Predicting Customer Churn Using Logistic Regression and Shallow ANN

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Use Case Overview

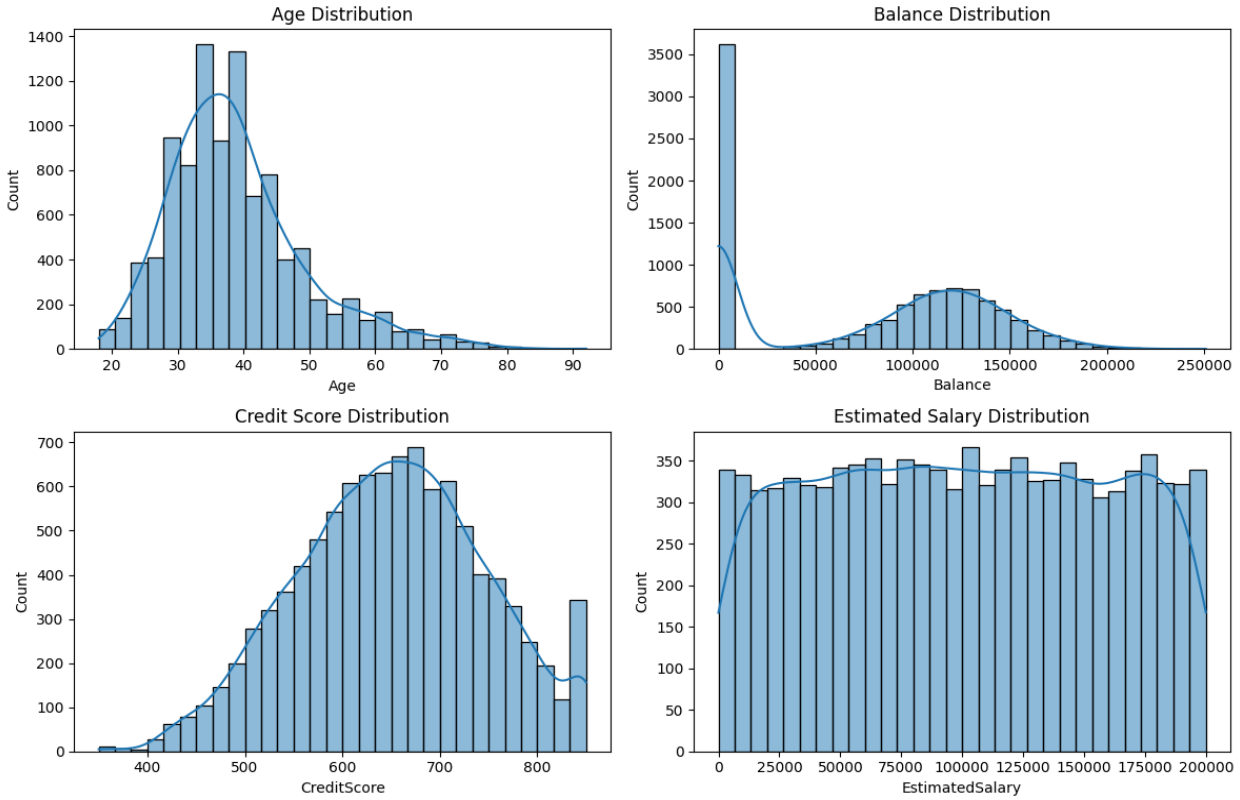
- Industry: Banking
- Problem: Customer churn leads to revenue loss
- Goal: Predict which customers are likely to churn
- Target Variable: Exited (0 = stayed, 1 = churned)

Dataset Summary

- Total records: 10000
- Features used:
    - Credit Score, Age, Tenure, Balance
    - Number of Products, Is ActiveMember
    - Geography, Gender(Encoded)
- Target: Exited

