Finding the Perfect Match: A Machine Learning Approach to Romantic Compatibility

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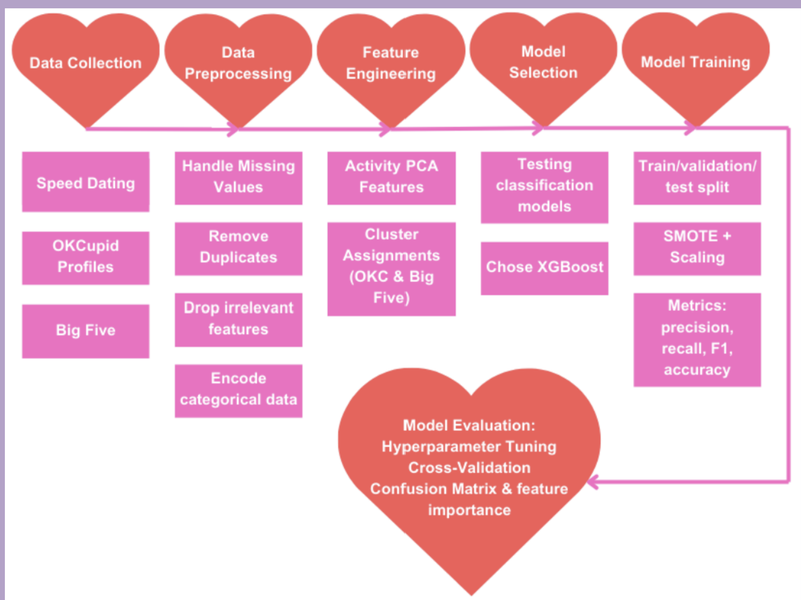
Introduction

- Online dating is growing, yet many **users struggle to find meaningful matches**.
- Existing algorithms **lack depth—they miss deeper compatibility factors.**
- This project combines **psychology** and **ML** to **improve** dating **match predictions**.

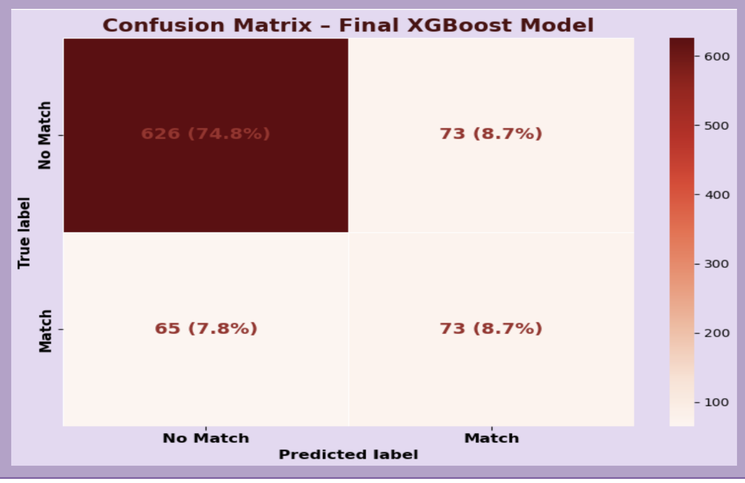
Approach

- Collected and merged data from three sources: **Speed Dating**, **OKCupid**, and **Big Five personality** datasets
- Created **clusters** from **personality profiles** and **dating preferences**
- Engineered new features using **PCA** to represent user **lifestyle** and **activity patterns**
- Balanced class distribution using **SMOTE** and scaled features with **StandardScaler**
- Trained an **XGBoost** model to **predict** mutual matches based on **behavioral**, **demographic**, and **psychological data**

