Unified Medication Network Analysis and Recommendation System

Supervised By : Dr. Hussein Hazimeh

Prepared by: Ayla Haidar , Batoul Shrara , Ali Helbawe

Academic Year: 2024–2025

Summary

- Introduction
- Problematic
- Objective
- Key contribution
- Technologies & Tools Used
- Work process
- Conclusion

Introduction
Overview of Medication Network Analysis and Recommendation System

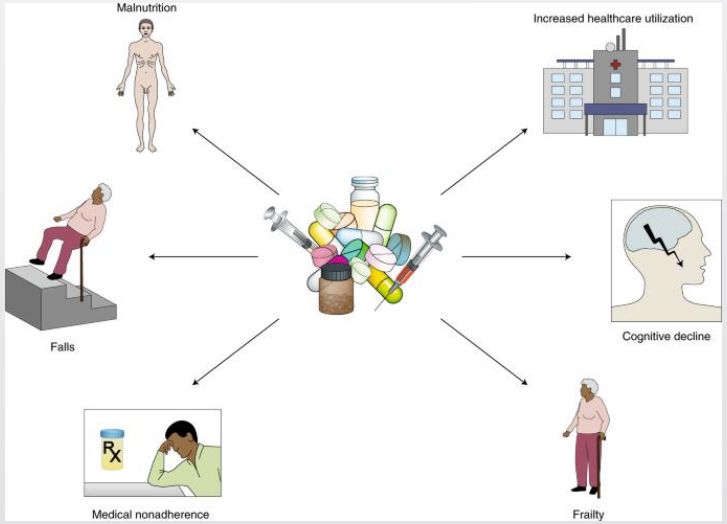
The Unified Medication Network Analysis and Recommendation System is an advanced healthcare decision-support platform to provide :

- ✓ Accurate
- ✓ Personalized
- ✓ Safe medication recommendations

Introduction
Overview of Medication Network Analysis and Recommendation System

In modern healthcare, patients often receive multiple medications (polypharmacy), increasing risks of:

- ✓ Adverse drug reactions
- ✓ Harmful interactions
- ✓ Reduced treatment efficacy



Problematic

Challenges

- Traditional tools can't capture complex relationships among drugs.

Limitations

- Absence of a smarter, network-driven solution that models the reality of co-prescription patterns.

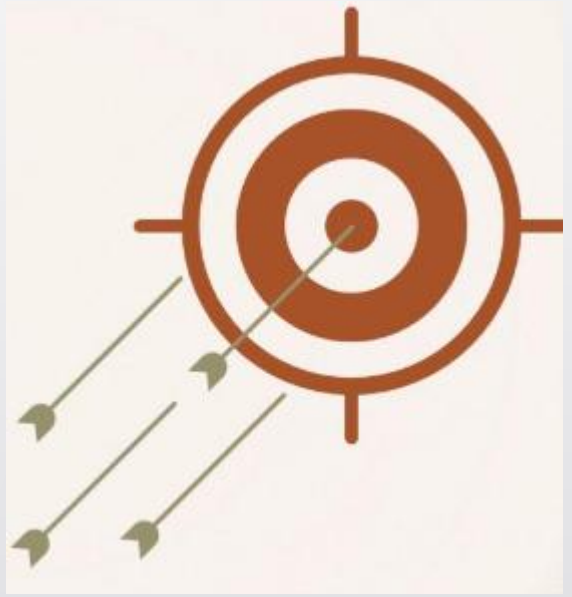
Goal

Design a system that uses network science and machine learning to understand how medications are co-prescribed.

- ✓ It identifies hidden relationships between drugs,
- ✓ Predicts new co-prescriptions,
- ✓ Suggests safer alternatives—delivered via a user-friendly web application.

Objective

- ✓ Reveal hidden co-prescription patterns using network science,
- ✓ Identify statistically unexpected medication combinations,
- ✓ Provide intelligent, data-backed medication recommendations,
- ✓ Offer age-specific insights to support personalized treatment,
- ✓ Predict billing costs using patient and treatment data.