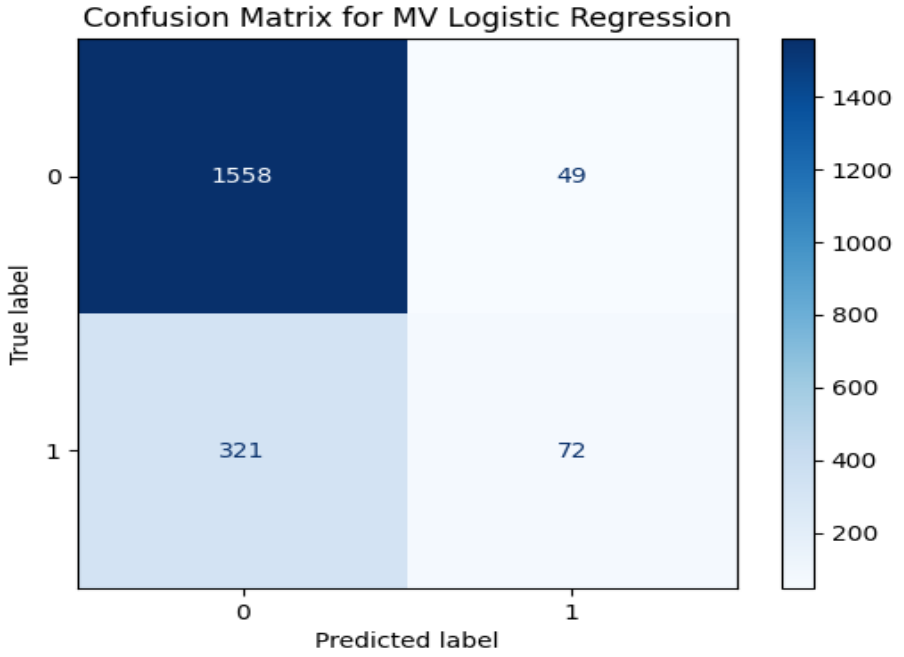
Data Preparation & EDA

- Dropped irrelevant columns: RowNumber, CustomerId, Surname
- Label encoded Gender & Geography
- Scaled all X feautres using StandardScaler
- 80/20 train-test split



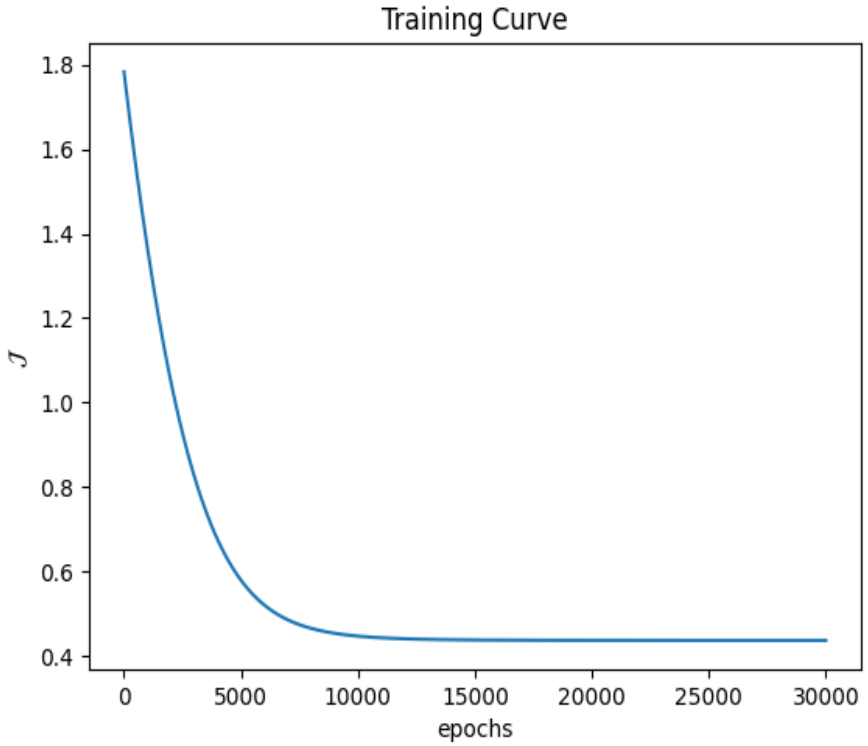
Model 1 – MV Logistic Regression

- Simple, interpretable model
- Output = probability of churn
- Used sigmoid + binary cross-entropy
- Achieved test accuracy: 81.55%
- Easy to interpret, fast to train.
- Imbalance issue: 1607:393



Classification Report:

	precision	recall	f1-score	support
0	0.83	0.97	0.89	1607
1	0.60	0.18	0.28	393
accuracy			0.81	2000
macro avg	0.71	0.58	0.59	2000
weighted avg	0.78	0.81	0.77	2000



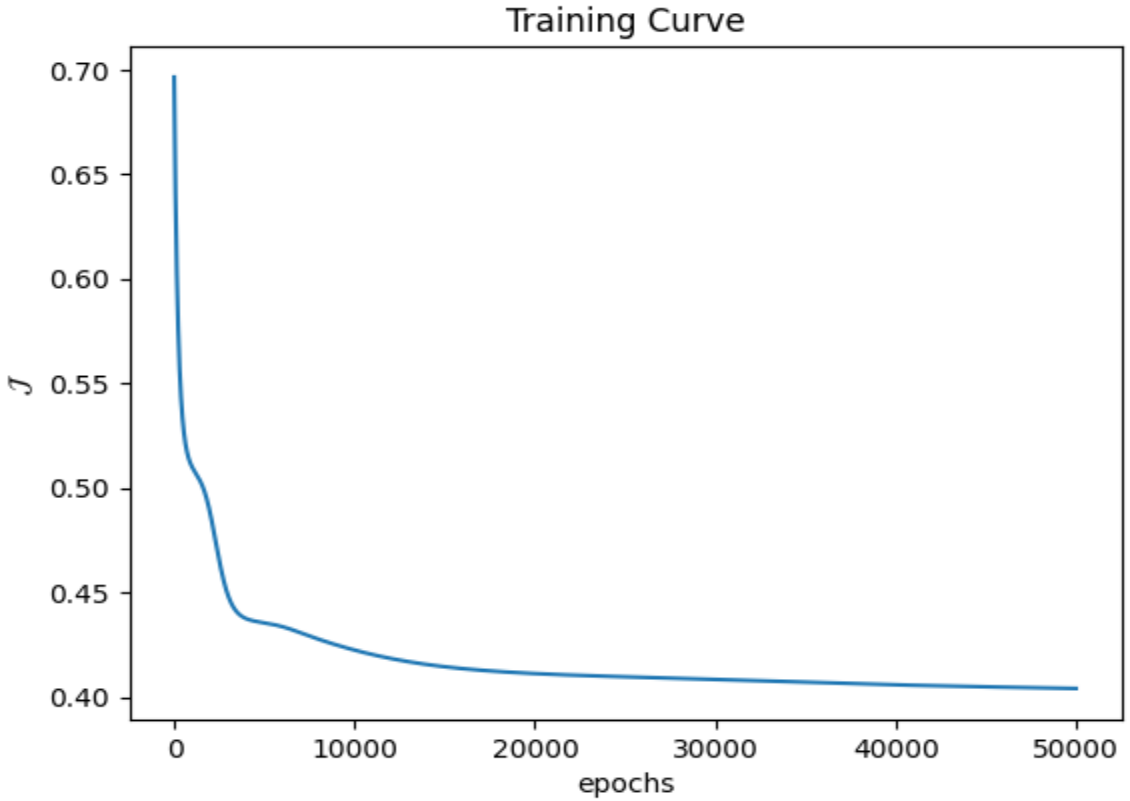
Model 2 – Shallow ANN

- Custom-built 2- layer network:

- Hidden Layer: tanh activation

- Output Layer: 1 neuron with sigmoid

- Loss: Binary cross-entropy
- Epochs: 5e4| Learning rate: 1e-2
- Weights initialized small to prevent saturation
- Loss Curve - Smooth convergence, stable training.
- Accuracy: 84.5%



Visualization (Shallow ANN)

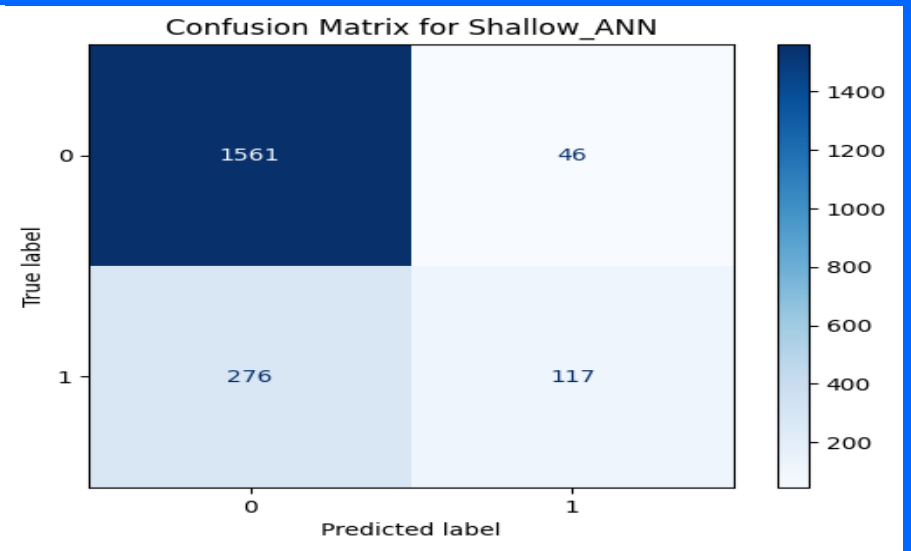
- 1561 – The model correctly predicted customers who did not churn
- 117 – The model correctly predicted customers who churned

- Precision (class 1) = 72% were correct
- Recall (class 1) = 30% was not detected.

Key Observation:
Strong performance on customers who did not churn than otherwise
Class imbalance – 393 out of 2000 churned

Classification Report:

	precision	recall	f1-score	support
0	0.85	0.97	0.91	1607
1	0.72	0.30	0.42	393
accuracy			0.84	2000
macro avg	0.78	0.63	0.66	2000
weighted avg	0.82	0.84	0.81	2000



Conclusion

- Both models can predict churn
- MVLR is simple, ANN is flexible
- ANN gave better accuracy but might need more tuning

Future Steps:

- Use more neurons
- Try better weight initialization
- Evaluate class balance
- Solve imbalance issue

Thank you

Q & A

Comparision Table: Original vs Modified Shallow ANN

Original(Multiclass)	Modified(Binary)	Reason for Change
K = number of classes	K = 1	Binary classification needs only one output neuron
One_hot_encode(y)	y.reshape(-1, 1)	No need for one_hot encoding in binary classification
Softmax in output layer	Sigmoid in output layer	Sigmoid outputs a single probability between 0 and 1
Cross_entropy() loss	Binary_cross_entropy() loss	Binary cross-entropy is appropriate for 2-class problems
Argmax() for prediction	(Z[L] > 0.5).astype(int)	Matches outshape for binary classification