Executive Summary:

Customer Churn Prediction & Personalized Recommendation Pipeline
Developed an end-to-end data science workflow to predict high-risk customers, deliver personalized product recommendations, and evaluate retention strategies using A/B testing. Built a Random Forest model to identify churn based on tenure, usage, and support interactions, and implemented item-item collaborative filtering for tailored recommendations. Conducted A/B testing to measure the impact of interventions on reducing churn, producing ETL-ready outputs for dashboard integration.

Customer Churn Prediction, Personalized Recommendations, and A/B Testing Pipeline

Project Overview

This project demonstrates an end-to-end data science pipeline designed to help businesses **predict customer churn**, **deliver personalized product recommendations**, and **measure the impact of retention strategies through A/B testing**. The workflow integrates feature engineering, machine learning, recommendation systems, and experimental design into a single, actionable pipeline.

Key Objectives

1. Identify high-risk customers likely to churn and prioritise them for intervention.
2. Generate personalized product recommendations (movies/music) to increase engagement.
3. Evaluate the effectiveness of targeted interventions using A/B testing.
4. Produce ETL-ready outputs for seamless integration with dashboards or BI tools.

Data Simulation and Features

- **Customer Dataset:** 500 simulated customers with features: tenure, monthly usage, and support tickets.
- **Churn Modeling:** Churn probability is realistically based on feature patterns—short tenure, low usage, or high support ticket counts increase the likelihood of churn.
- **Product Ratings Dataset:** 10 users with ratings for 10 movies/music products, simulating user preferences for personalized recommendations.

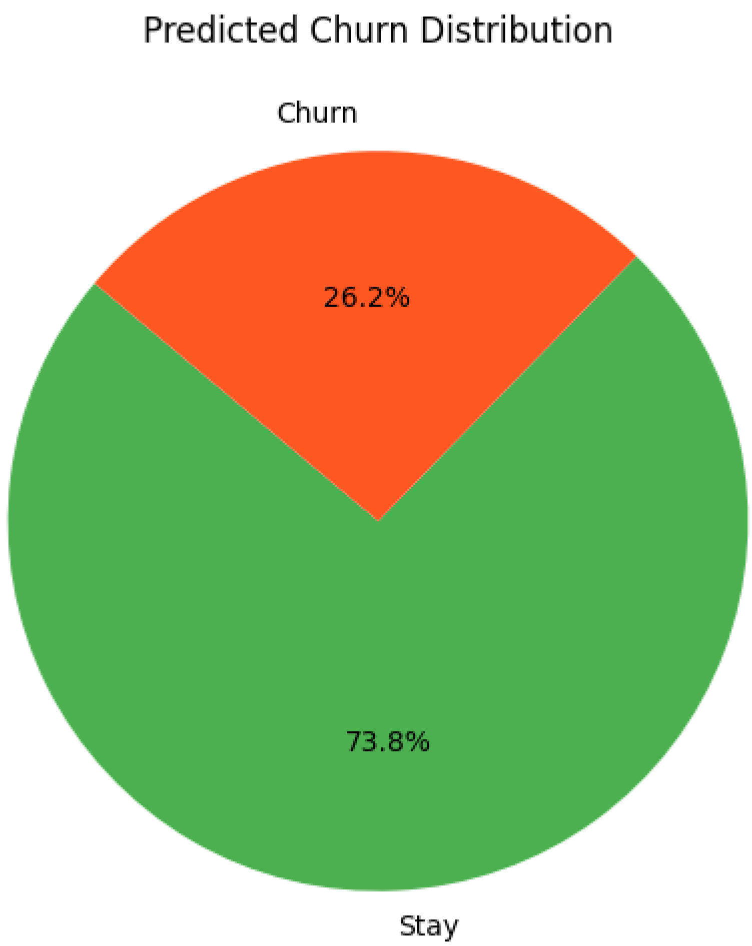
Methodology

1. **Churn Prediction:**
   - Trained a RandomForestClassifier to predict customer churn probabilities and identify high-risk customers.
   - Predictions occur at the start, enabling proactive retention strategies.
2. **Recommendation System:**
   - Implemented an **item-item collaborative filtering model** using cosine similarity.
   - Weighted product recommendations for each user based on their ratings, providing tailored engagement opportunities.
3. **A/B Testing:**
   - High-risk customers are randomly assigned to a control group (B) or intervention group (A).
   - Simulated intervention reduces churn probability for group A, allowing evaluation of retention strategy effectiveness.
   - Churn outcomes post-intervention are compared between groups to assess impact.