Technologies & Tools Used

- ✓ **Languages & Frameworks:** Python, Streamlit
- ✓ **Libraries:** pandas, NetworkX, scikit-learn, plotly, XGBoost
- ✓ **Algorithms:** Node2Vec, Leiden, Jaccard Similarity, Random Forest
- ✓ **Visualization:** pyvis, plotly
- ✓ **Model Persistence:** joblib, pickle

Data Acquisition and Preprocessing

- ✓ Loaded the Excel data of patients and prescriptions
- ✓ Cleaned missing/duplicate values
- ✓ Standardized medication names (e.g., remove dosages, brand variations)
- ✓ Split comma-separated meds into patient-med pairs

Network Construction Methodology

Bipartite graph: patients ↔ medications

Projected into medication-medication network

Jaccard Similarity for edge weight normalization

Disparity Filter for statistically significant edges

Community Detection & Embeddings

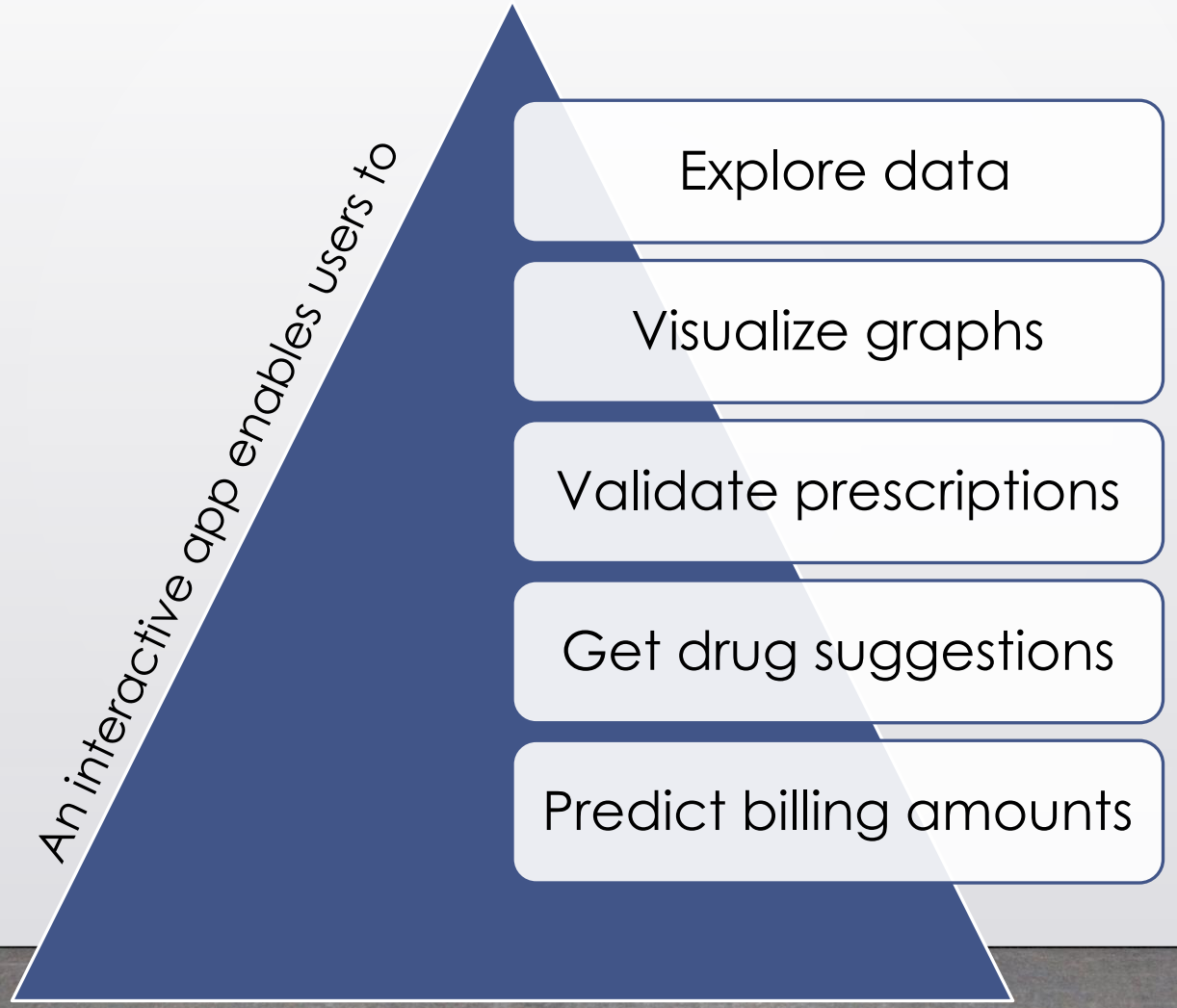
- ✓ Leiden algorithm grouped meds into clusters
- ✓ Node2Vec created embeddings (vector representations)
- ✓ UMAP reduced dimensions
- ✓ HDBSCAN discovered thematic clusters
- ✓ These techniques allow discovering similar or commonly co-prescribed drugs.

Network Centrality Analysis

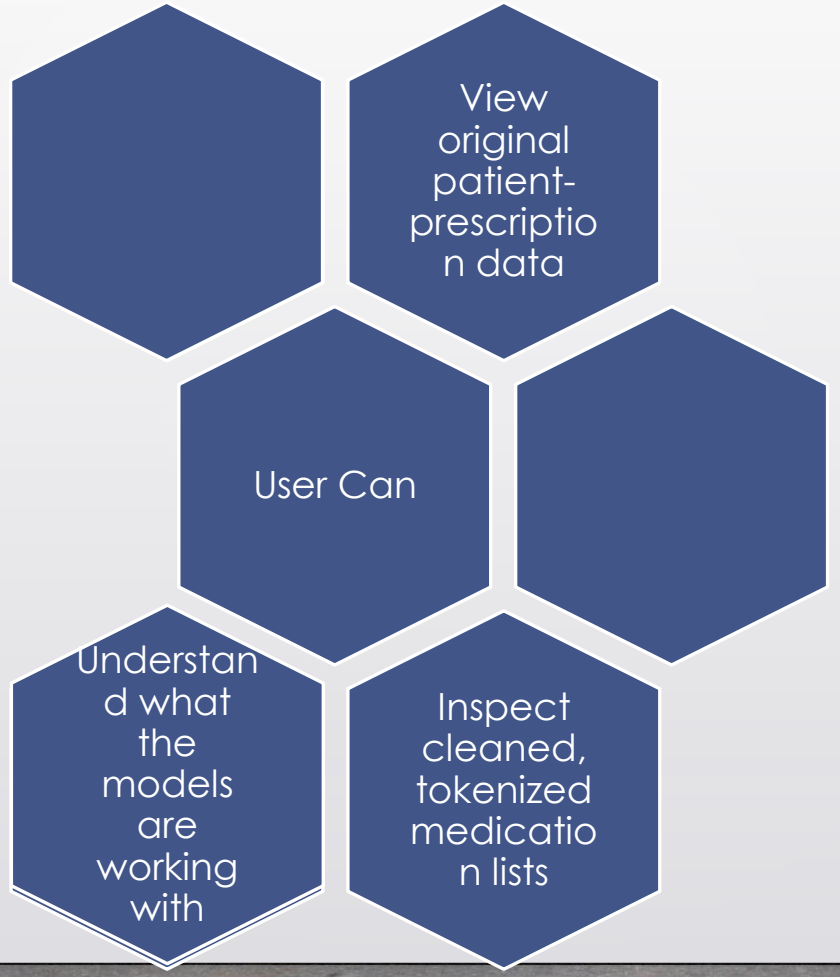
Calculated centrality scores to identify key medications:

- ✓ **Degree:** How many direct connections
- ✓ **Closeness:** Average distance to others
- ✓ **Betweenness:** Acts as a bridge
- ✓ **Eigenvector:** Influence based on neighbors' importance

The Stream lit Web Application



Data Exploration Page



Network Visualization & Insights

- ✓ Hover on meds to view connections
- ✓ See clusters via node colors
- ✓ Spot highly connected medications

Link Prediction Module

- ✓ Trained model on features:
  - ➢ Preferential Attachment
  - ➢ Jaccard Coefficient
- ✓ Predicts new potential co-prescriptions
- ✓ Highlights unexpected links

Recommendation Engine

Validate

- Check coherence of a list of medications

Suggest:

- Recommend similar or more compatible alternatives
- Uses thematic embeddings and partner strength

Thematic Similarity & Embeddings

- Node2Vec maps each medication into a vector space. Cosine similarity identifies close neighbors, even across different clusters.

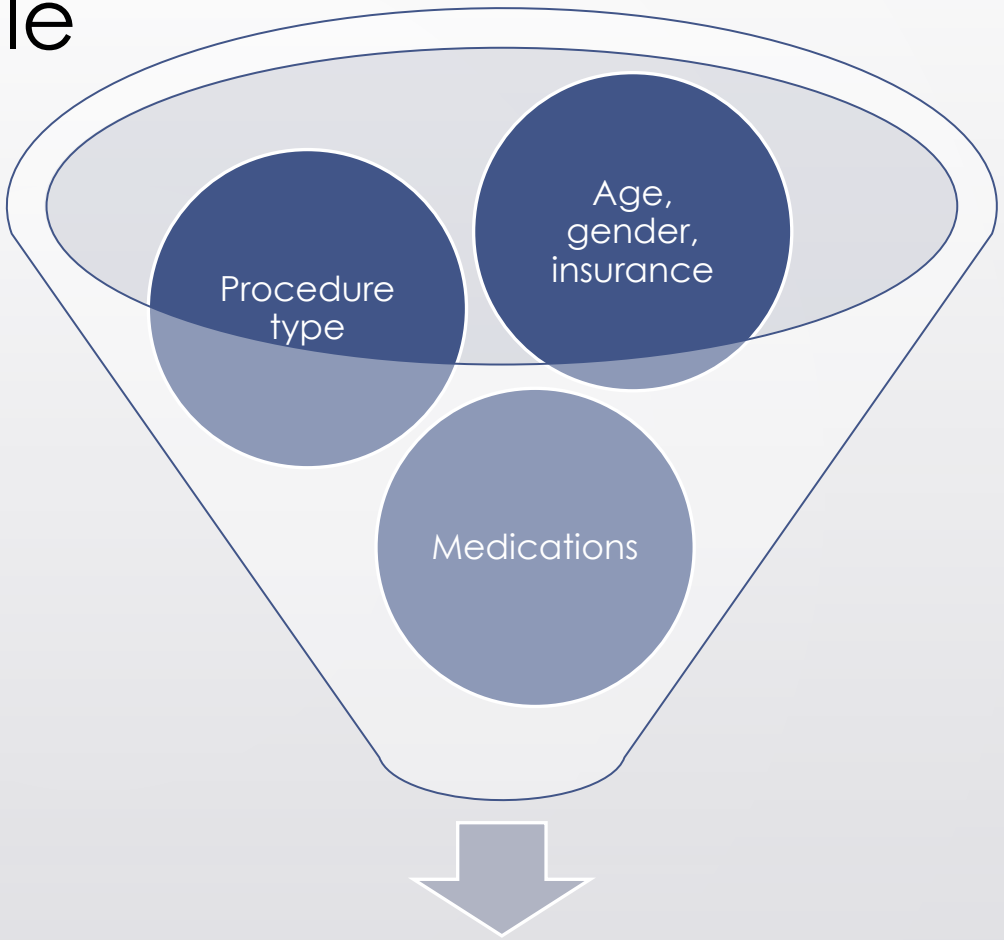
Age-Based Clustering & Predictions

Grouped patients by age

Clustered based on med basket similarity (KMeans)

