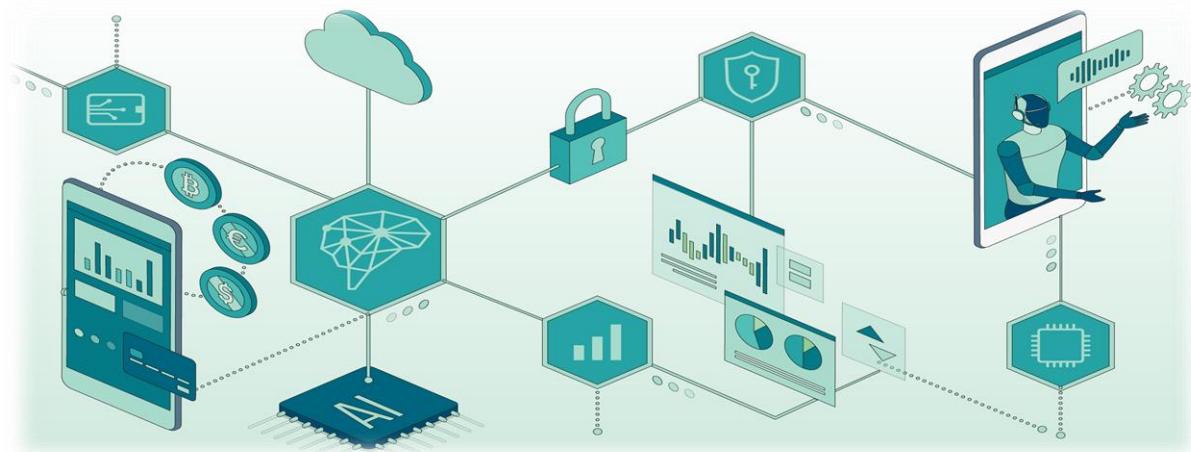
The current financial landscape lacks a comprehensive and accessible solution for individuals to receive personalized investment advice. The savings are going to negative side since the government's spending demands outweighed its revenue. Over the last ten years, government dissaving has averaged 2.1% of GDP. The majority of gross savings are contributed by households, accounting for approximately 65% in 2022–2023. Existing advisory services are often expensive, lack customization, and struggle to provide real-time insights plus they don't provide personalized decision or strategy.

There is a pressing need for an Automated Personalized Investment Advisory Platform that leverages artificial intelligence and machine learning to offer tailored guidance, empowering individuals to make informed investment decisions aligned with their unique financial goals and risk profiles like retiring time, whether to buy car, house at that price, or wait for some time etc.

Introduction

The financial ecosystem is evolving rapidly, driven by technological advancements and market dynamics. Individuals, ranging from novice investors to seasoned professionals, encounter challenges in deciphering the intricate web of investment opportunities. Traditional advisory services, while offering a semblance of support, often lack the agility and personalization required in the face of ever-changing market conditions.

Also, since savings are going to negative side due to inflation, pandemic, post war effects and with the government's spending demands outweighing its revenue. Over the last ten years, government dissaving has averaged 2.1% of GDP. The majority of gross savings are contributed by households, accounting for approximately 65% in 2022–2023 and it is highly necessary to invest these in good return investment than just storing and getting depleted by inflation and other economic problems.



Lack of knowledge and the overload of information is getting investors to believe they can manage everything themselves without professional help. The advent of private equity funded digital platforms, whose value proposition is free advice, is not helping matters. This is where this platform can change the game by processing this big hill of updating information and predicting relevant patterns and customer status without being biased or faulty.

The significance of the Automated Personalized Investment Advisory Platform lies in its potential to democratize access to sophisticated investment advice. By harnessing the capabilities of artificial intelligence and machine learning, the platform aims to empower individuals with tailor-made strategies that align with their unique financial goals and risk preferences. This enhances financial literacy and cultivates informed decision-making in personal finance.

This initiative delves into the development of a comprehensive platform that adapts to individual needs. The scope encompasses leveraging advanced technologies to create a user-friendly

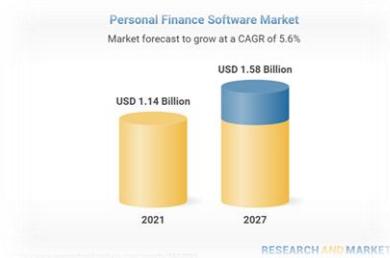
interface that delivers real-time insights and personalized investment recommendations. The platform's capabilities extend to portfolio optimization, market analysis, and continuous adaptation to ever-evolving financial landscapes.

Market/Customer/Business Need Assessment

While this platform can empower individuals, it can place the onus on them to make complex financial decisions without expert guidance. At the same time, advances in artificial intelligence and machine learning are creating new opportunities for automated personalized solutions. But looking at its need from all side is equally important to making this platform feasible:

If we look onto current market needs:

- The do-it-yourself investing market is huge and growing. As of 2020, over 50 million households managed over \$11 trillion in self-directed retirement accounts like 401(k)s. This number is expected to grow significantly in the coming years.
- The mutual funds industry in India has grown at a CAGR of over 20% in recent years to over \$400 billion in assets. However, penetration remains quite low indicating huge future growth potential.
- Many individuals lack investing expertise and confidence. Managing investments requires ongoing research, analysis and decision making which most people do not have time or skills for. This creates a need for advice and guidance.
- Traditional financial advisors are too expensive for the average investor. The typical minimum account size to work with an advisor is \$250k. This leaves many individuals on their own to manage their savings.
- Existing robo-advisors offer automated low-cost options but lack personalization. Their advice is generic and not tailored to each user's unique situation. This limits their appeal and effectiveness.
- An aging population is increasing demand for retirement planning advice. As baby boomers retire, there will be greater need to invest savings properly for income in retirement. Market volatility in recent years has shaken confidence. Events like the 2020 COVID crash highlighted the importance of professional guidance during unstable periods.



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- Financial literacy remains low. Many lack understanding of basic concepts like diversification, asset allocation, risk tolerance etc. Automated personalized advice could help educate as well.

Similarly, for customer side they need our platform to be:

- Easy to use platform that requires minimal time/effort from customers to get started and manage their investments.
- Personalized recommendations tailored to their unique financial situation, goals, risk tolerance etc.



- Low fees compared to traditional advisors.
- Continuous monitoring of investments and rebalancing as needed.
- Transparent recommendations and ability to understand advice.

With the current market trends and customer lifestyle and thinking a great Business Opportunities can be opened here:

- Large and growing target market as it takes more control of retirement savings.
- Recurring revenue model from management fees on assets under management.
- Opportunity to scale easily with an automated platform and acquire new customers cost effectively online.
- Potential to offer additional paid services like financial planning, tax advice, banking etc. to cross-sell and boost revenues
- Data from many users can be leveraged to continuously improve ML models and advice over time.



Target Specifications and Implementation

There is a need for an affordable yet robust automated investment advisory platform that can provide personalized portfolio management and guidance services to individual investors across India. The solution will leverage artificial intelligence and machine-learning strategies to deliver an easy to use, highly scalable digital experience that empowers customers to meet their long-term financial goals in a cost-effective manner.

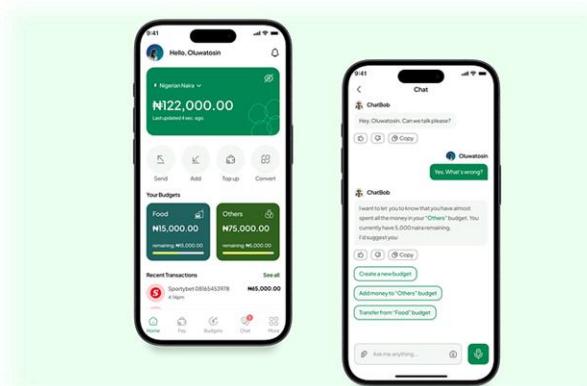
Basic footsteps of its working will be:

The platform will first target individual investors between 25-50 years of age with investible assets between Rs. 10,000 - Rs. 1,000,000 looking for affordable automated investment solutions and this customer segmentation can be changed with updating customers financial background by leveraging machine-learning algorithm to assist in these customer- segmentation.

We can enhance this by increasing platform's Accessibility and Usability:

- Mobile responsive web and app interfaces will be used that allow 24/7 access from any internet enabled device.
- Intuitive UI/UX designing based on customer research for easy onboarding, portfolio oversight and support.
- Multi-lingual support inclusion for major Indian languages to meet needs of target segment across the country.

After segmenting them, it will further target these remaining customers by building a detailed risk profile on these, which is very crucial for risk assessment in any investment. This will be taken care of by platform by doing Scientific risk profiling questionnaire backed by academic research and apply machine-learning strategy on their financial background build from questionnaire and research to accurately assess customer risk profile and match to optimal portfolio. (***this has been implemented by me and included in report***).



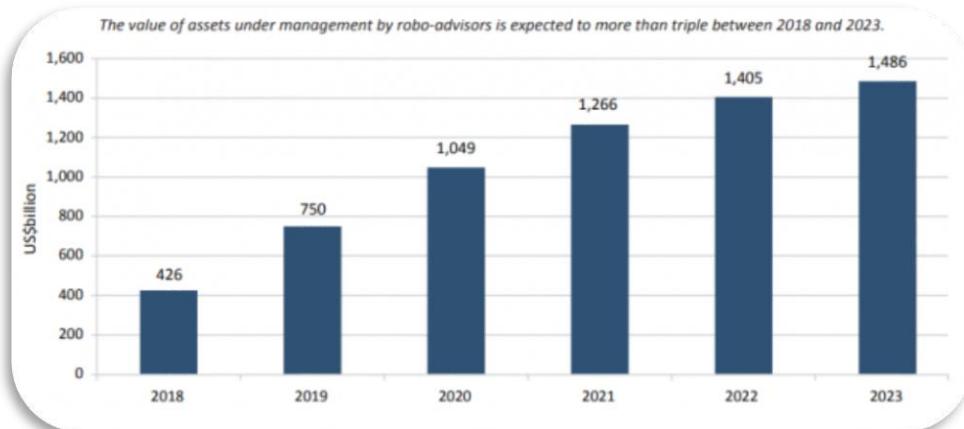
After this crucial step, it will perform automated portfolio creation and periodic rebalancing through back testing and machine learning algorithms to meet long term financial goals in line with risk tolerance and then finally it can provide range of customized investment recommendations and portfolio adjustments over time as customer's needs change to ensure continued suitability and with continuous updates in market trends by following price returns API's from commodity and stock market.

