ChatGPT και Εφαρμογές AI για Ιατρούς

8th session – **Σύνθετη κλινική εξαγωγή συμπερασμάτων μέσω Med Gemini και Medical Graph Algorithms**

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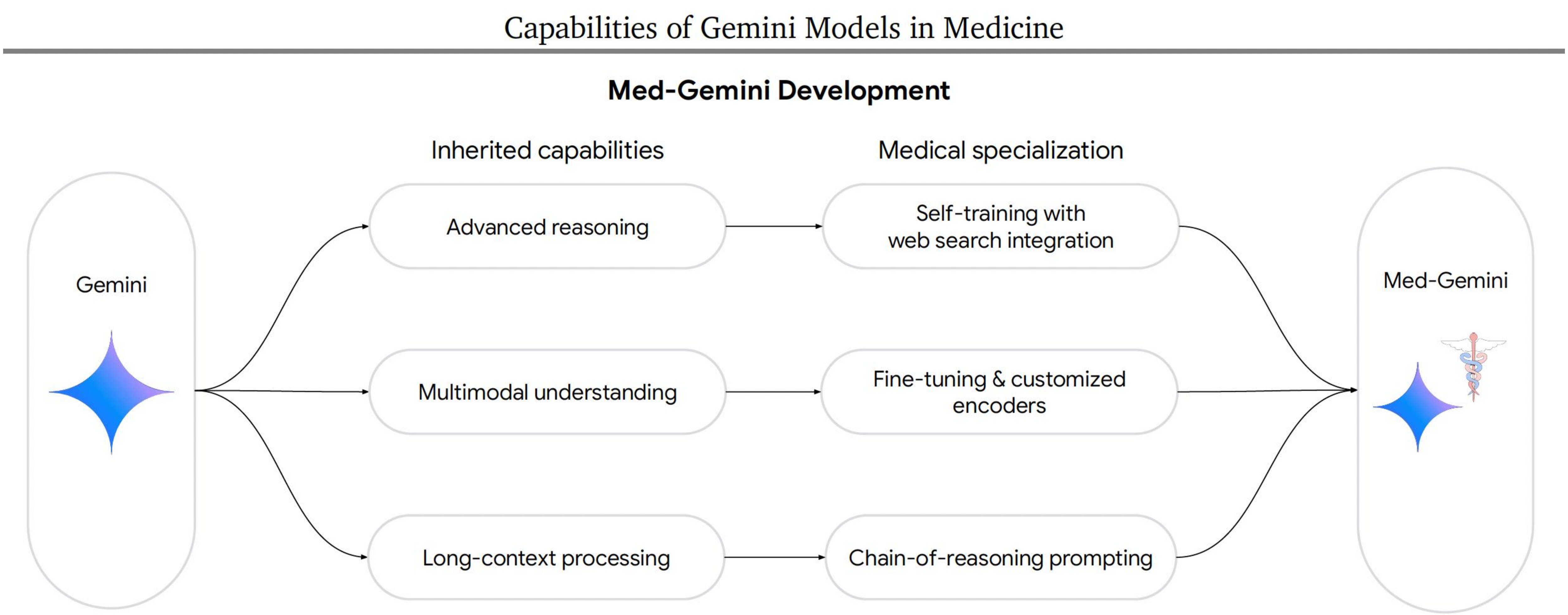
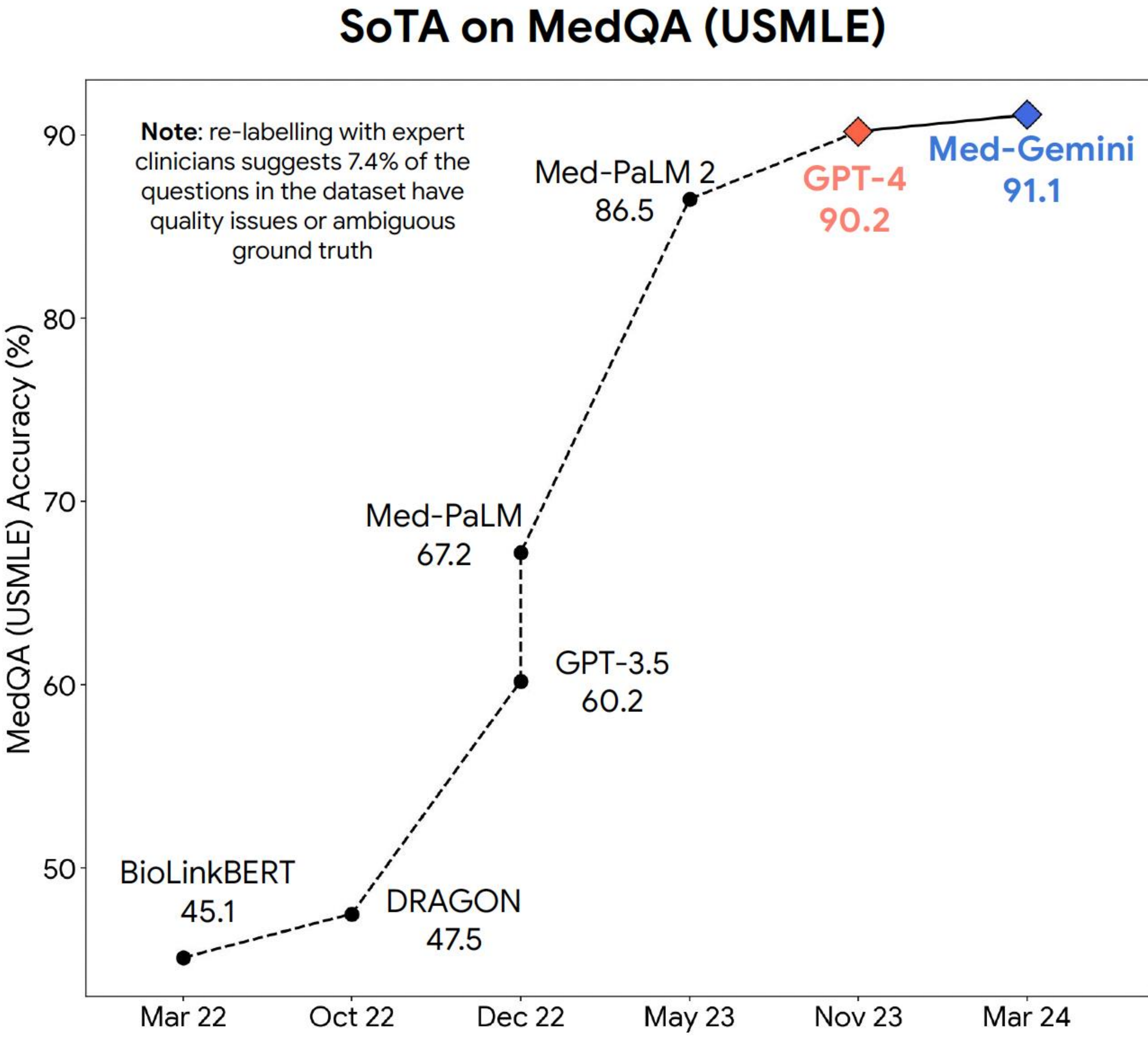
Med Gemini Capabilities in Medicine



Med Q&A benchmark

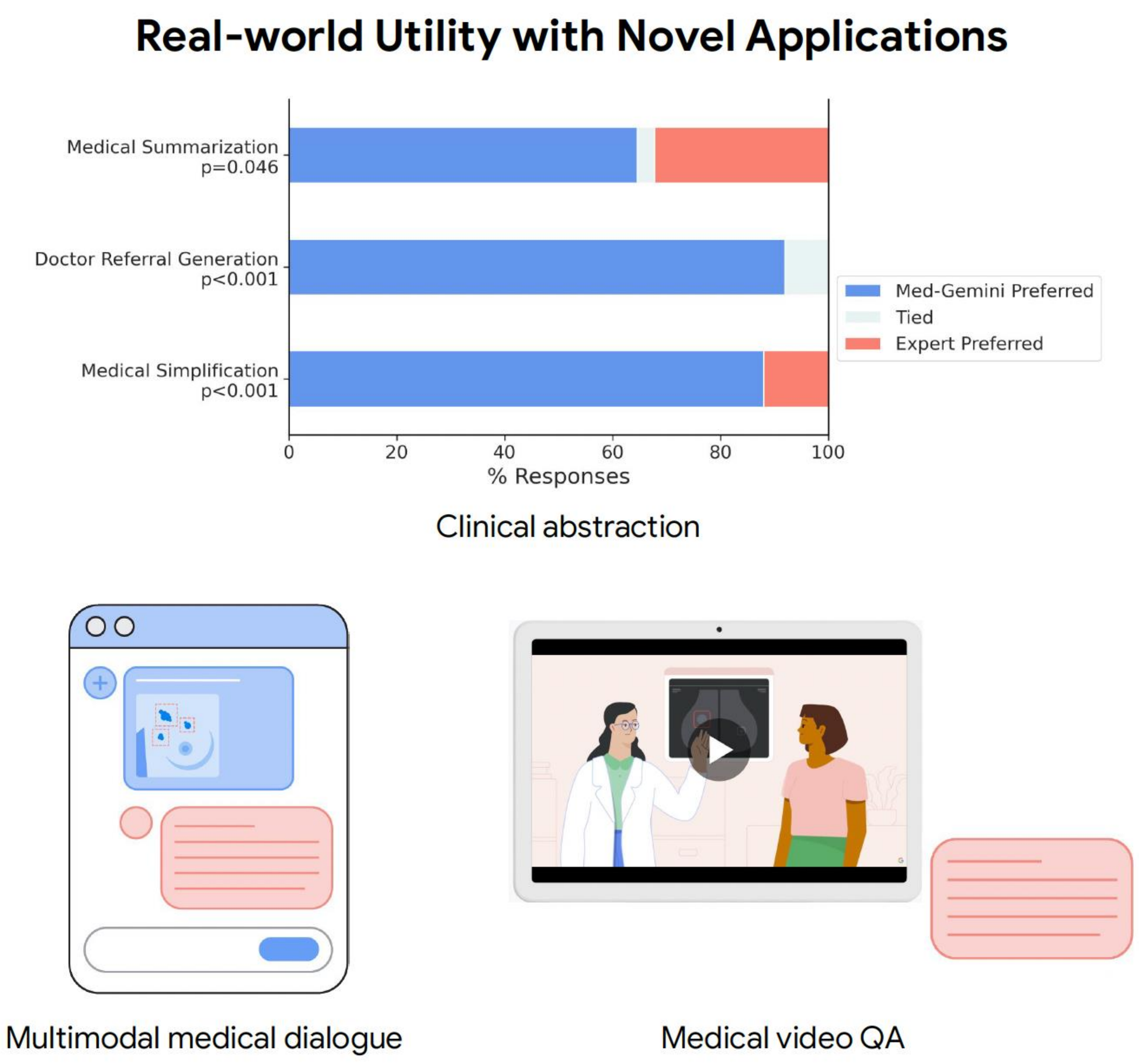
US Medical License Exam (USMLE)

- *Med-Gemini achieves SoTA performance of 91.1% accuracy, and outperforms GPT-4 with performance of 90.2%*

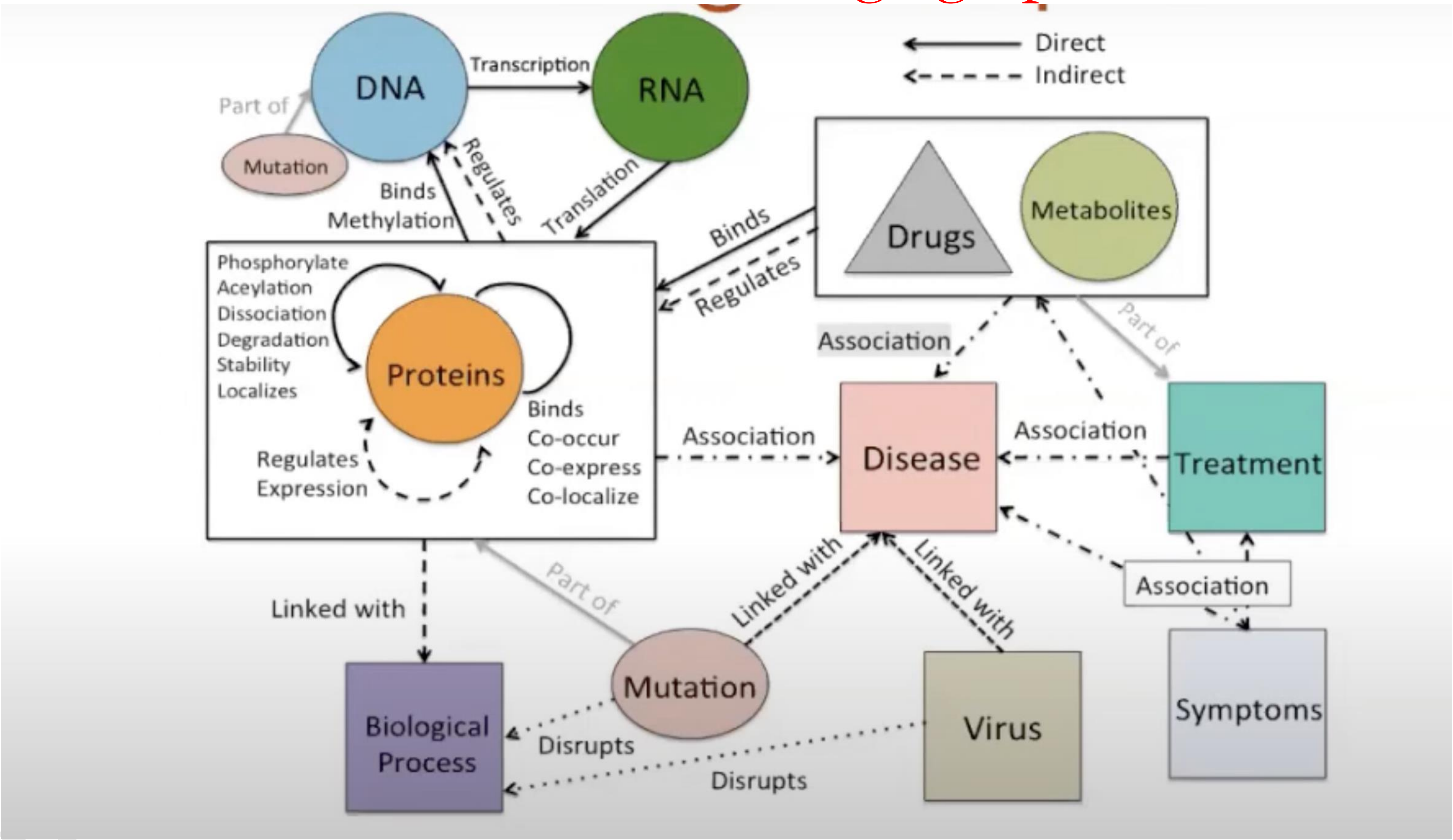


Med Gemini vs. Human Experts

- *medical summarization,*
- *referral letter generation,*
- *and medical simplification tasks where Med-Gemini models outperform human experts*



medical knowledge graphs

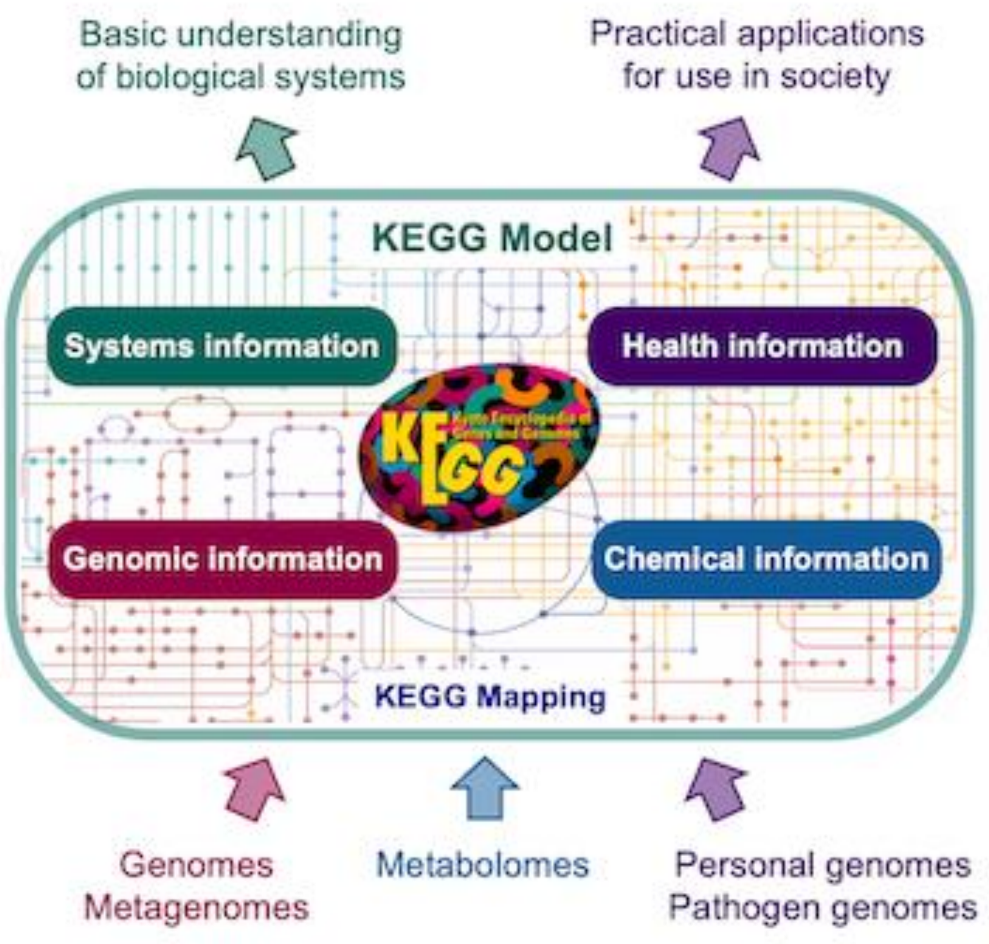


Introduction to KEGG

KEGG is a comprehensive database resource that helps understand high-level functions of biological systems such as cells, organisms, and ecosystems.

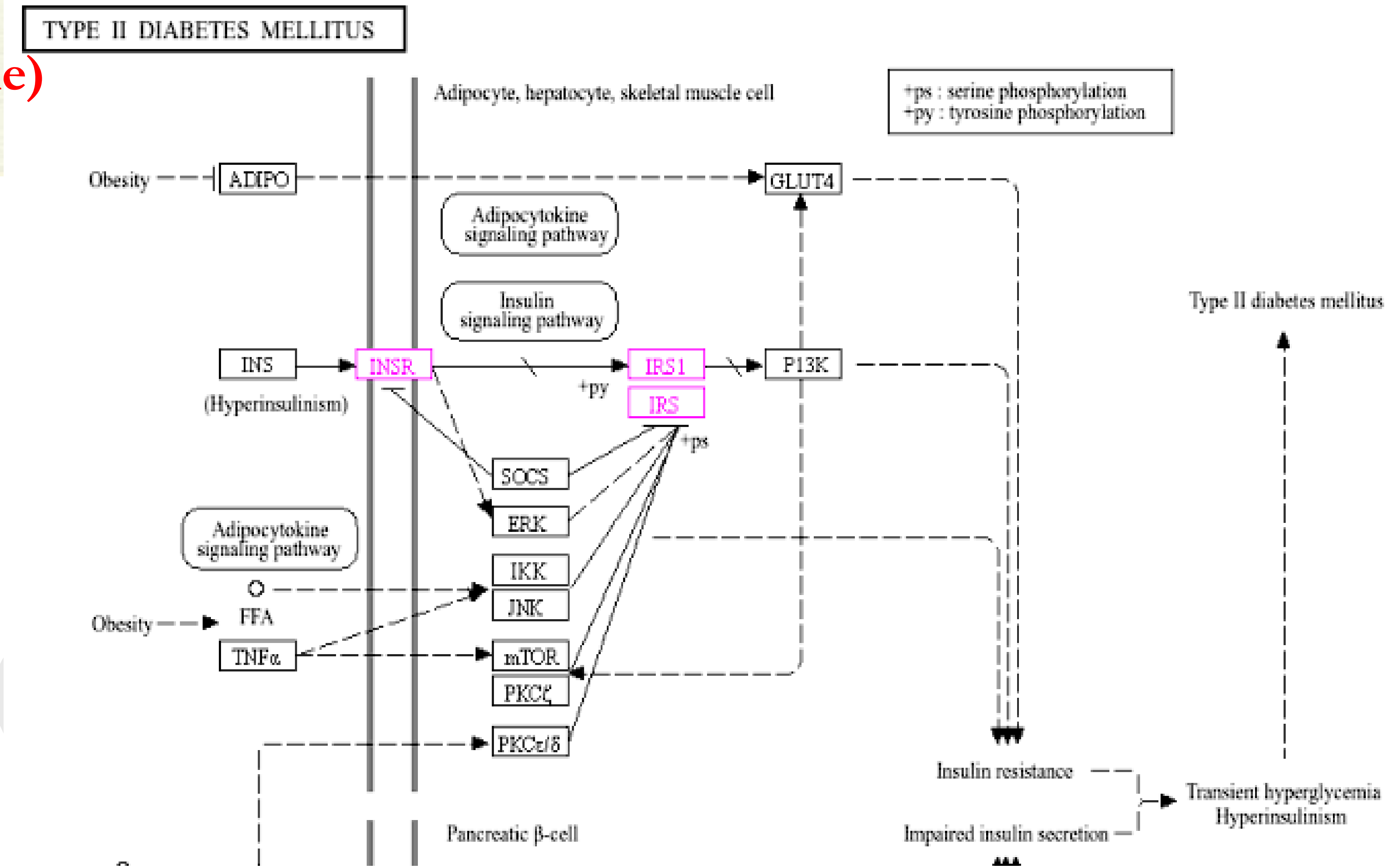
KEGG Usage Statistics:

- As of 2023, KEGG contains more than **20,000 pathways** covering various biological processes across species.
- The database includes over **5,000 species**, from bacteria to humans.
- KEGG has been cited in over **50,000 scientific publications** globally, making it one of the most widely used biological databases.



Disease Pathways (Diabetes Example)

- **INSR** (Insulin receptor): Primary receptor for insulin signaling.
- **IRS1/2** (Insulin receptor substrates): Mediators of insulin action.
- **AKT** and **PI3K**: Crucial molecules in glucose uptake.
- **GLUT4**: Glucose transporter, responsible for glucose uptake in response to insulin.