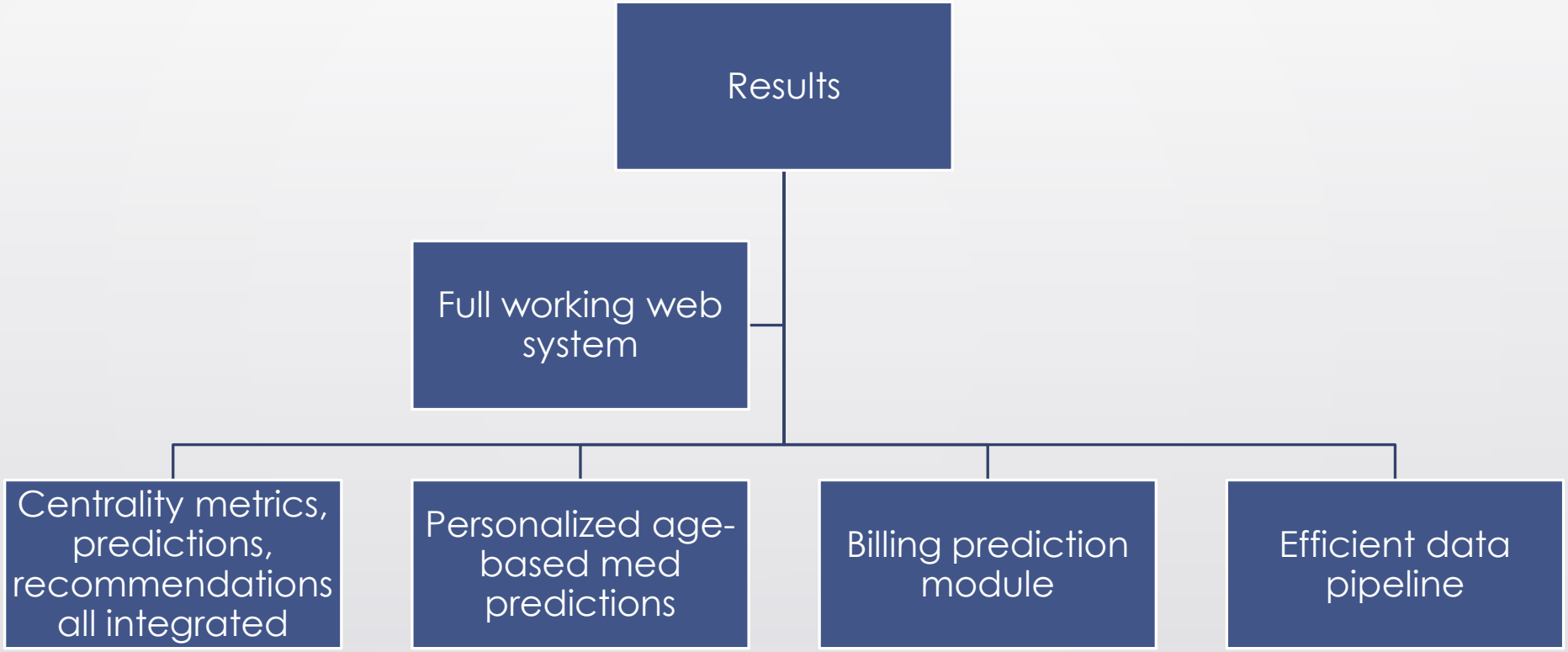
Predicted top meds for new ages via closest cluster

Billing Prediction Module



Trained XGBoost model

Key Results and Achievements



Challenges Faced

Messy data (inconsistent drug names)

Choosing correct similarity measures

Tuning Node2Vec, HDBSCAN

Embedding HTML graph in Streamlit

Conclusion and Future Work

We built a powerful and intuitive system to enhance medication decisions.

As a future work:

- Add diagnosis codes
- Introduce time-based prescription analysis
- Improve model interpretability (explainable AI)