To make this platform feasible and also affordable for users we can charge some Subscription fees starting at 0.5-1% of AUM, lower than traditional financial advisors and benchmarked against global robo advisors, to make automated investing accessible for target segment.

External search (information sources)

A review of industry reports and research papers revealed the following insights into the global robo advisory market:

- The robo advisory market is expected to grow at a CAGR of over 21% through 2025 as investors seek low-cost automated solutions (<https://www.iimcal.ac.in/FinLab/email-template3/res/ArtiChandani.pdf>).



- Top players like Betterment, Wealth front and Ellevest have shown that a mobile-first approach with simple UI/UX and educational resources can attract younger customers (<https://www.forbes.com/sites/forbestechcouncil/2022/07/21/15-emerging-uiux-design-trends-tech-companies-must-prepare-for/?sh=28c70797453e>).
- AI/ML algorithms for risk profiling and portfolio optimization are the key to delivering personalized experiences at scale (<https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf>).

These insights make clear that the proposed model have a larger market to capture and can be beneficial to all segments side and apart from these to see how the platform use the financial and social background of customer to build an accurate risk profile (i.e. high or low) , I took a loan defaulter dataset where based on borrower complete background could provide a better risk profile in judging whether or not user could repay the loan or not for given loan amount.

The dataset used for this risk analytics implementation can be found on Kaggle :
<https://www.kaggle.com/datasets/gauravduttakiit/loan-defaulter>

Similarly, after doing risk assessment and categorizing various portfolios judging appropriate returns w.r.t to market conditions, it is important for platform to see whether the user should invest based on his/her risk involved judged by their risk score. To grasp this, I have implemented a mini version of this where using the risk score and other relevant details of user can tell whether he should buy car or not?

The dataset used for this right time investment in buying car can be found on Kaggle:
<https://www.kaggle.com/datasets/pasinduranasinghe123/can-you-buy-a-new-car>

Benchmarking (*with Global leading robo-advisor in investment*)

Sr No.	Criteria	Better Ment	Wealth Front	Ellevest	Our Advisor
1	Account Minimum	\$20,000	\$1000	\$1,000,000	\$100-500 (0.1-5% AUM)
2	Risk Profiling	Uses Credit Score Model type approaches like FICO (Fair Isaac Corporation) model but shifting towards ML version.	Uses advanced statistical tools, NLP and portfolio simulations like Monte Carlo etc.	Uses Statistical Methods and thresholds	Uses advanced AI-ML algorithm with continual adaption of model weights with external trends
3	Customizations	Very limited	Can't go entirely with our choice and has to go along with expert advice	Present but limited for big investments.	Will be available at every stage and for any investment amount.

4	Education Content	Moderate	Extensive but caters for general investment	Extensive but caters for general investment	Will be extensive and AI will select best resources for users based on their investment
5	Target User	Caters to investors who are getting started but its users comprise mostly young tech-savvy investors	Millennial investors	Specifically targets women investors	Not biased based on gender or investment amount but targets 25-50 years who can bear minimal risk

In conclusion, the proposed platform offers many clear advantages through its use of advanced AI/ML technologies to deliver superior risk profiling, portfolio customization, education and overall client experience compared to existing leading players. This differentiated value proposition can help us achieve a significant market share by addressing a wider cross-section of investors in a highly personalized manner.

Applicable Patents

A search was conducted for patents applicable to developing an AI-powered robo advisory platform. The following patents were identified as most relevant:

Patent 1: Title: Algorithm-based risk assessment and portfolio management using machine learning Patent Number: US20150161736A1

- This patent describes the use of machine learning algorithms and predictive modeling to analyze user data such as financial history and risk tolerance to determine an optimal investment portfolio.
- The risk profiling and portfolio optimization approach described in this patent is applicable to developing the AI engine that will power personalized recommendations. The machine learning models need to accurately assess risk appetite and goals to select suitable investments. This patent provides useful insights on how to design and train such algorithms.

Patent 2: Title: Cloud-based investment and wealth management platform Patent Number: US20160267542A1

- This patent outlines a digital wealth management system hosted on the cloud with microservices architecture. It enables functions such as online account opening, fund selection and transactions through modular independent services.

Applicable Standards

The following standards were identified as applicable to developing a digital wealth management platform in India:

1)SEBI Investment Advisers Regulations, 2013

- The Securities and Exchange Board of India (SEBI) regulates investment advisors and intermediaries. As an automated advisory service, the platform will require SEBI registration and compliance with KYC/AML guidelines.
- This impacts product development as user onboarding and recommendations need to adhere to regulatory requirements. Data security, record keeping, and periodic reporting standards also need to be followed.

2)ISO/IEC 27001:2013 - Information Security Management

- This international standard specifies requirements for an information security management system. It contains controls in wide areas like asset management, human resource security, access control etc.
- The platform will require robust information security practices to safeguard user data and assets. This standard provides a framework to systematically identify and mitigate risks through continuous evaluation and improvement.

3)WCAG 2.1 - Web Content Accessibility Guidelines

- WCAG defines how to make web content more accessible to people with disabilities. It addresses various aspects like visual, auditory, and physical disabilities.
- Since the platform is web-based, it is important to ensure accessibility for all users. The guidelines will be followed to develop a design that is perceivable, operable, understandable, and robust.

Applicable Constraints

Internal Constraints:

- Customer reluctance to provide personal financial data - Customers may not be comfortable sharing sensitive information like income, assets, liabilities, transaction history etc. needed for personalized recommendations. This limits the ability to provide tailored advice.

- Lack of digital literacy/skills among target customers - older customers or those from less tech-savvy backgrounds may find online platforms difficult to navigate independently. This poses constraints on user interface design and onboarding process complexity.
- Trust issues in new fintech platforms - Customers used to traditional advisors may be hesitant to trust a digital platform, especially for significant financial decisions. Extra efforts are needed to build credibility.
- Preference for human interaction - Some customers may prefer speaking to a live advisor rather than an automated platform. These constraints the ability to fully automate the advisory process.
- Low digital adoption in target segments - Reaching customers from rural areas or lower income groups requires solutions optimized for basic digital access like feature phones.
- Inability to explain complex products - Simplified explanations are needed for customers with low financial literacy and risk appetite for advanced offerings.



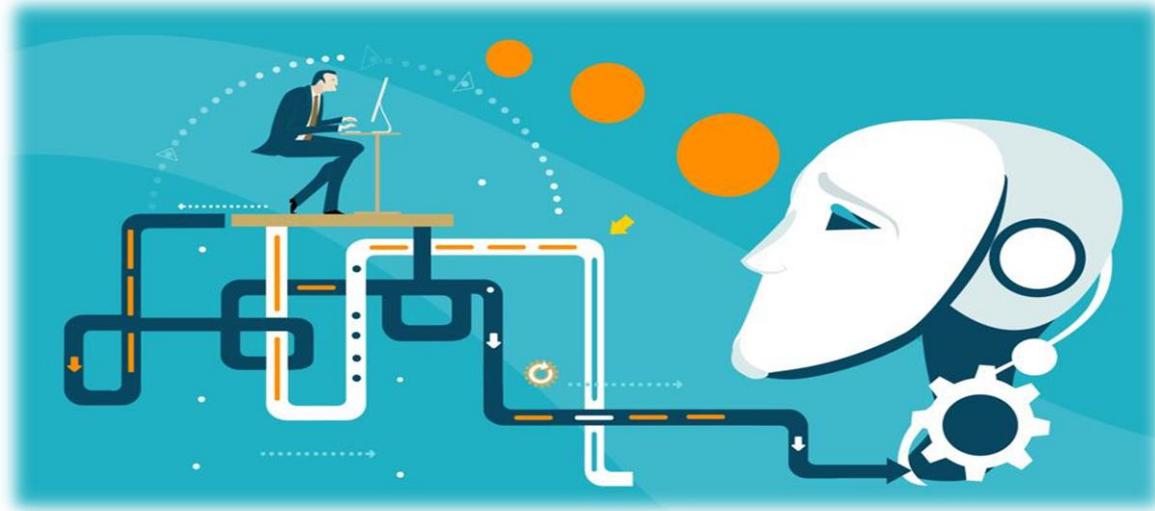
External Constraints:

- Regulatory Compliance - Regulations around financial services, data privacy, cybersecurity etc. require time and resources to adhere to.
- Market Competition - Many fintech players already exist, requiring unique value proposition and more advertising or reach to targeted users to gain user traction
- Technology Limitations - Current AI/ML capabilities may be insufficient for some intended functions like complex forecasting.
- Economic/Political Conditions - Factors like recession, trade wars, tax policies can impact demand for investment products.
- Environmental Factors - Events like pandemics and natural disasters can disrupt operations, funding, or demand in unpredictable ways.

Business Opportunity

This project aims to develop a digital wealth management platform to provide personalized investment advisory services to retail investors in India.

As referenced in the Business Opportunity Statement, there is a large addressable market opportunity in this space. Traditional wealth management in India has been limited to High-Net-Worth Individuals (HNIs) due to high minimum investment amounts and fees. However, growing incomes, availability of online investment options, and greater financial awareness among the masses has increased interest in long term wealth creation even among the mass affluent segment (households with investible assets of 50k–500k).



Existing robo-advisory solutions in India are still in their initial stages and focus mainly on passive investment options like mutual funds. There is a white space to offer advanced personalized advisory leveraging technologies like AI/ML to integrate more goals-based, tax-efficient, and holistic financial planning tailored for the mass affluent. This can help address the gap between assisted and automated advice while providing superior customer experience.

With the right solution, there is an opportunity to efficiently serve millions of underserved retail investors and become a leading digital wealth management platform in India. The proposed platform aims to capitalize on this large unmet demand by developing an advanced yet affordable advisory solution.

Concept Generation

- **Problem Clarification:** We used the black box model to clarify the problem. The platform needs to intake user data like financial goals, risk profile, timeline etc. and output personalized investment recommendations. The key functions are data collection, analysis, recommendation generation and portfolio management.

Concept Generation: Some key ideas generated were:

- Web/mobile based platform for data collection and recommendations
- Integrates with existing financial accounts for portfolio management
- Uses algorithms and machine learning to analyze user data, build their risk score and market trends
- Generates static or dynamic recommendations based on risk profiling
- Allows customization of recommendations based on user preferences
- Provides educational content on investments



Figure shows our morphological chart mapping the different subsystem concepts for data collection, analysis, recommendation generation and portfolio management.

Initial Screening for Feasibility and Effectiveness:

We evaluated the concepts on parameters like technical feasibility, cost, user-friendliness, customization options etc. The most viable concepts were:

- A web and mobile based platform that collects user data via questionnaires and integrates with existing financial accounts. It uses algorithms and machine learning on user data and market trends to generate and update personalized investment recommendations on ETFs and MFs.

- A hybrid robotic advisory platform that generates initial recommendations through algorithms but allows users to customize further with the help of a virtual assistant. It manages model portfolios for users.
- A robo-advisory app that collects basic user info and risk profile and provides ready investment advice considering their financial goals like retiring, buying car etc. Advanced users can customize further through educational tutorials on the app.

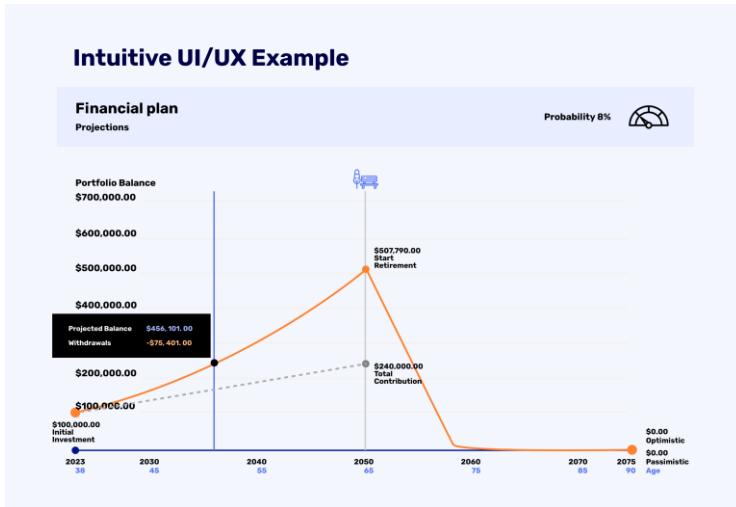


Fig shows an intuitive UI/UX example where platform is highlighting when to take retirement decision

The above concepts could be technically feasible, cost-effective, can provide customization and educate users on investments. I have shortlisted these concepts for further evaluation and refinement.

Final Product Prototype

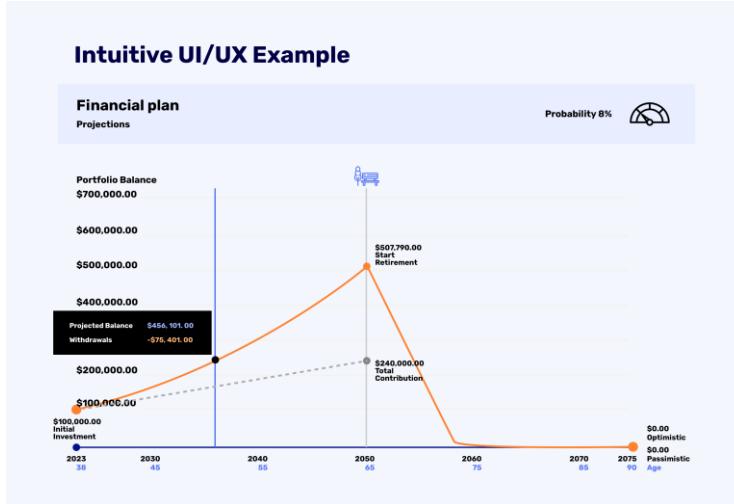
Final Detailed Design: The final design is a hybrid robo-advisory platform that can be accessed via a web and mobile app for early-stage deployment.

User Interface (UI) and User Experience (UX):

- Web and Mobile Accessibility: The platform will feature a responsive web interface and mobile app accessible 24/7 from any internet-enabled device.

- Intuitive Design: The UI/UX design will be based on extensive customer research to ensure easy onboarding, portfolio oversight, and support.
- Multi-lingual Support: Inclusion of major Indian languages to cater to a diverse user base across the country.

For general example: Catering to users who want to decide when to retire and know what its repercussion will be on its portfolio.



Risk Profiling and Customer Segmentation (Implementation done for risk profiling):

- Scientific Risk Profiling Questionnaire: A detailed risk profiling questionnaire, backed by academic research, will be employed to assess customer risk tolerance.
I have implemented this part of platform on small scale where our bot will take info of users like their gender, possess own car, has house or flat, number of children, income of client, credit amount of investment, its annuity etc. (details included in implementation)

Part of a big feature list used in risk profiling model:

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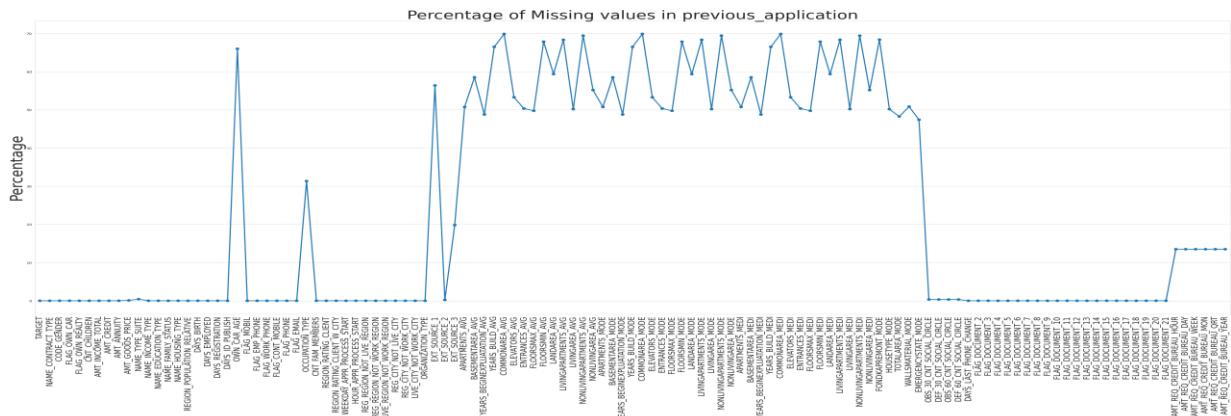
columns_description = pd.read_csv('columns_description.csv.csv', skiprows = 1)
display('columns_description')
columns_description=columns_description.drop(['1'],axis=1)
display(columns_description)

```

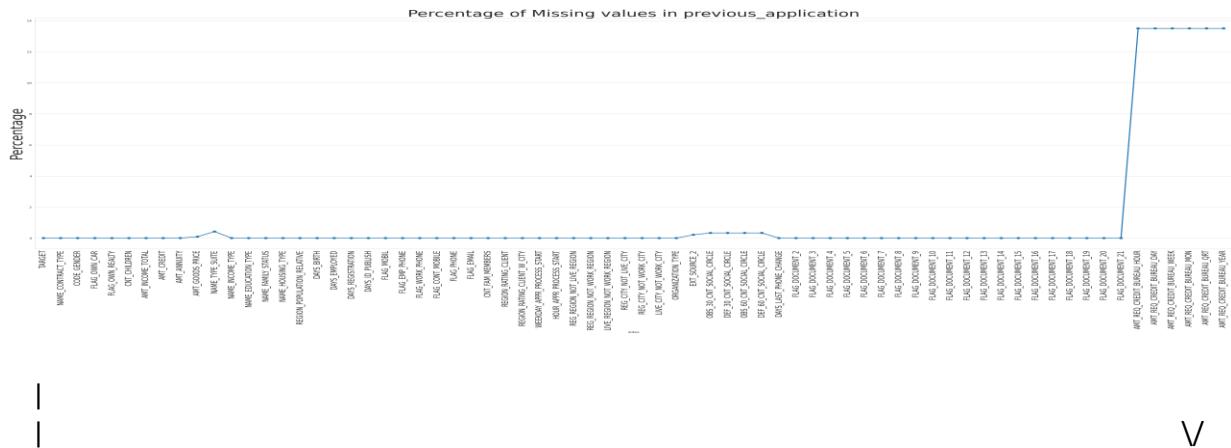
	application_data	TARGET	Description	Type
0	application_data	TARGET	Target variable (1 - client with payment diffi...	NaN
1	application_data	NAME_CONTRACT_TYPE	Identification if loan is cash or revolving	NaN
2	application_data	CODE_GENDER	Gender of the client	NaN
3	application_data	FLAG_OWN_CAR	Flag if the client owns a car	NaN
4	application_data	FLAG_OWN_REALTY	Flag if client owns a house or flat	NaN
5	application_data	CNT_CHILDREN	Number of children the client has	NaN
6	application_data	AMT_INCOME_TOTAL	Income of the client	NaN
7	application_data	AMT_CREDIT	Credit amount of the loan	NaN
8	application_data	AMT_ANNUITY	Loan annuity	NaN
9	application_data	AMT_GOODS_PRICE	For consumer loans it is the price of the good...	NaN
10	application_data	NAME_TYPE_SUITE	Who was accompanying client when he was applyi...	NaN
11	application_data	NAME_INCOME_TYPE	Clients income type (businessman, working, mat...	NaN
12	application_data	NAME_EDUCATION_TYPE	Level of highest education the client achieved	NaN
13	application_data	NAME_FAMILY_STATUS	Family status of the client	NaN
14	application_data	NAME_HOUSING_TYPE	What is the housing situation of the client (r...	NaN
15	application_data	REGION_POPULATION_RELATIVE	Normalized population of region where client l...	normalized
16	application_data	DAYS_BIRTH	Client's age in days at the time of application	time only relative to the application
17	application_data	DAYS_EMPLOYED	How many days before the application the perso...	time only relative to the application
18	application_data	DAYS_REGISTRATION	How many days before the application did clien...	time only relative to the application
19	application_data	DAYS_ID_PUBLISH	How many days before the application did clien...	time only relative to the application
20	application_data	OWN_CAR_AGE	Age of client's car	NaN

	application_data	FLAG_MOBIL	Description	Type
21	application_data	FLAG_MOBIL	Did client provide mobile phone (1=YES, 0=NO)	NaN
22	application_data	FLAG_EMP_PHONE	Did client provide work phone (1=YES, 0=NO)	NaN
23	application_data	FLAG_WORK_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
24	application_data	FLAG_CONT_MOBILE	Was mobile phone reachable (1=YES, 0=NO)	NaN
25	application_data	FLAG_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
26	application_data	FLAG_EMAIL	Did client provide email (1=YES, 0=NO)	NaN
27	application_data	OCCUPATION_TYPE	What kind of occupation does the client have	NaN
28	application_data	CNT_FAM_MEMBERS	How many family members does client have	NaN
29	application_data	REGION_RATING_CLIENT	Our rating of the region where client lives (1...	NaN
30	application_data	REGION_RATING_CLIENT_W_CITY	Our rating of the region where client lives wi...	NaN
31	application_data	WEEKDAY_APPR_PROCESS_START	On which day of the week did the client apply ...	NaN
32	application_data	HOUR_APPR_PROCESS_START	Approximately at what hour did the client appli...	rounded
33	application_data	REG_REGION_NOT_LIVE_REGION	Flag if client's permanent address does not ma...	NaN
34	application_data	REG_REGION_NOT_WORK_REGION	Flag if client's permanent address does not ma...	NaN
35	application_data	LIVE_REGION_NOT_WORK_REGION	Flag if client's contact address does not matc...	NaN
36	application_data	REG_CITY_NOT_LIVE_CITY	Flag if client's permanent address does not ma...	NaN
37	application_data	REG_CITY_NOT_WORK_CITY	Flag if client's permanent address does not ma...	NaN
38	application_data	LIVE_CITY_NOT_WORK_CITY	Flag if client's contact address does not matc...	NaN
39	application_data	ORGANIZATION_TYPE	Type of organization where client works	NaN
40	application_data	EXT_SOURCE_1	Normalized score from external data source	normalized
41	application_data	EXT_SOURCE_2	Normalized score from external data source	normalized
42	application_data	EXT_SOURCE_3	Normalized score from external data source	normalized
43	application_data	APARTMENTS_AVG	Normalized information about building where th...	normalized
44	application_data	BASEMENTAREA_AVG	Normalized information about building where th...	normalized
45	application_data	YEARS_BEGINEXPLUATATION_AVG	Normalized information about building where th...	normalized

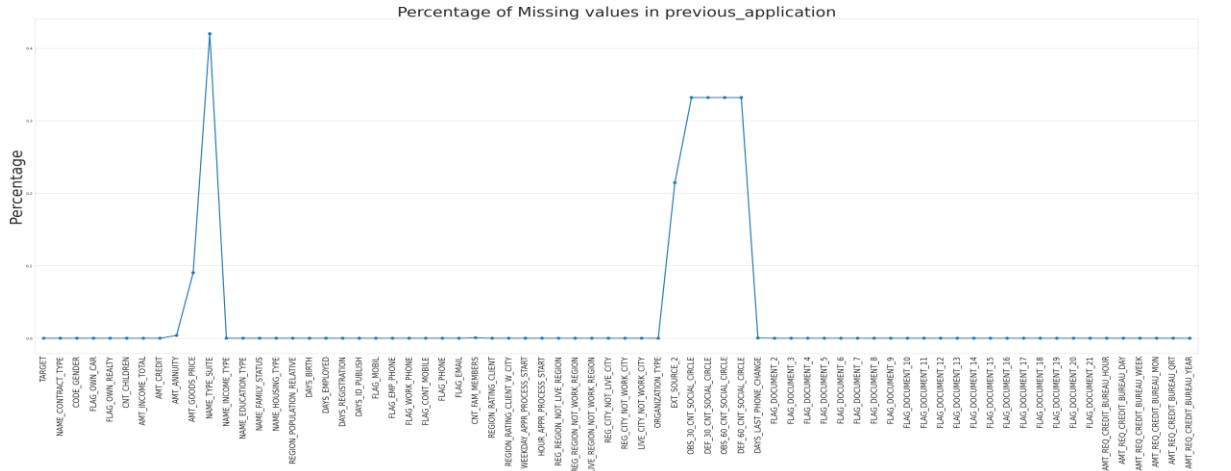
Data Cleaning Process of quite big dataset chunk with large features:



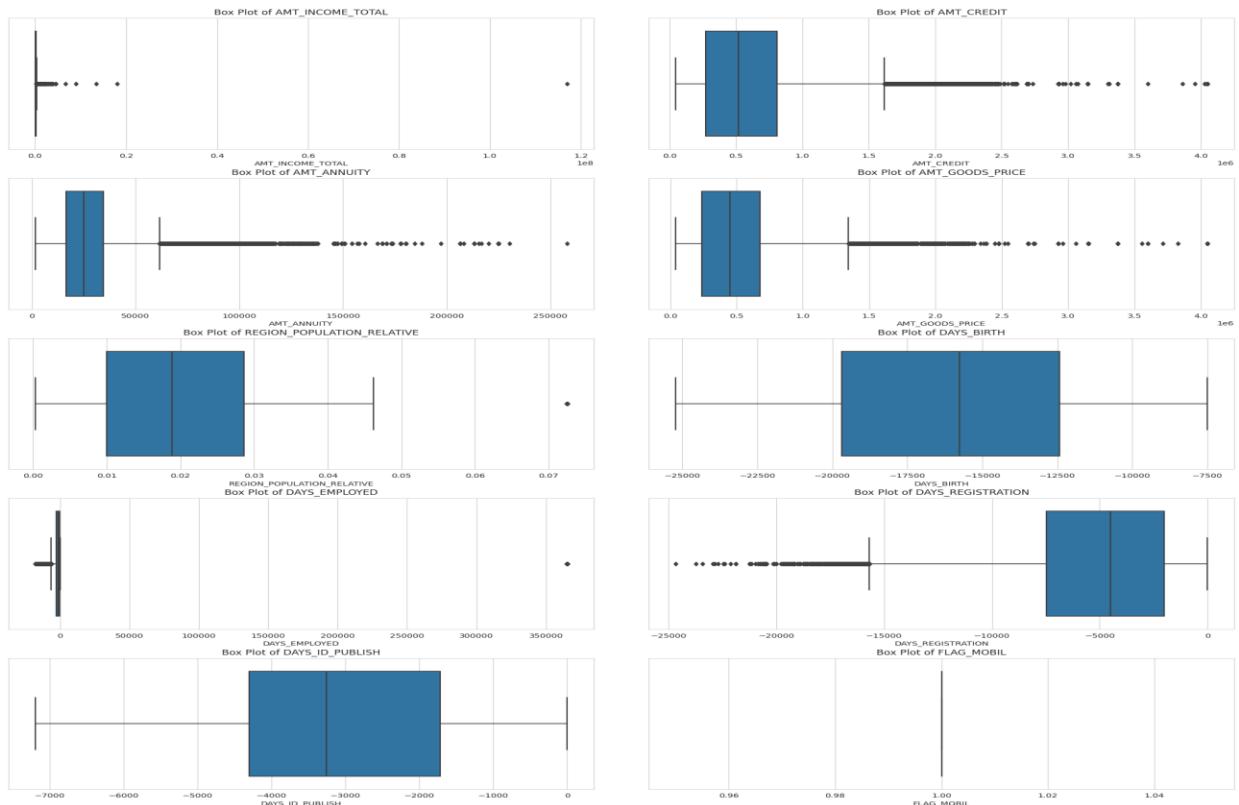
| (don't have same scale on y-axis but decreasing)



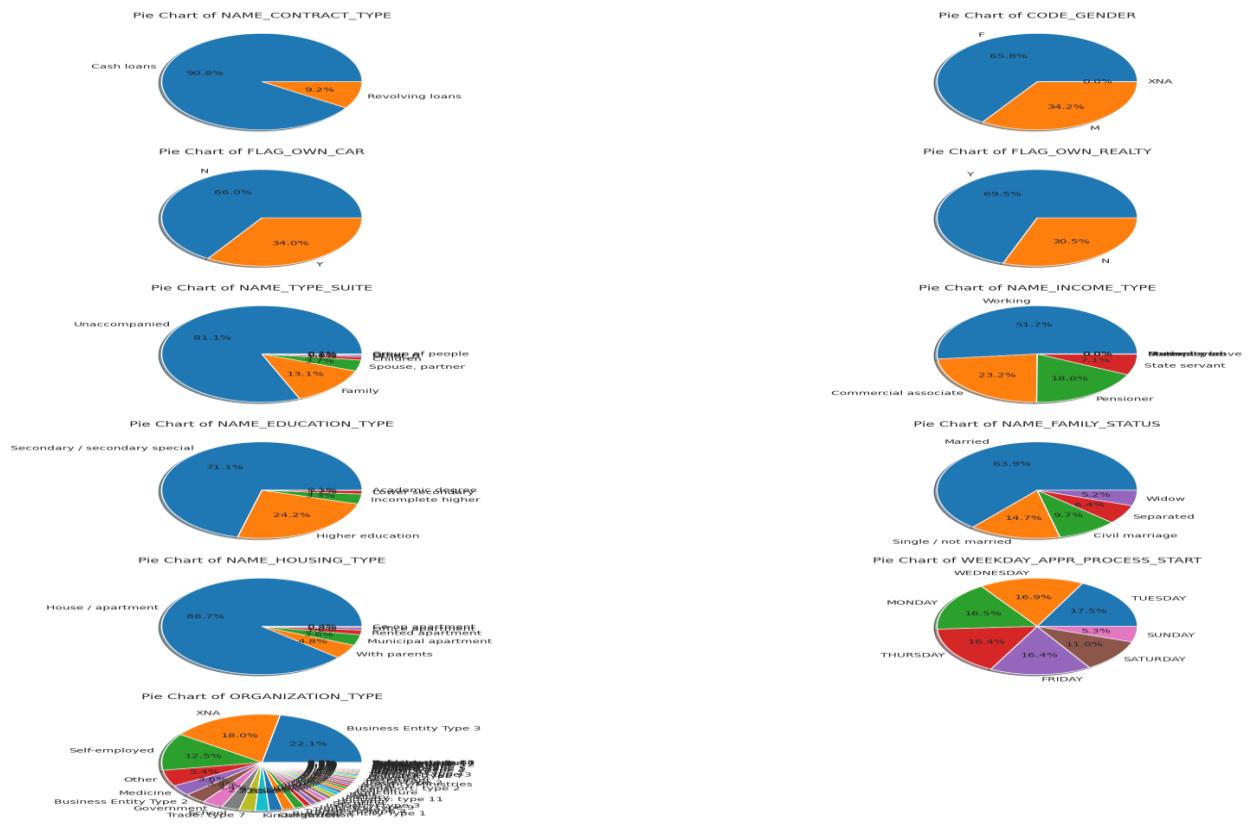
V



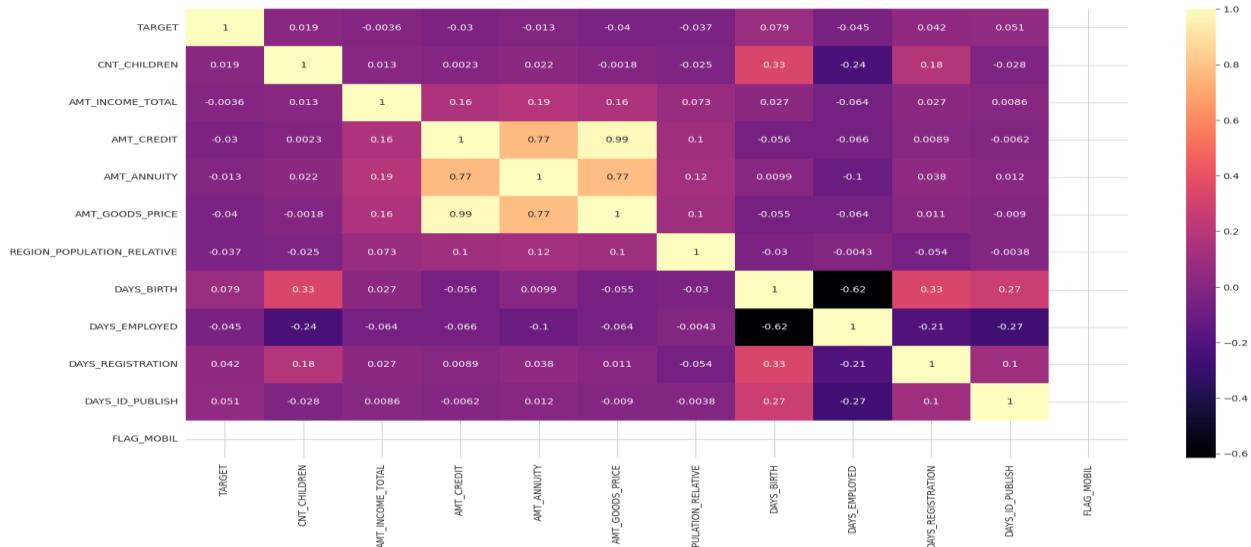
Data Analysis of Dataset (Numerical features)



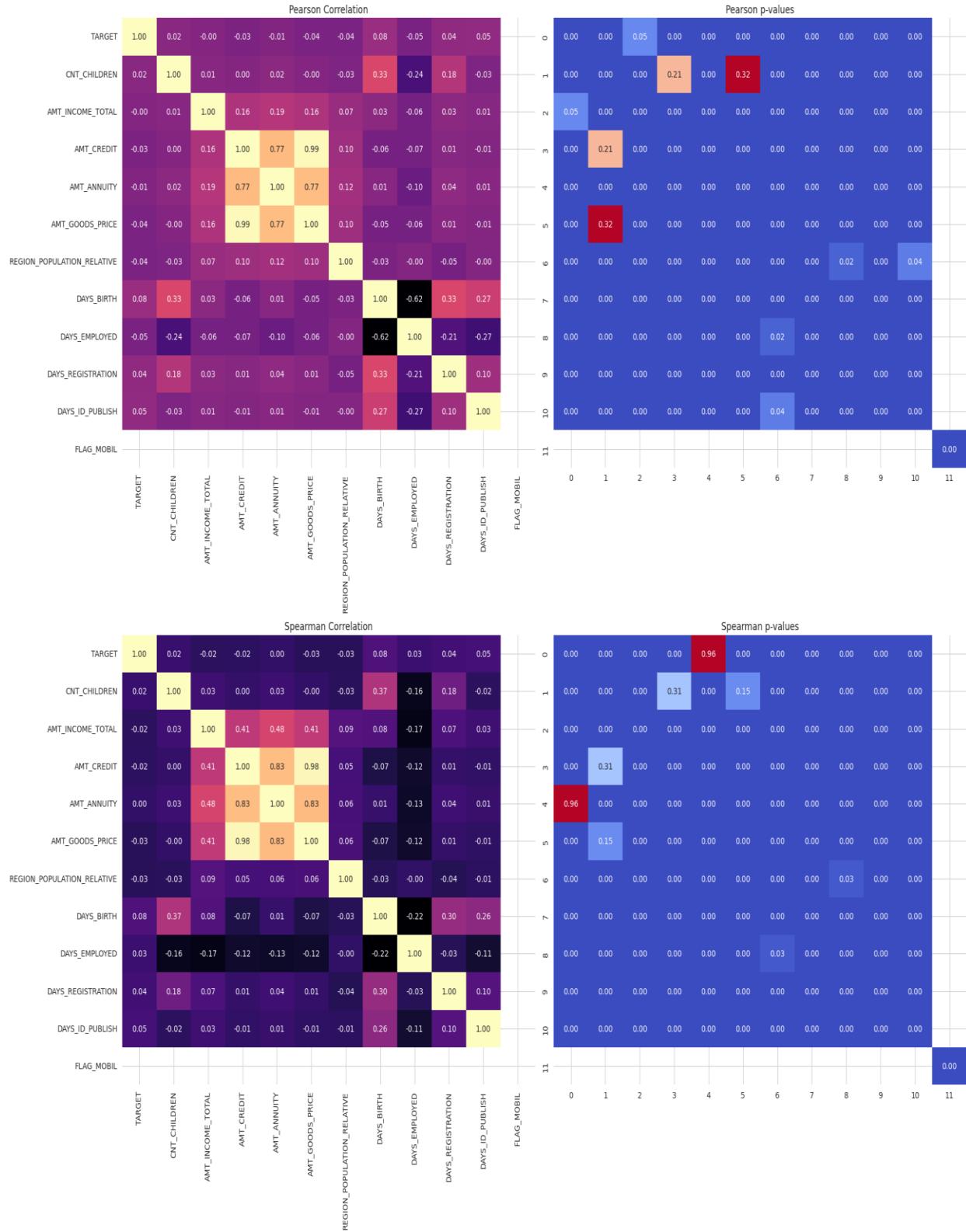
Data Analysis of Dataset (Categorical features)



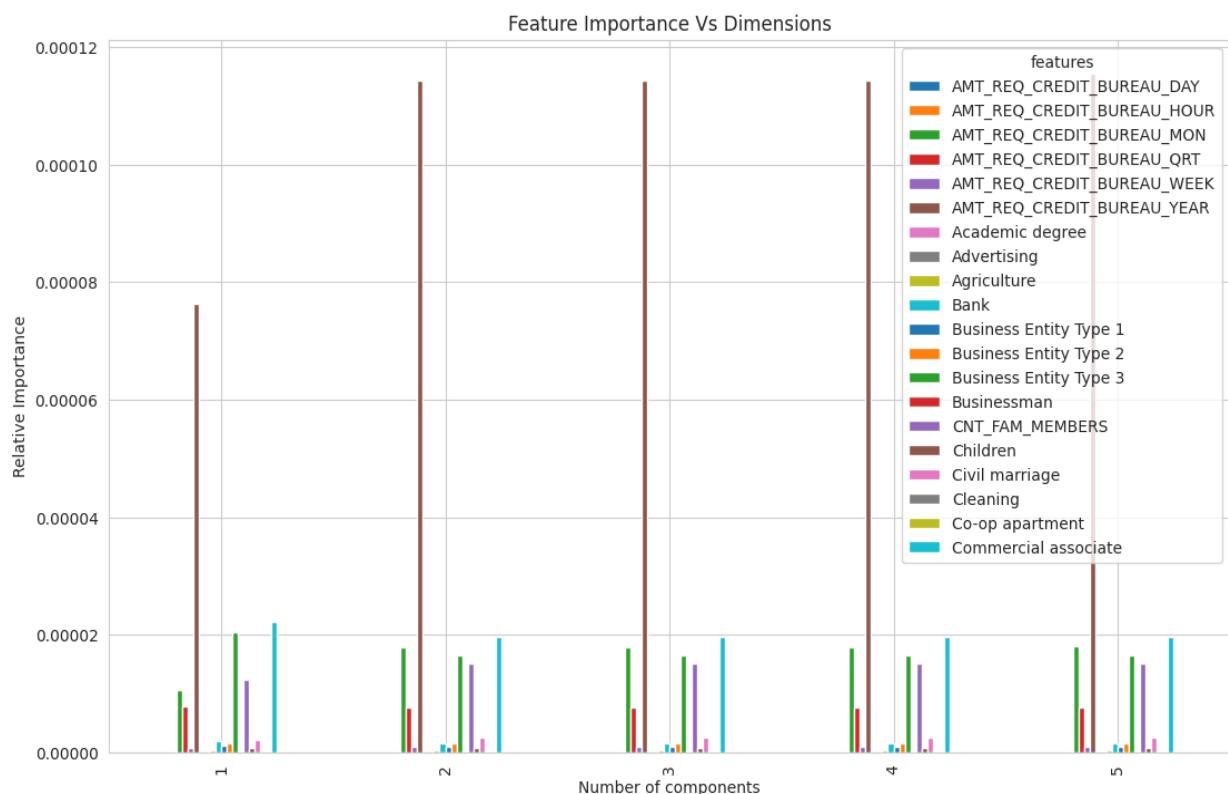
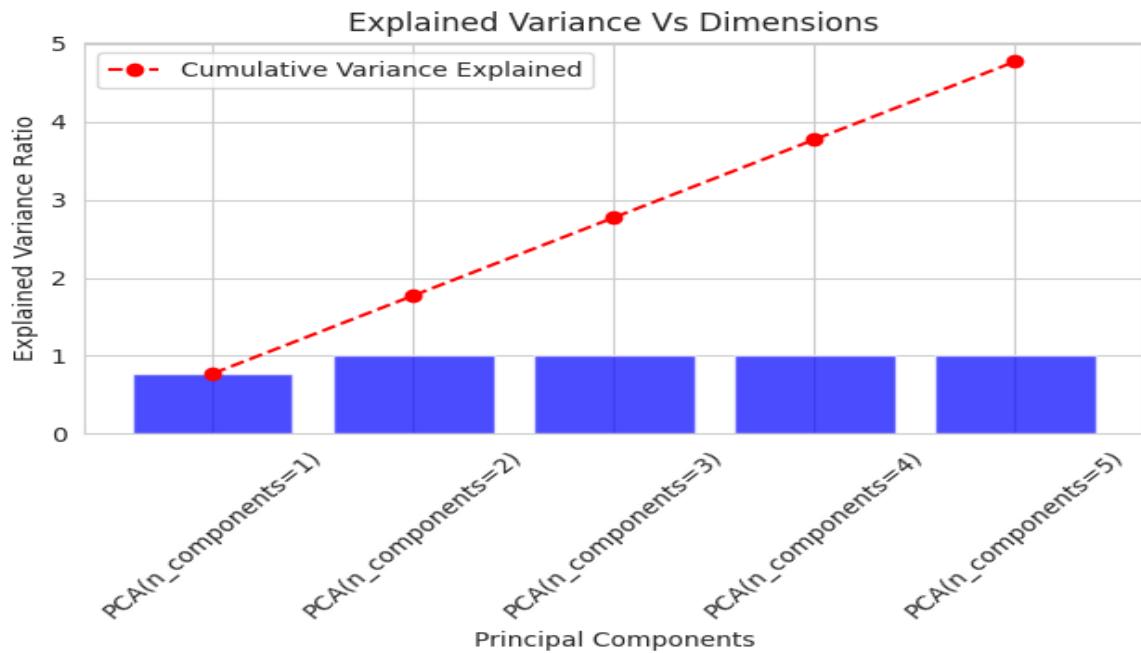
Basic Correlation between Feature space



Pearson and Spearman Correlation

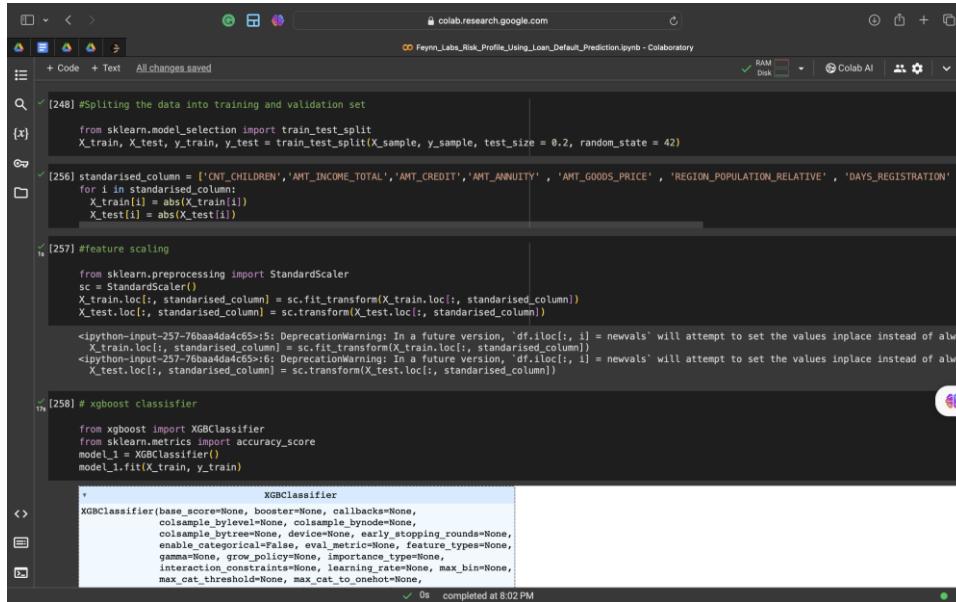


PCA Analysis and Feature Importance (used for Continuous Adaptation of platform to see which feature to give more weightage based on users financial and market trends)



- Machine-Learning Algorithm: The system will use machine learning strategies to analyze customer responses and financial backgrounds, adapting to changing market conditions and customer profiles over time. In implementation I have used statistical ML algorithms like XGBoost Classifier, Logistic Regression, Random Forest, ANN models. (But on large scale using AutoML library to apply all algorithms automatically should be preferred)

1) Data Preprocessing, Splitting



```
[248] #Splitting the data into training and validation set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_sample, y_sample, test_size = 0.2, random_state = 42)

[256] standarised_column = ['CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE', 'DAYS_REGISTRATION'
for i in standarised_column:
    X_train[i] = abs(X_train[i])
    X_test[i] = abs(X_test[i])

[257] #feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train.loc[:, standarised_column] = sc.fit_transform(X_train.loc[:, standarised_column])
X_test.loc[:, standarised_column] = sc.transform(X_test.loc[:, standarised_column])

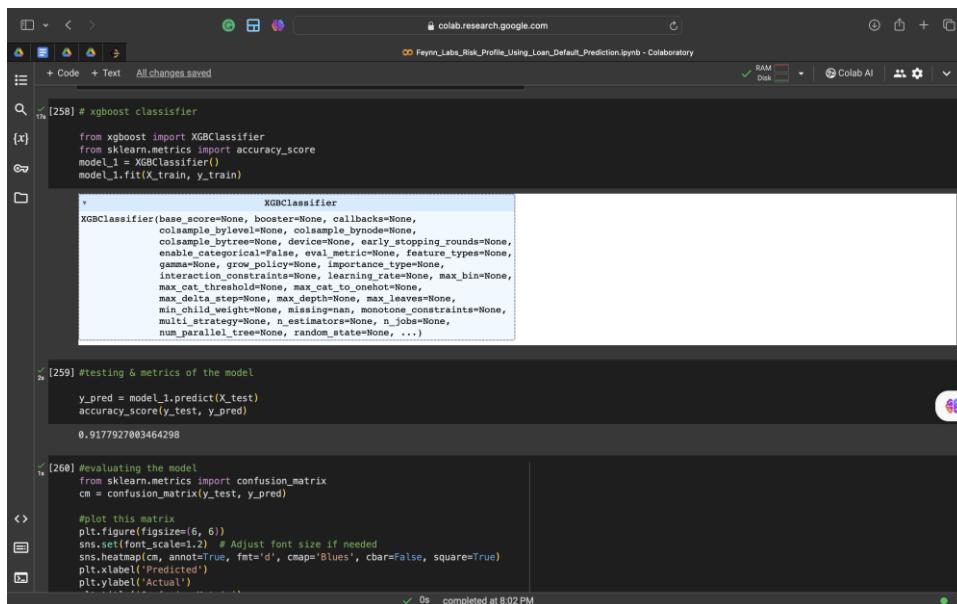
<ipython-input-257-76baa4d4c65>: DeprecationWarning: In a future version, 'df.loc[:, i] = newvals' will attempt to set the values inplace instead of alw
<ipython-input-257-76baa4d4c65>: DeprecationWarning: In a future version, 'df.loc[:, i] = newvals' will attempt to set the values inplace instead of alw
X_train.loc[:, standarised_column] = sc.transform(X_test.loc[:, standarised_column])

[258] # xgboost classifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
model_1 = XGBClassifier()
model_1.fit(X_train, y_train)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bytree=None, colsample_bynode=None,
              colsample_bylevel=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
```

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2) XGBoost Classifier



```
[258] # xgboost classifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
model_1 = XGBClassifier()
model_1.fit(X_train, y_train)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bytree=None, colsample_bynode=None,
              colsample_bylevel=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing='nan', monotone_constraints=None,
              multi_class_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)

[259] #testing & metrics of the model
y_pred = model_1.predict(X_test)
accuracy_score(y_test, y_pred)
0.9177927003464298

[260] #evaluating the model
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)

#plot this matrix
plt.figure(figsize=(6, 6))
sns.set(font_scale=1.2) # Adjust font size if needed
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, square=True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

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The screenshot shows a Google Colab notebook titled "Feyn_Labs_Risk_Profile_Using_Loan_Default_Prediction.ipynb - Colaboratory". The code cell at the top contains Python code for calculating evaluation metrics (Accuracy, Precision, Recall, F1 Score) and printing them. The output cell below shows the results:

```
[261] #defining evaluation criteria for each model
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix

def calculate_results(y_true, y_pred):
    results = {}

    # Calculate accuracy
    accuracy = accuracy_score(y_true, y_pred)
    results['Accuracy'] = accuracy

    # Calculate precision, recall, and F1-score
    precision = precision_score(y_true, y_pred, average = 'weighted')
    recall = recall_score(y_true, y_pred, average = 'weighted')
    f1 = f1_score(y_true, y_pred, average = 'weighted')
    results['Precision'] = precision
    results['Recall'] = recall
    results['F1 Score'] = f1

    # Calculate confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    results['Confusion Matrix'] = cm

    return results

results = calculate_results(y_test, y_pred)

print("Accuracy:", results['Accuracy'])
print("Precision:", results['Precision'])
print("Recall:", results['Recall'])
print("F1 Score:", results['F1 Score'])

Xgboost = {'accuracy': results['Accuracy'], 'precision': results['Precision'], 'recall': results['Recall'], 'F1 Score' : results['F1 Score']}

```

Output:

```
Accuracy: 0.9177927003464298
Precision: 0.8787107035308898
Recall: 0.9177927003464298
F1 Score: 0.8805342096067196
```

- Accuracy of Model: 91.78%
- Precision of Model: 87.87%
- Recall: 91.78%
- F1 Score: 88.05%

2) Logistic Regression

The screenshot shows a Google Colab interface with a Jupyter notebook titled "Feynn_Labs_Risk_Profile_Using_Loan_Default_Prediction.ipynb". The code cell contains Python code for building a logistic regression model, calculating metrics, and plotting a confusion matrix. A warning message from scikit-learn's logistic.py is displayed, suggesting increasing iterations or scaling data. The output section shows the calculated metrics: Accuracy: 91.81%, Precision: 88.39%, Recall: 91.81%, and F1 Score: 87.90%.

```
[262]: from sklearn.linear_model import LogisticRegression
model_2 = LogisticRegression()
model_2.fit(X_train, y_train)

#testing of model
y_pred = model_2.predict(X_test)

#evaluating metrics of model
results = calculate_results(y_test, y_pred)

print("Accuracy:", results['Accuracy'])
print("Precision:", results['Precision'])
print("Recall:", results['Recall'])
print("F1 Score:", results['F1 Score'])

cm = results['Confusion Matrix']

#plotting confusion matrix

plt.figure(figsize=(6, 6))
sns.set(font_scale=1.2) # Adjust font size if needed
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, square=True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

logistic_Regression = {'accuracy': results['Accuracy'], 'precision': results['Precision'], 'recall': results['Recall'], 'F1 Score': results['F1 Score']}

/usr/local/lib/python3.10/dist-packages/scikit-learn/_linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/_linear_model.html#logistic-regression
n_iter_i = _check_optimize_result(
Accuracy: 0.9181046513537032
Precision: 0.8839016436355351
Recall: 0.9181046513537032
F1 Score: 0.8790016570867071
```

- Accuracy of Model: 91.81%
- Precision of Model: 88.39%
- Recall of Model: 91.81%
- F1_Score: 87.90%

3)Artificial Neural Network (ANN)

```
[263] #lets build DNN Architecture
import tensorflow as tf
from tensorflow.keras import layers

model_3 = tf.keras.Sequential([
    layers.Dense(64, activation = 'relu'),
    layers.Dense(128, activation = 'relu'),
    layers.Dense(512, activation = 'relu'),
    layers.Dropout(0.3),
    layers.BatchNormalization(),
    layers.Dense(3, activation = 'softmax')
])

model_3.compile(loss = 'sparse_categorical_crossentropy', optimizer = 'adam', metrics = ['accuracy'])

[264] history = model_3.fit(X_train, y_train, validation_data = (X_test,y_test), epochs = 10)

Epoch 1/10
7614/7614 [=====] - 121s 16ms/step - loss: 0.2765 - accuracy: 0.9170 - val_loss: 0.2706 - val_accuracy: 0.9181
Epoch 2/10
7614/7614 [=====] - 46s 6ms/step - loss: 0.2661 - accuracy: 0.9192 - val_loss: 0.2650 - val_accuracy: 0.9181
Epoch 3/10
7614/7614 [=====] - 51s 7ms/step - loss: 0.2645 - accuracy: 0.9192 - val_loss: 0.2642 - val_accuracy: 0.9181
Epoch 4/10
7614/7614 [=====] - 46s 6ms/step - loss: 0.2635 - accuracy: 0.9192 - val_loss: 0.2630 - val_accuracy: 0.9181
Epoch 5/10
7614/7614 [=====] - 50s 7ms/step - loss: 0.2626 - accuracy: 0.9192 - val_loss: 0.2657 - val_accuracy: 0.9181
Epoch 6/10
7614/7614 [=====] - 51s 7ms/step - loss: 0.2619 - accuracy: 0.9192 - val_loss: 0.2636 - val_accuracy: 0.9181
Epoch 7/10
7614/7614 [=====] - 47s 6ms/step - loss: 0.2612 - accuracy: 0.9192 - val_loss: 0.2627 - val_accuracy: 0.9180
Epoch 8/10
7614/7614 [=====] - 45s 6ms/step - loss: 0.2613 - accuracy: 0.9192 - val_loss: 0.2640 - val_accuracy: 0.9181
Epoch 9/10
7614/7614 [=====] - 45s 6ms/step - loss: 0.2609 - accuracy: 0.9191 - val_loss: 0.2648 - val_accuracy: 0.9174
Epoch 10/10
7614/7614 [=====] - 46s 6ms/step - loss: 0.2604 - accuracy: 0.9192 - val_loss: 0.2636 - val_accuracy: 0.9181

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```



```
[266] [267] #reinterating predictions for evaluation criteria
y_prob = model_3.predict(X_test)
y_pred = tf.argmax(y_prob, axis = 1)

1984/1984 [=====] - 4s 2ms/step

[268] #evaluating metrics of model
results = calculate_results(y_test, y_pred)

print("Accuracy:", results['Accuracy'])
print("Precision:", results['Precision'])
print("Recall:", results['Recall'])
print("F1 Score:", results['F1 Score'])

cm = results['Confusion Matrix']

#plotting confusion matrix
plt.figure(figsize=(6, 6))
sns.set(font_scale=1.2) # Adjust font size if needed
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, square=True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

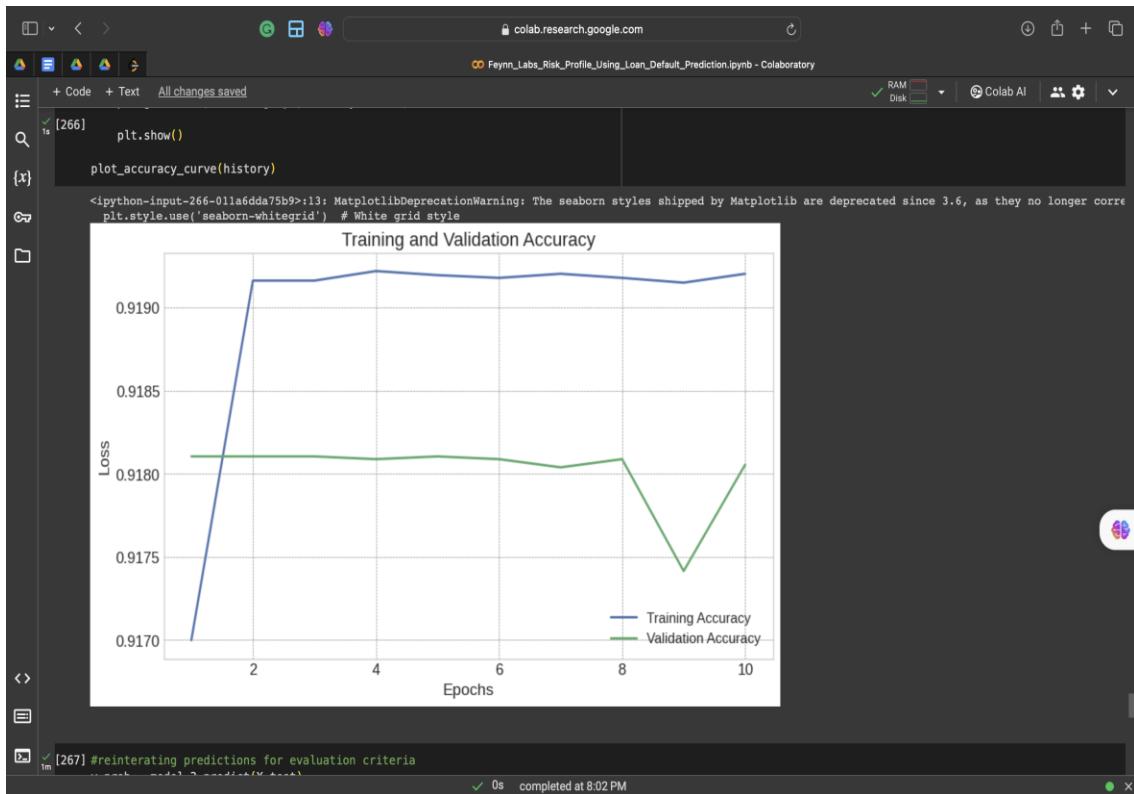
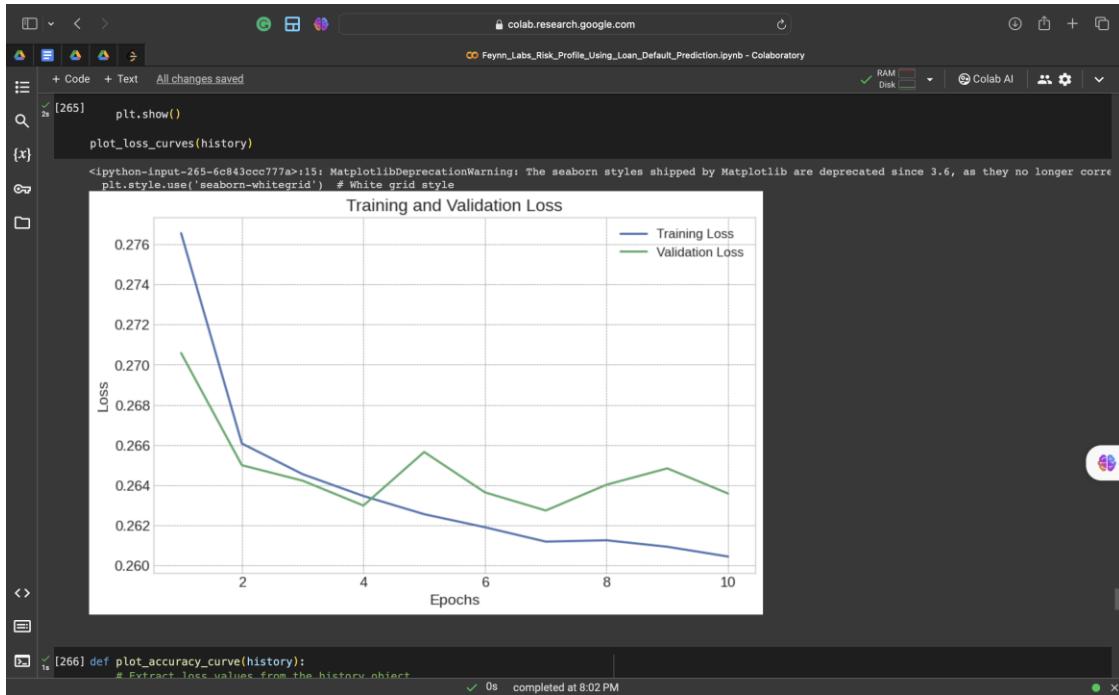
DNN = {'accuracy': results['Accuracy'], 'precision': results['Precision'], 'recall': results['Recall'], 'F1 Score' : results['F1 Score']}

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels
  _warn_prf(average, msg_start, len(result))
Accuracy: 0.918055393915021
Precision: 0.875048550560404
Recall: 0.918055393915021
F1 Score: 0.879059166169740976

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```

- Accuracy of Model: 91.80%
- Precision of Model: 87.57%
- Recall of Model: 91.80%
- F1_Score: 87.90%

Visualization of Epoch Losses and accuracy while training



3)Random Forest

The screenshot shows a Google Colab notebook titled "Feynn_Labs_Risk_Profile_Using_Loan_Default_Prediction.ipynb". The code cell at the top defines a Random Forest classifier with 1500 estimators and entropy criterion:

```
#random forest classifier
from sklearn.ensemble import RandomForestClassifier
model_4 = RandomForestClassifier(n_estimators=1500,criterion='entropy',random_state = 42)
model_4.fit(X_train, y_train)
```

An auto-suggestion dropdown appears over the classifier definition, showing the full class name and its parameters.

The next cell tests the model and calculates metrics:

```
#testing of model
y_pred = model_4.predict(X_test)

#evaluating metrics of model
results = calculate_results(y_test, y_pred)

print("Accuracy:", results['Accuracy'])
print("Precision:", results['Precision'])
print("Recall:", results['Recall'])
print("F1 Score:", results['F1 Score'])

cm = results['Confusion Matrix']

#plotting confusion matrix

plt.figure(figsize=(6, 6))
sns.set(font_scale=1.2) # Adjust font size if needed
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, square=True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

The output of the cell displays the calculated metrics:

```
Random_Forest = {'accuracy': results['Accuracy'], 'precision': results['Precision'], 'recall': results['Recall'], 'F1 Score' : results['F1 Score']}
```

```
Accuracy: 0.9180718144055692
Precision: 0.8429136817953374
Recall: 0.9180718144055692
F1 Score: 0.8788888890937654
```

The status bar at the bottom indicates the cell completed at 8:02 PM.

- Accuracy of Model: 91.80%
- Precision of Model: 84.29%
- Recall of Model: 91.80%
- F1_Score: 87.88%

Summary of Various Model Performance in risk profiling:

The screenshot shows a Google Colab notebook titled "Feynn_Labs_Risk_Profile_Using_Loan_Default_Prediction.ipynb". The code cell contains Python code to create a performance summary DataFrame:

```
#Creating a dataframe to summarise which model have performed better
model_perf = pd.DataFrame({"XGBoost":Xgboost,"Logistic Regression":Logistic_Regression,"Deep Neural Network":DNN, "Random Forest":Random_Forest})
model_perf = model_perf.transpose()
model_perf.sort_values(by=['accuracy'],ascending=False)
```

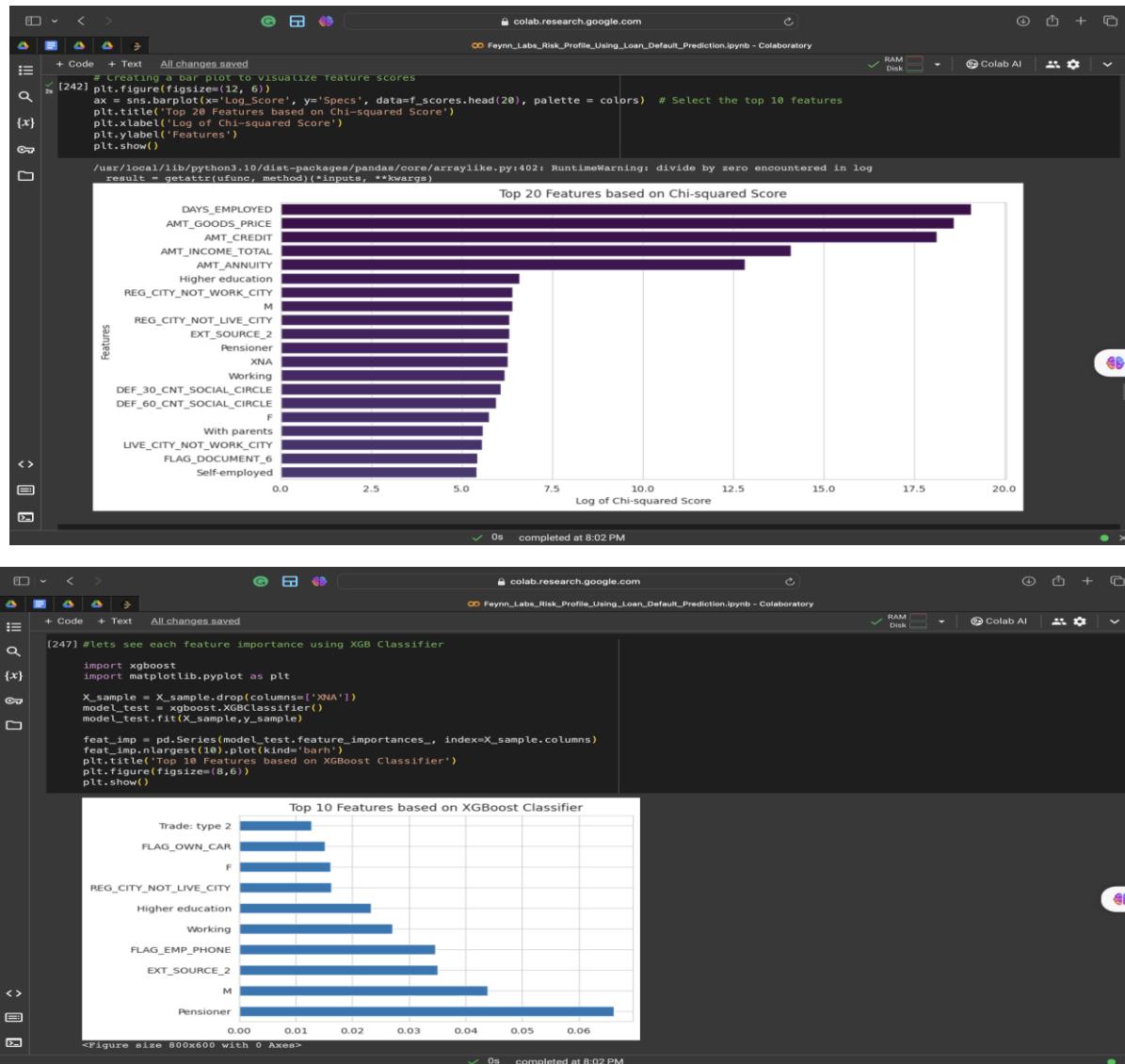
The resulting DataFrame is displayed below:

	accuracy	precision	recall	F1 Score
Logistic Regression	0.918105	0.883902	0.918105	0.879002
Random Forest	0.918072	0.842914	0.918072	0.878889
Deep Neural Network	0.918055	0.875735	0.918055	0.879017
XGBoost	0.917793	0.878711	0.917793	0.880534

The bottom status bar indicates "0s completed at 8:02 PM". A small AI icon is visible in the bottom right corner.

Automated Portfolio Management:

- Targeted Customer Segment: Initially focusing on investors aged 25-50 with investible assets between Rs. 10,000 - Rs. 1,000,000, the system will continuously update customer financial backgrounds using machine learning algorithms.
- Continuous Adaptation: The platform will use back testing and machine learning algorithms for automated portfolio creation and periodic rebalancing to align with long-term financial goals and risk tolerance. (*a small implementation done on these where model categories which user information as feature can affect their risk profile and also their portfolio creation*)
- Figure below depicts based on various user's profile getting with flow of time and changes in market trends can help platform how to give weightage to features in model with duration. Here I have showed it using popular statistical technique called chi-square score using F-test and popular bagging approach called XGBoost model:



- Real-time Market Analysis: Integration with price returns APIs from commodity and stock markets to provide continuous updates on market trends.

Educational Content (Optional):

- Customized Recommendations: The system will generate a range of personalized investment recommendations and portfolio adjustments over time, considering changing customer needs.
- Educational Tutorials: Advanced users can customize further through educational tutorials integrated into the platform, improving financial literacy.

The design refinement process involves evaluating multiple concepts based on technical feasibility, cost, user-friendliness, and customization options. The final design has emerged from a hybrid approach, combining the most viable aspects of different concepts. Continuous feedback from customer research, industry insights, and testing of prototypes will play a crucial role in refining and finalizing the design.

Implementation:

Notebook Link: https://colab.research.google.com/drive/1ED1GuoEo-3LdlFCHN7IWppWQ_MXiBSSV?usp=sharing