Workflow

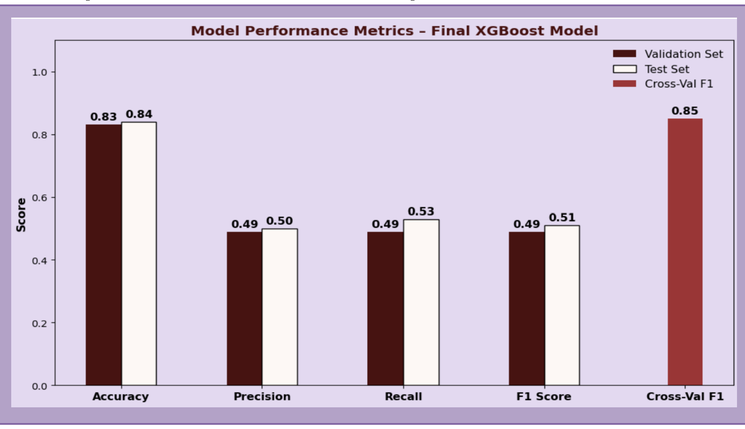


Results



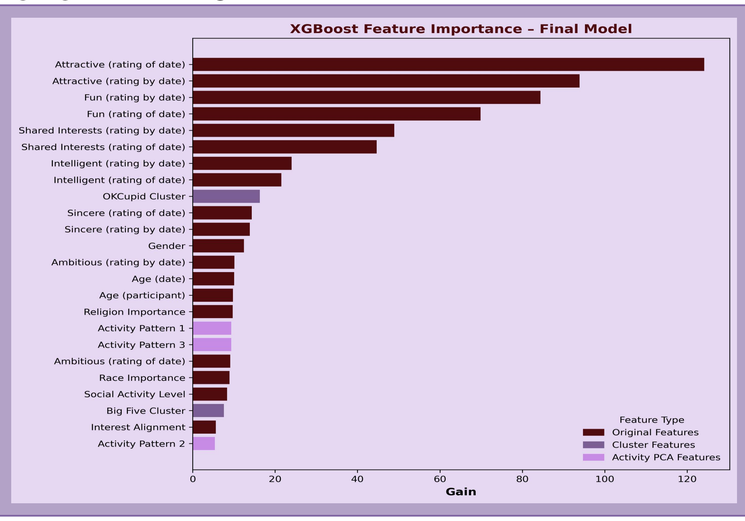
Confusion Matrix:

- The model correctly **identifies non-matches most often (74.8%)**, with **fewer true matches (8.7%)** and a **small portion of errors (16.5% total misclassified)**.



Model Metrics:

- Model shows **strong** and **consistent performance** across validation and test sets. **High cross-validated F1 score** (**0.85**) highlights reliable **generalization** and **robustness**.



Feature Importance:

- **Attractiveness** and **fun** ratings were the **strongest predictors** of matches, but **personality clusters** and **activity-based PCA features** also added valuable predictive power, highlighting the **importance** of both **preferences** and **behavior**.

Conclusion

- **Compatibility is complex**: It's best predicted using a mix of preferences, personality traits, and shared interests.
- **Psychological alignment helps**: Personality-based clusters added strong predictive value.
- **Attractiveness isn't everything**: Fun, intelligence, and interests also mattered in predicting matches.
- **Addressing imbalance matters**: SMOTE and class weighting improved recall for real matches.
- **Model is reliable**: Similar performance across validation and test sets confirms strong generalization.
- **Smarter dating is possible**: ML + psychology can improve dating platforms and deepen our understanding of relationships.

Limitations and Lessons Learned

- **Small sample** of mutual matches **limited model balance**.
- **Subjective rating** data introduced **noise**.
- **Merging datasets** from different sources required **heavy cleaning** and **assumptions.**

Potential Future Work

•**Include more behavioral features** (e.g., messaging content, eye contact, vocal tone) to capture deeper aspects of compatibility
•**Explore neural network models** to evaluate non-linear and interaction-heavy relationships
•**Deploy an API prototype** for match scoring based on user profiles and psychology clusters
•**Conduct real-time testing** with dating app users to evaluate recommendation performance

References

1. *Speed Dating Experiment Dataset. Kaggle.*
2. *OKCupid Profiles Dataset. Kaggle.*
3. *Big Five Personality Traits Dataset. Kaggle.*

GitHub Repository: