

AI Driven Hyper Personalization and Recommendations

Team: DLTA

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Introduction

- **AI-driven hyper personalization** tailors content, products, and services in real-time.
- Uses **AI, machine learning, and big data** to adapt to user preferences dynamically.
- Improves **engagement, satisfaction, and retention** by delivering relevant experiences.
- Businesses benefit from **higher conversions, customer loyalty, and optimized marketing.**

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Problem Statement

Modern customers expect highly personalized experiences that cater to their unique preferences. In this hackathon, participants will develop a Generative AI-driven solution that enhances hyper-personalization by analyzing customer profiles, social media activity, purchase history, sentiment data, and demographic details. The challenge is to design a system that generates personalized recommendations for products, services, or content while also providing actionable insights for businesses to optimize customer engagement

Our Solution

Preferred products

- Suggesting financial products from our options based on user history
- Considering User information evaluate the best financial products

Gen AI integration

- Leveraging GenAI to understand customer requirements
- Helping customer to understand the recommended products

Tech Stack Used

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- 1.React js
 - 2.Flask
 - 3.TensorFlow, Keras,
XGBoost, Pandas, Kaggle

Model Description

Dataset

- We used two publicly available datasets for this project: (a) **Santander Product Recommendation** and (b) **Loan Approval Prediction**.
- The first dataset is **Santander Product Recommendation** ([link](#)). This dataset contains 1.5 years of customers behavior data from Santander bank to predict what new products customers will purchase. The dataset contains **23 products** which we've grouped into **7 product lines** to recommend.
- The second dataset is **Loan Approval Prediction** ([link](#)). This dataset relates to loan approval applications and is generated using data from a real-life financial institution.

Dataset Sample: (a)

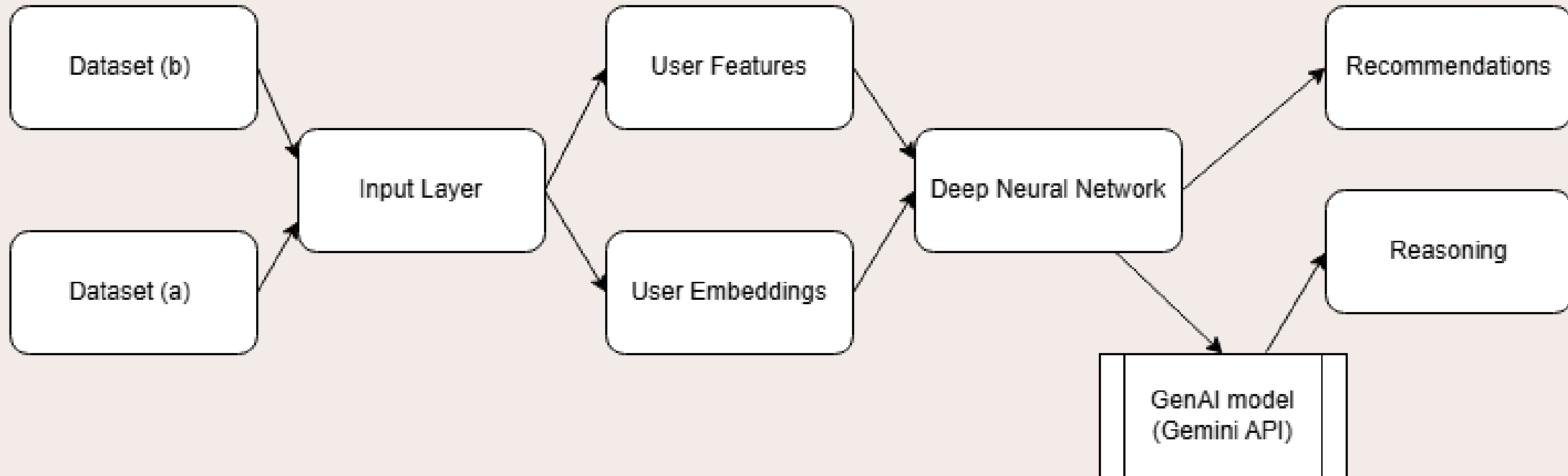
	fecha_dato	ncodpers	ind_empleado	pais_residencia	sexo	age	fecha_alta	ind_nuevo	antiguedad	indrel	...	ind_hip_fin_ult1
0	2015-01-28	1375586	N	ES	H	35	2015-01-12	0.0	6	1.0	...	0
1	2015-01-28	1050611	N	ES	V	23	2012-08-10	0.0	35	1.0	...	0
2	2015-01-28	1050612	N	ES	V	23	2012-08-10	0.0	35	1.0	...	0
3	2015-01-28	1050613	N	ES	H	22	2012-08-10	0.0	35	1.0	...	0
4	2015-01-28	1050614	N	ES	V	23	2012-08-10	0.0	35	1.0	...	0

_pres_fin_ult1	ind_reca_fin_ult1	ind_tjcr_fin_ult1	ind_valo_fin_ult1	ind_viv_fin_ult1	ind_nomina_ult1	ind_nom_pens_ult1	ind_recibo_ult1
	0	0	0	0	0.0	0.0	0
	0	0	0	0	0.0	0.0	0
	0	0	0	0	0.0	0.0	0
	0	0	0	0	0.0	0.0	0
	0	0	0	0	0.0	0.0	0

Dataset Sample: (b)

id	person_age	person_income	person_home_ownership	person_employment_status	loan_intent	loan_grade	loan_amnt	loan_int_rate	loan_purpose	cb_person_on_file	cb_person_status	loan_status
0	37	35000	RENT	0.0	EDUCATION	B	6000	11.49	0.17	N	14	0
1	22	56000	OWN	6.0	MEDICAL	C	4000	13.35	0.07	N	2	0
2	29	28800	OWN	8.0	PERSONAL	A	6000	8.9	0.21	N	10	0
3	30	70000	RENT	14.0	VENTURE	B	12000	11.11	0.17	N	5	0
4	22	60000	RENT	2.0	MEDICAL	A	6000	6.92	0.1	N	3	0
5	27	45000	RENT	2.0	VENTURE	A	9000	8.94	0.2	N	5	0
6	25	45000	MORTGAGE	9.0	EDUCATION	A	12000	6.54	0.27	N	3	0
7	21	20000	RENT	0.0	PERSONAL	C	2500	13.49	0.13	Y	3	0
8	37	69600	RENT	11.0	EDUCATION	D	5000	14.84	0.07	Y	11	0
9	35	110000	MORTGAGE	0.0	DEBTCONSOLIDATION	C	15000	12.98	0.14	Y	6	0
10	30	78000	MORTGAGE	5.0	VENTURE	B	12800	10.59	0.17	N	5	0
11	22	33000	RENT	6.0	PERSONAL	B	10000	11.12	0.3	N	2	1
12	25	33000	MORTGAGE	1.0	EDUCATION	B	4000	10.75	0.12	N	3	0
13	31	70000	MORTGAGE	2.0	DEBTCONSOLIDATION	B	16000	11.14	0.23	N	9	0
14	27	100000	RENT	1.0	HOMEIMPROVEMENT	C	5000	13.57	0.05	Y	7	0
15	29	33000	OWN	8.0	MEDICAL	A	7300	8.9	0.23	N	8	0
16	26	80000	RENT	2.0	HOMEIMPROVEMENT	D	17000	14.11	0.21	Y	3	0
17	29	60000	OWN	13.0	MEDICAL	A	15000	6.62	0.25	N	9	0
18	22	84000	MORTGAGE	6.0	DEBTCONSOLIDATION	B	5950	11.12	0.07	N	4	0

Model Flow



Model

- We use **TensorFlow** and **Google Gemini** to build our model. We first use TensorFlow's **Keras** API to design a Deep Neural Network that utilizes the concept of **embeddings** to store a hypothetical profile for each user in the system, then using these **embeddings** and other collected information about the user to train the Neural Network to output recommendations.
- We then feed the output of the Neural Network into a genAI model to generate **reasoning** for the produced output, in order to create actionable insights.
- We used open-source GPUs on **Kaggle** to train our models.

Screenshots of UI

DLTA Recommendation System

Please tell us about your requirements

i like to invest for future with marginal risk

i just want little to be used as emergency funds

i want options with least risk

ADD

SUBMIT

DLTA Recommendation System

Customer ID:

Here's what we understand about you:

Based on the information we have gathered, the customer's primary financial goal is long-term investment for the future, with a preference for minimal risk. They are also looking to maintain a small emergency fund. They specifically seek investment options characterized by the lowest possible risk profile.

Submit

DLTA Recommendation System

Here is what we know about you:

Age:	60
Annual Income:	\$20,792
Bank Account History:	0
Credit Score:	848
Dependents:	2
Education:	High School
Employment Status:	Employed
Gender:	Female
Marital Status:	Married
Occupation Type:	Business
Residential Status:	Rent
Transaction Frequency:	7

SUBMIT

Preferred Products



Short Term Deposit



Loans

SELECT

DELETE



Investments

Reason for Preferred Products:

Based on the information we have gathered, we have suggested these products to you because of your goals and financial profile:

- **Investments:** Given the primary goal of long-term investment for the future with a preference for minimal risk, investment options are crucial. We would explore strategies to align with this need.
- **Short-Term Deposit:** Considering the desire for a small emergency fund, short-term deposits can provide a safe and accessible place to keep funds readily available for unforeseen expenses, complementing your investment strategy.
- **Loans:** While the initial assessment doesn't highlight a specific loan need, we've included the

Challenges & Future Scope

Personalized Recommendations

With having multiple options to pick from for customer, we can help customer in selection

Understands current needs of customer

Niche markets

Pursue scalable customer service through sustainable strategies

We can see the trends the market to change the suggestions us GENAI

Robust Scalable app

With using financial data trained LLM, we can get even robust explanations and suggestions.

Meet our team



Lokesh Tejavath



Aditya Srivastava



Stubh Lal



Yukti Dahiya

Thank you