Using ML for recommendations in various domains

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Recommendation Systems

What are they:	Recommendation Systems are those systems whose main task is to select and propose objects that meet the user's preferences or needs
Aim:	Increase sales Promote items Increase user satisfaction Increase confidence on service

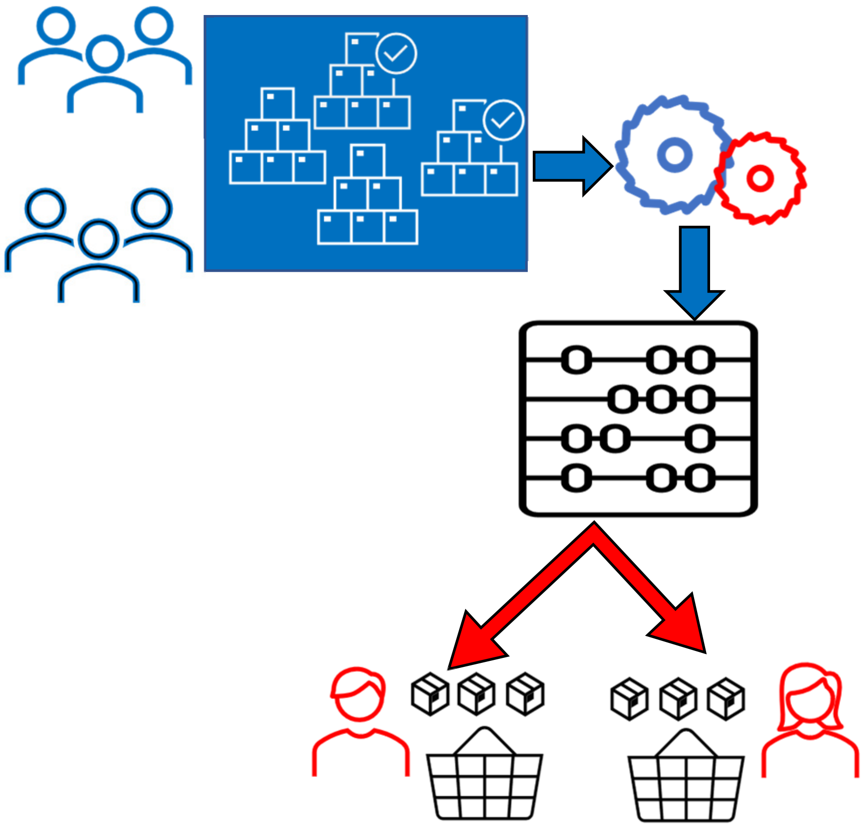
Recommendation systems applications

- E-commerce
- Physical stores
- Digital products
- Updates

- Social networks
- Online entertainment
- E-learning
- ....Everywhere!!!

Basic concepts

- User
- Item
- Transaction / record
- Ratings
  - ➢ explicit ratings
  - ➢ implicit ratings



Recommendation System Problems

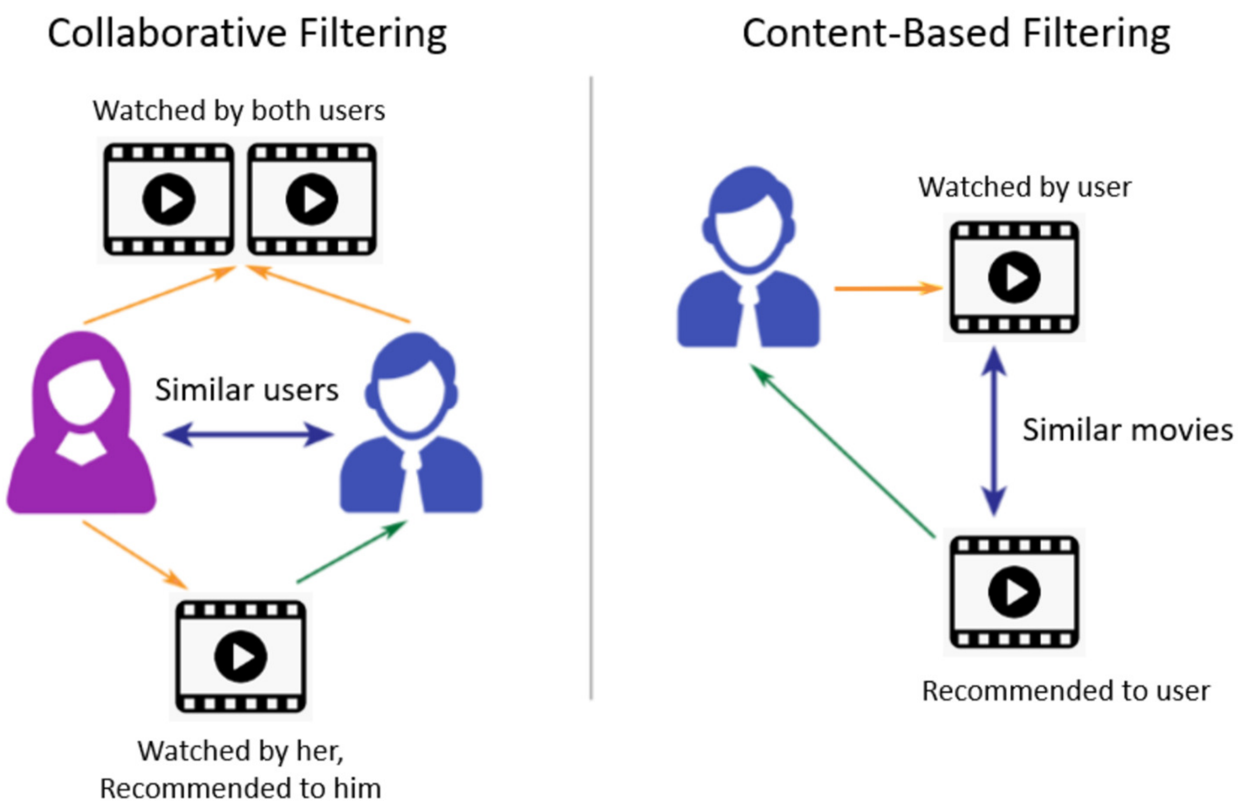
Data sparsity

Cold start

Κατηγορίες Συστημάτων Συστάσεων

- Collaborative Filtering
- Content-based Filtering
- Hybrid Filtering
- Demographic
- Knowledge based
- Context-aware
- Session-based