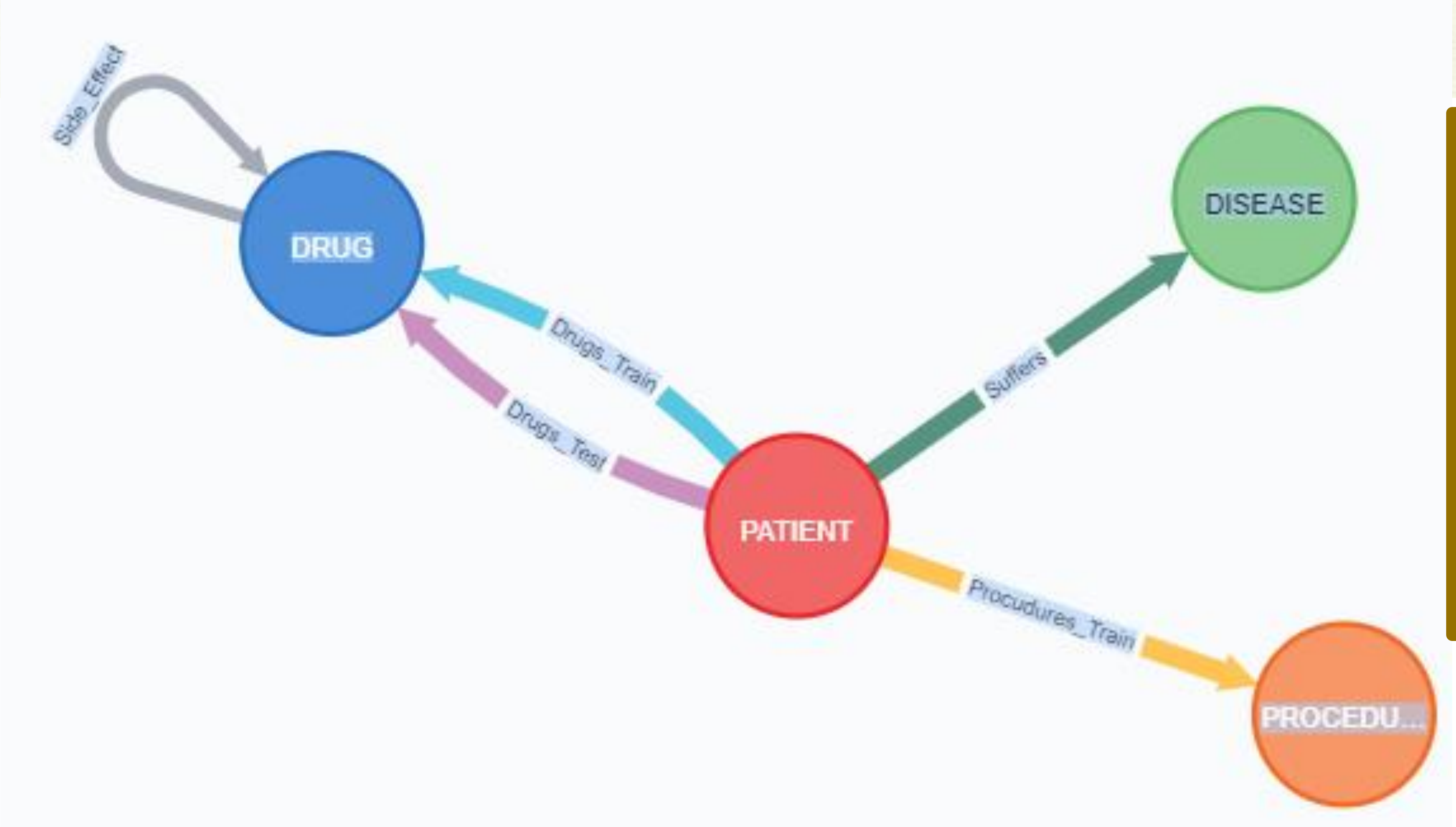


Graph-based Methods for Personalized Health

Published work

1. Safe, effective and explainable drug recommendation based on medical data integration (Symeonidis et al., UMUAI journal, 2022)
2. Treatment Recommendations for COVID-19 Patients along with Robust Explanations (Symeonidis et al., IEEE CBMS 2021)
3. Recommending what drug to prescribe next for accurate and explainable medical decisions (Symeonidis et al., IEEE CBMS 2021)

Knowledge Graph for Medical Data (RDF triples)



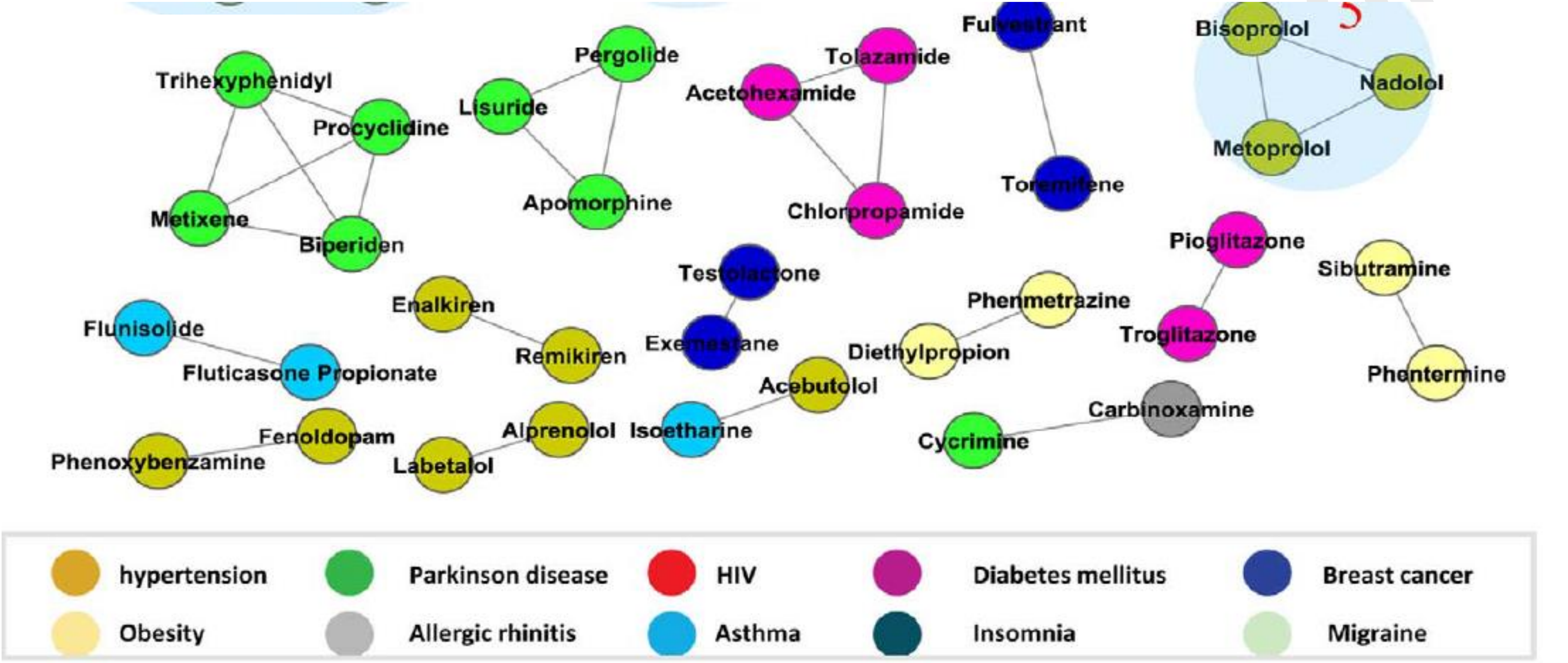
Participating entities

1. Patient
2. Drug
3. Disease
4. Procedure
5. Side Effect

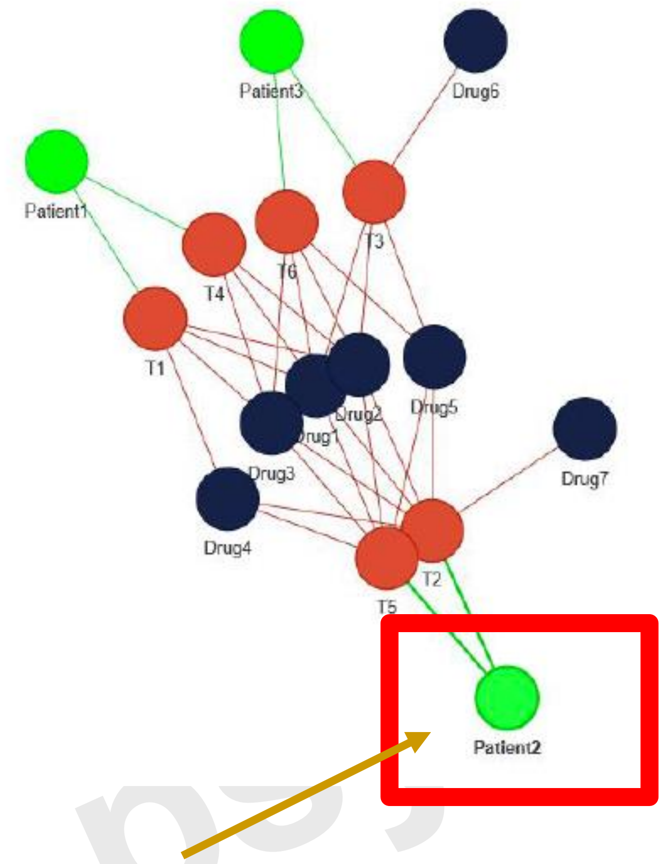
Patients take Drugs to cure Diseases, but may also have side Effects

Similarity Search and Relevance in Graphs

- Different graph-based algorithms (SimRank, RWR, etc.) can be used to infer Drug-Drug Similarity Network.



Our proposed meta path-based Explanations



Which drug should we recommend for patient 2?

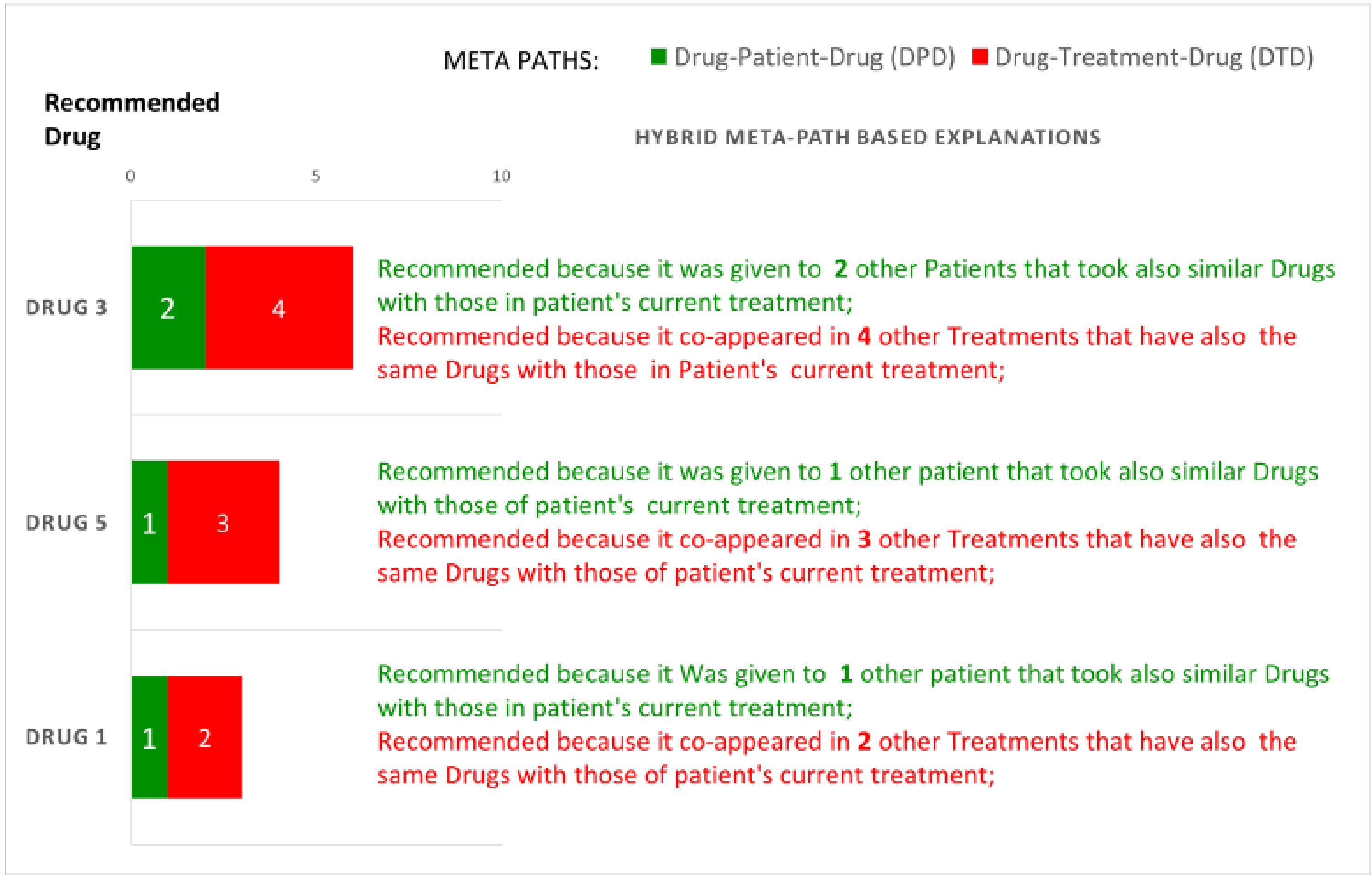


Fig. 4: Drug Recommendations along with explanation for patient 2. Drug 3 is recommended because it has the most frequent meta paths supporting it.

Graph Convolution Neural Networks Formula:

- Propagation/convolution rule:

$$h_i^{(1+1)} = \sigma\left(\sum_{r\in R} \sum_{j\in N_i r} \frac{1}{c_{i,r}} \cdot W_r^{(l)} \cdot h_j^{(1)}\right)$$

  - $h_i^{(l+1)}$:Representation of node i.
  - $h_j^{(l)}$: Latent representation of neighbor node j in l-layer of convolutional neural network.
  - $W_r^{(l)}$: Table of weights in the l-layer with respect to r-type directed edges.
  - N_i^r : Number of neighboring nodes of the considered node i connected to it by directed edges of type r ∈ R.
  - $C_{i,r}$=|N_i^r| : Number of neighbors of node i in terms of directed edges of type r (Two types of directed edges r).
  - σ: Non-linear activation function (eg sigmoid function).