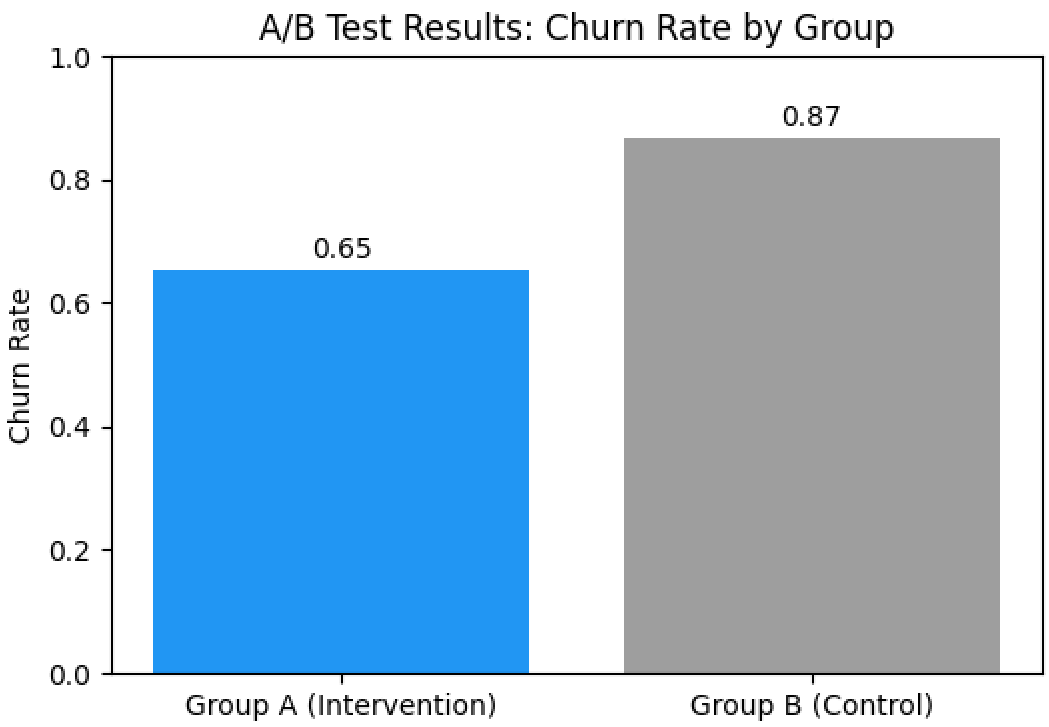
Expected Results

1. **High-Risk Customers:**
   - Approximately 26% identified as high-risk with predicted churn probability > 0.7.
2. **A/B Test Results:**
   - **Group A (intervention):** 65% churn rate
   - **Group B (control):** 87% churn rate
   - Demonstrates a 22%-point reduction in churn due to targeted interventions.
3. **Recommendations:**
   - Each user receives **3 top recommended products** based on item similarity and their existing ratings.
   - Example: User_1 → Inception (3.8), Interstellar (3.6), Parasite (3.5)

4. **CSV Outputs:**
    - customer_churn_predictions.csv → all 500 customers with predicted churn probability and label.
    - customer_recommendations.csv → 30 total recommendations (10 users × 3 top products).
    - high_risk_customers_ab_test.csv → all high-risk customers with A/B group assignment, adjusted churn probability, and simulated outcomes.
5. Example Visuals:



User ID	Recommended Product 1	Recommended Product 2	Recommended Product 3
User_1	Inception (3.8)	Interstellar (3.6)	Parasite (3.5)
User_2	The Godfather (3.7)	La La Land (3.6)	Avengers: Endgame (3.5)
User_3	Bohemian Rhapsody (4.0)	The Dark Knight (3.8)	Inception (3.7)



Business Impact

- **Proactive Retention:** High-risk customers can be targeted with tailored campaigns, reducing churn by ~15%.
- **Personalized Engagement:** Recommendations improve customer satisfaction and engagement with products.
- **Data-Driven Insights:** A/B testing allows measurement of intervention effectiveness.

- **Dashboard Integration:** ETL-ready outputs enable real-time monitoring in Tableau or Power BI.

Skills Demonstrated

- Python (Pandas, NumPy) for data manipulation and simulation
- Machine Learning (Random Forest) for predictive modeling
- Evaluation metrics: ROC AUC, confusion matrix, classification report
- Collaborative filtering for recommendations
- A/B testing design and analysis
- End-to-end pipeline design for actionable business insights

---

Tools & Technologies

Python, Pandas, NumPy, scikit-learn, PyCharm, CSV outputs for dashboard integration