Categories of Recommendation Systems



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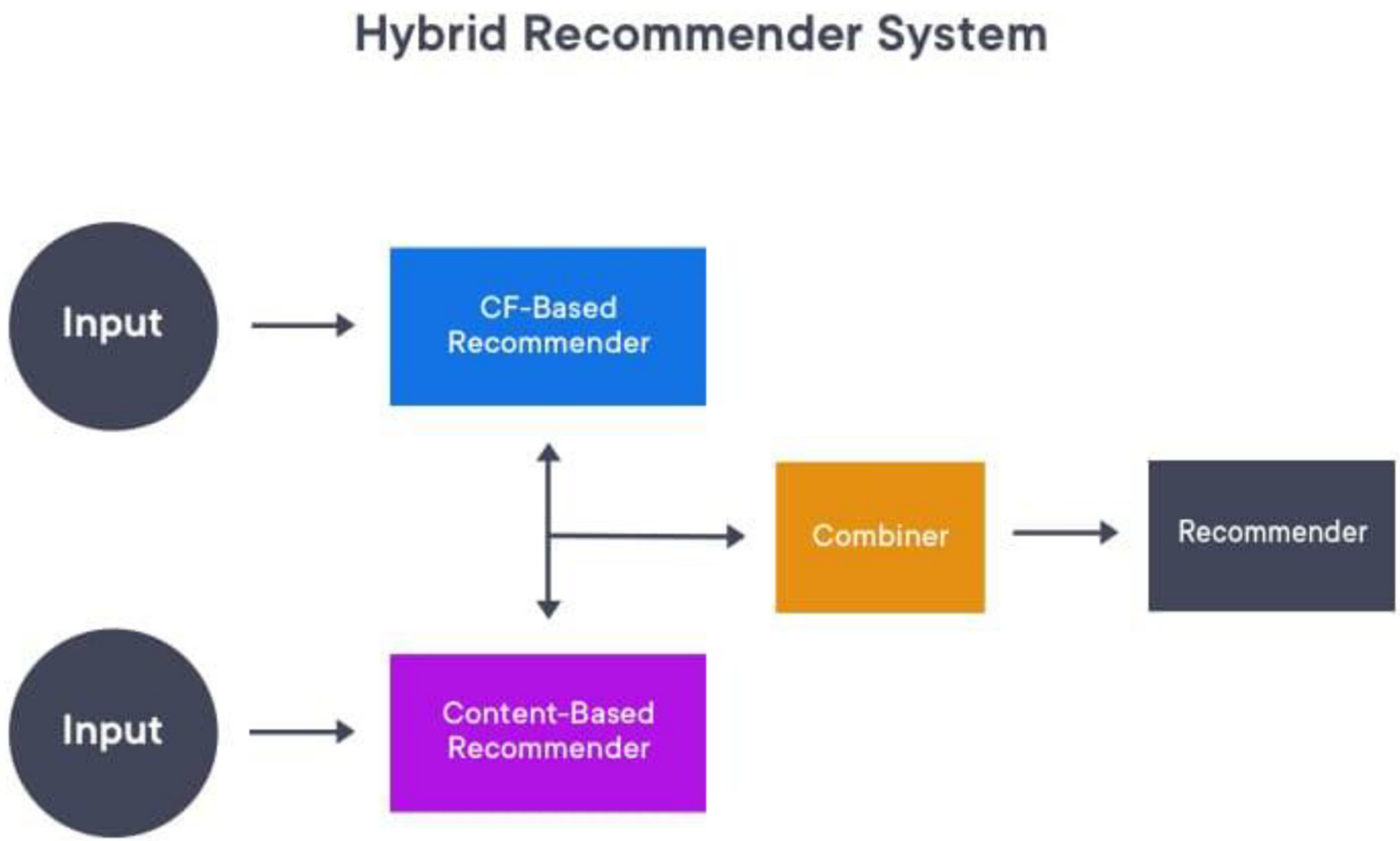
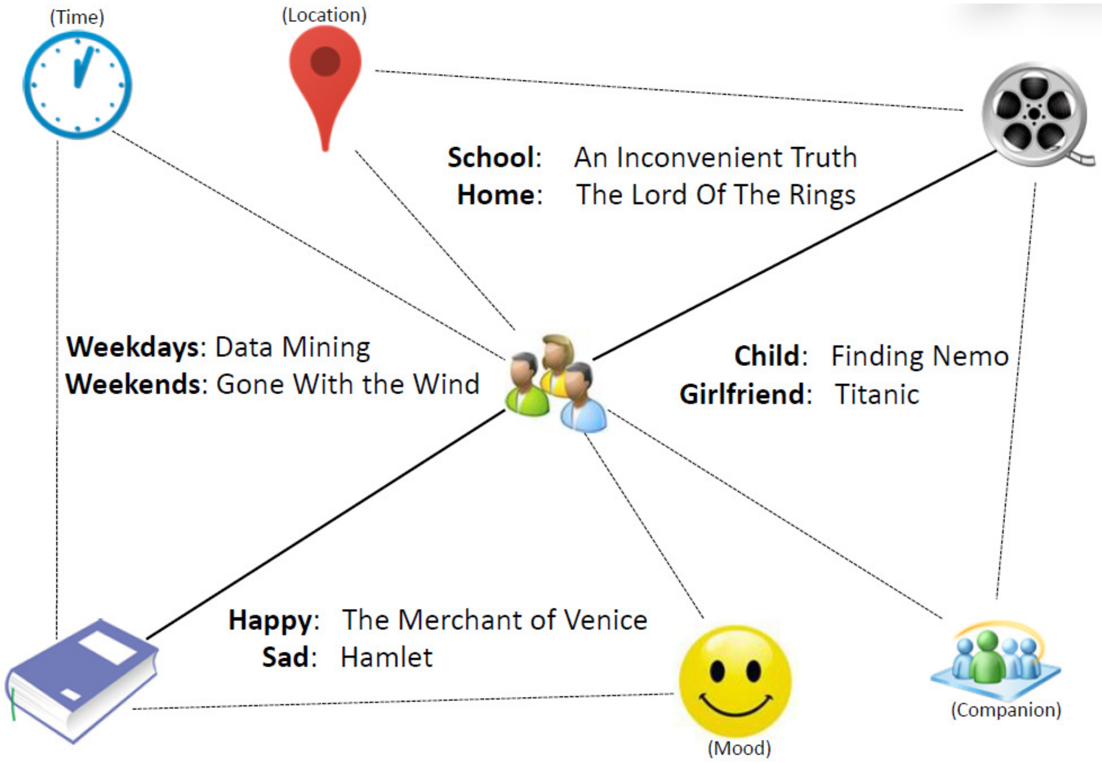


Categories of Recommendation Systems



Context-Aware RS

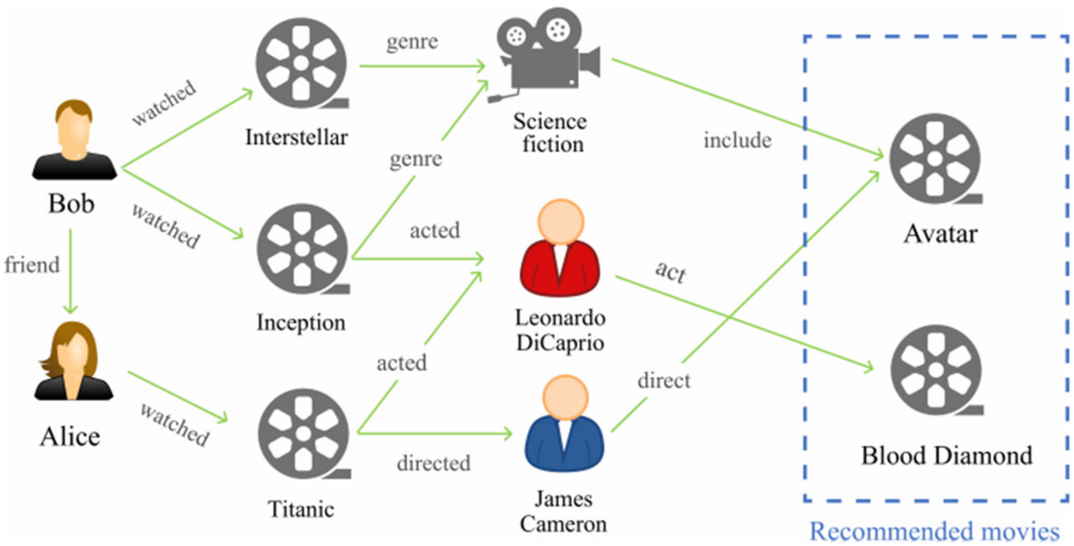
User preferences may vary depending on :

- Time
- Day
- Season
- Mood
- Location

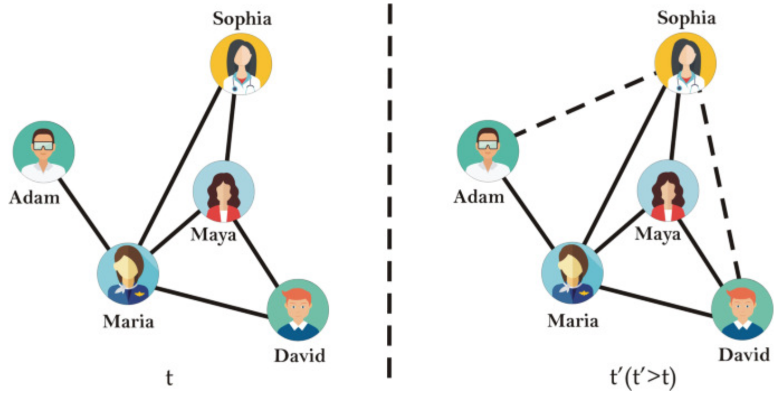
Categories of Recommendation Systems

Graph-based RS (GBRS)

entity-relationship-entity



- Nodes
- Edges
- Attributes



Categories of Recommendation Systems

Session-Based RS (SBRS)

- The evolution of a user's preferences within a set of transactions

$$S = \{I_{t1}, I_{t2}, \dots, I_{tk}, \dots, I_{tn}\} \quad \rightarrow \quad I_{tn+1}$$

- Anonymous website or online store visitors
- Three central groups of algorithms in relation to their output for recommendation:

  next (best) item recommendation

  next (best) session/basket recommendation

  next (best) action/event recommendation

Recommendation systems for retail and services

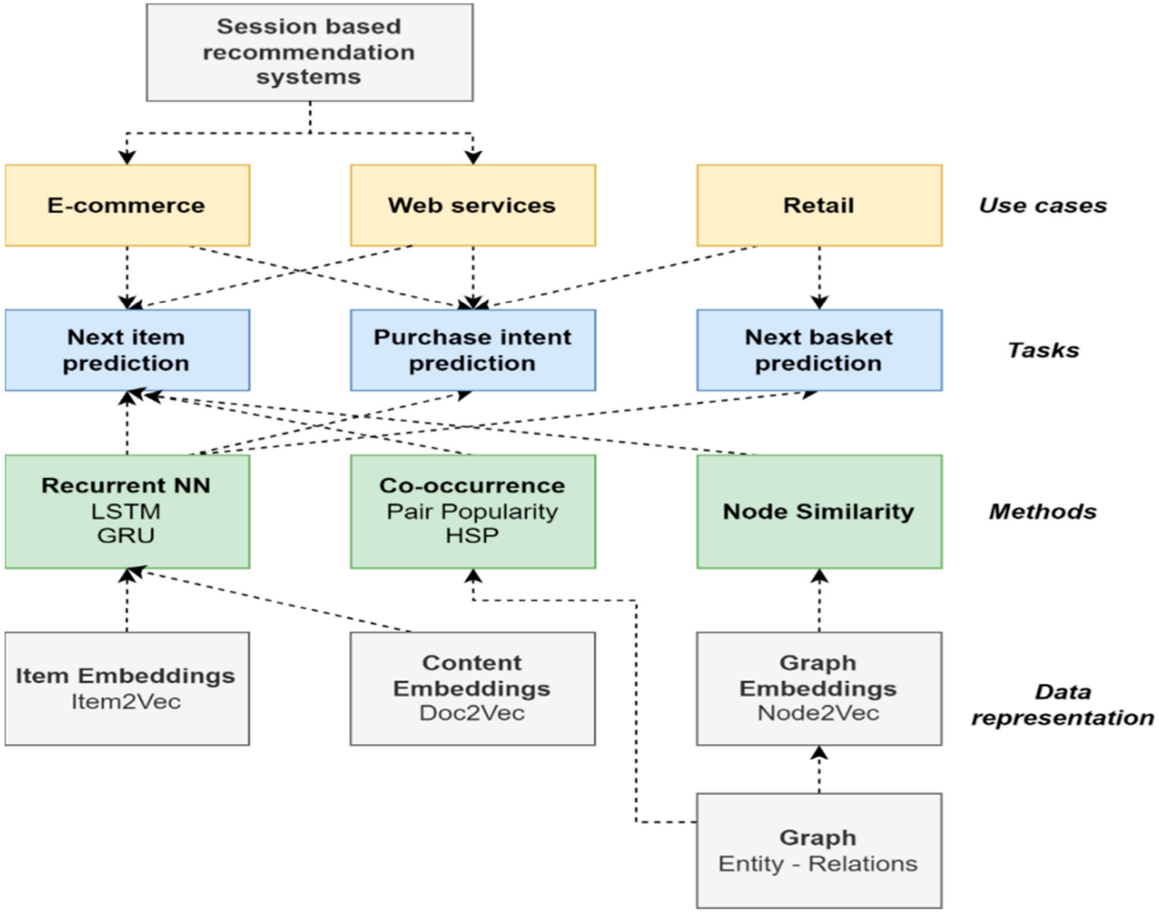
Flexible Recommender Systems on Big Data

FRES

https://www.fres-project.gr/

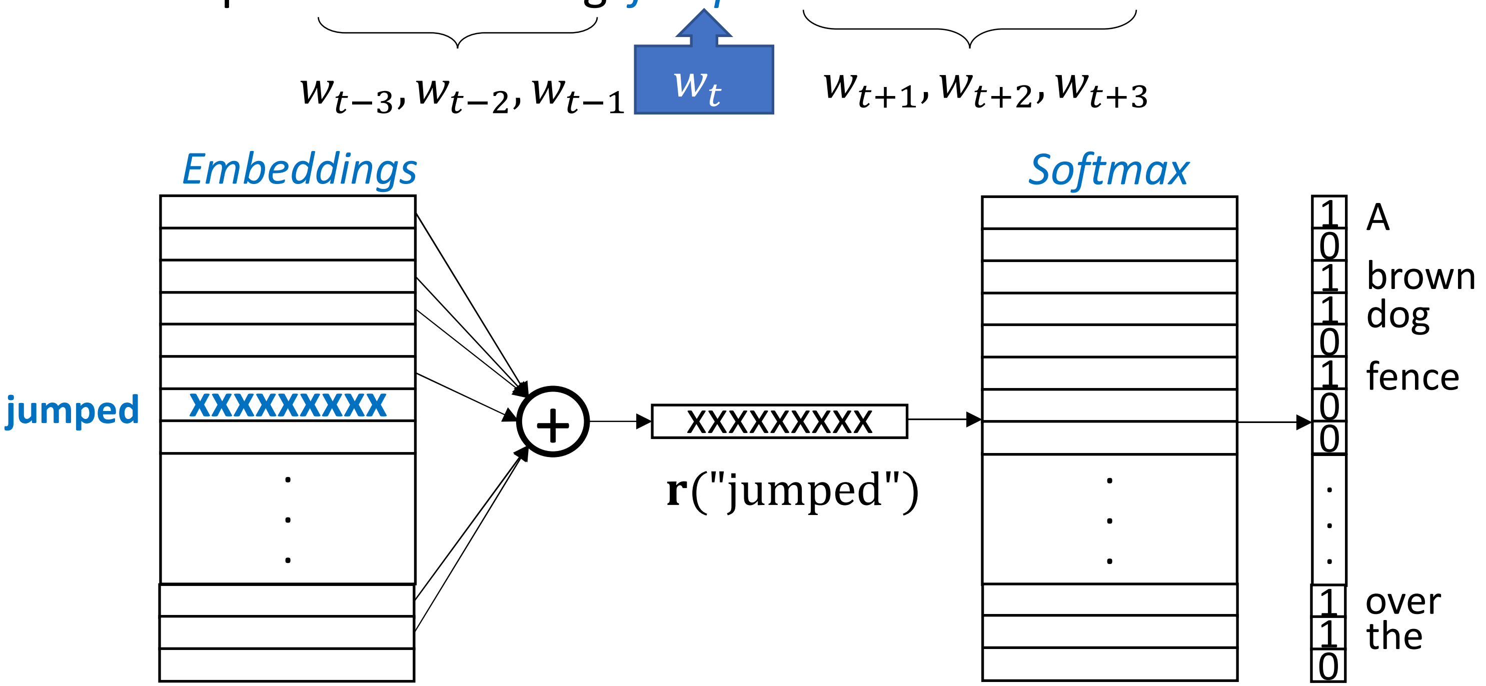
European Union
European Structural and Investment Funds
HELLENIC REPUBLIC
Ministry of Economy and Finance
Special Secretariat for ERDF & CF Programmes
Managing Authority of "Competitiveness" Programme
EPAnEK 2014-2020
OPERATIONAL PROGRAMME
COMPETITIVENESS
ENTREPRENEURSHIP
INNOVATION
ΕΣΠΑ 2014-2020
ανάπτυξη - εργασία - αλληλεγγύη
Partnership Agreement 2014 - 2020
Co-financed by Greece and the European Union

A flexible recommender system

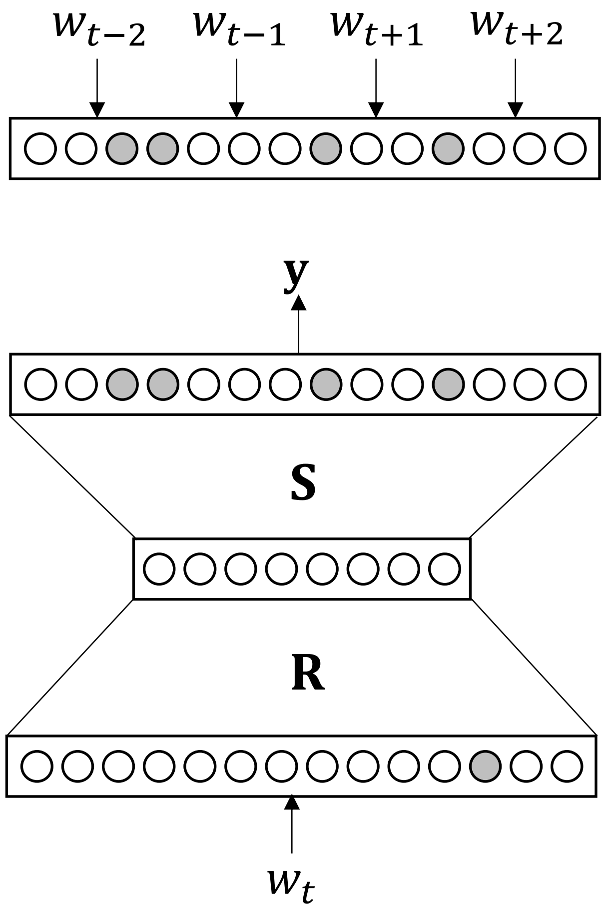


Basics: Embeddings

- Vector representation of items and/or users. Similar items → close embeddings in vector space
- Motivated by Natural Language representations
- Example: "A brown dog *jumped* over the fence"



Word2Vec



$$\mathbf{target} = \sum_{\substack{j=-n \\ j\neq 0}}^{n} \mathbf{u}(w_{t+j})$$

$$y_i = \frac{\exp(-\mathbf{s}_i^T \mathbf{h})}{\sum_j \exp(-\mathbf{s}_j^T \mathbf{h})}$$

$$\mathbf{h} = \mathbf{R} \cdot \mathbf{in} = \mathbf{r}(w_t)$$

$$\mathbf{in} = \mathbf{u}(w_t)$$

Word2Vec and Doc2Vec

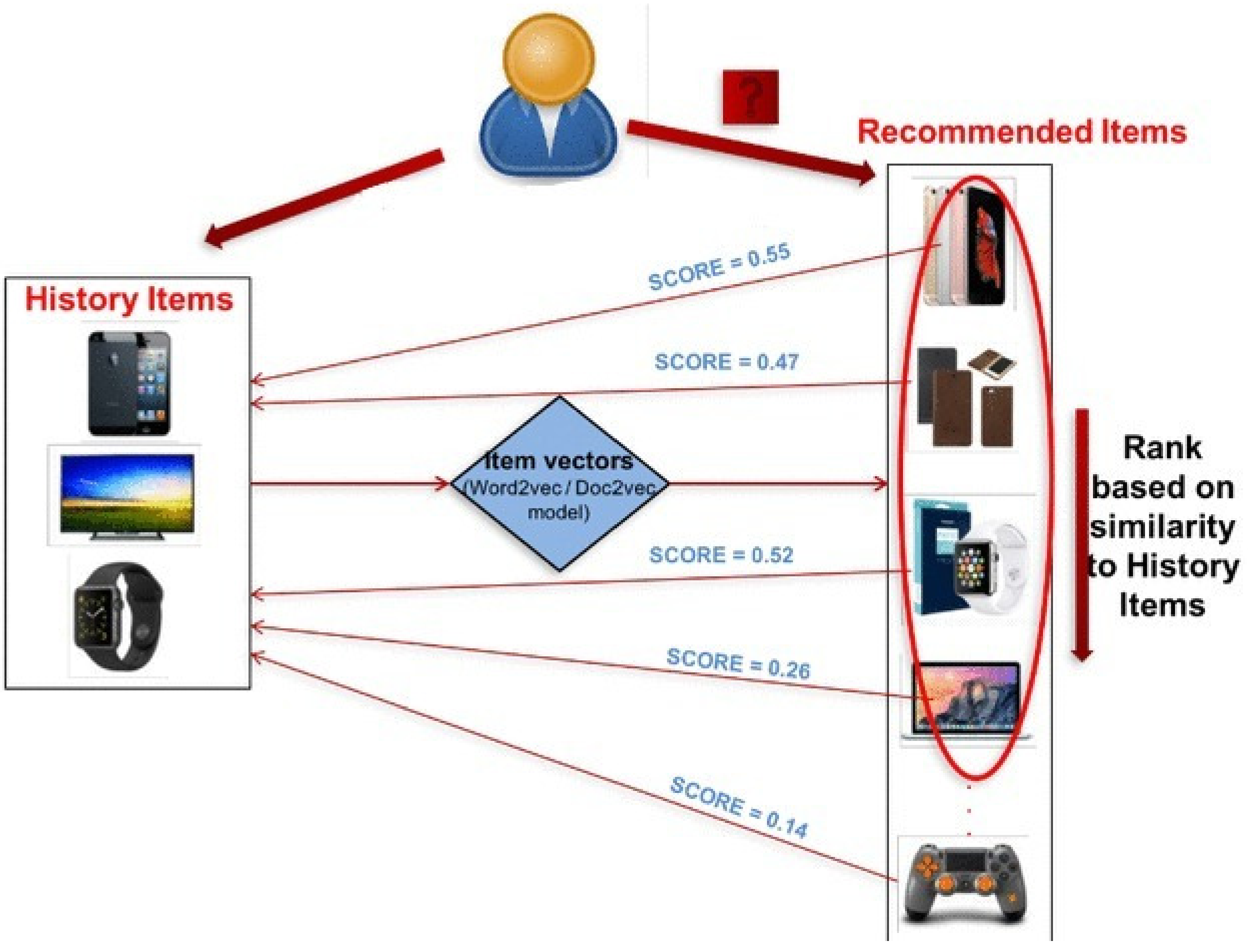
- ***Word2Vec***: encoding (representing) words with vectors such that semantically similar words have similar representations
- ***Doc2Vec***: representing a sentence or a document with a single vector
- Doc2Vec can be used in RS when textual information is known about the item. This is essentially "content based" filtering

Item2Vec training

- What if, instead of words we have items and instead of sentences we have baskets?

→ Item2Vec = vector representation of items. Items most commonly purchased together have similar vectors

Recommend items with Item2Vec



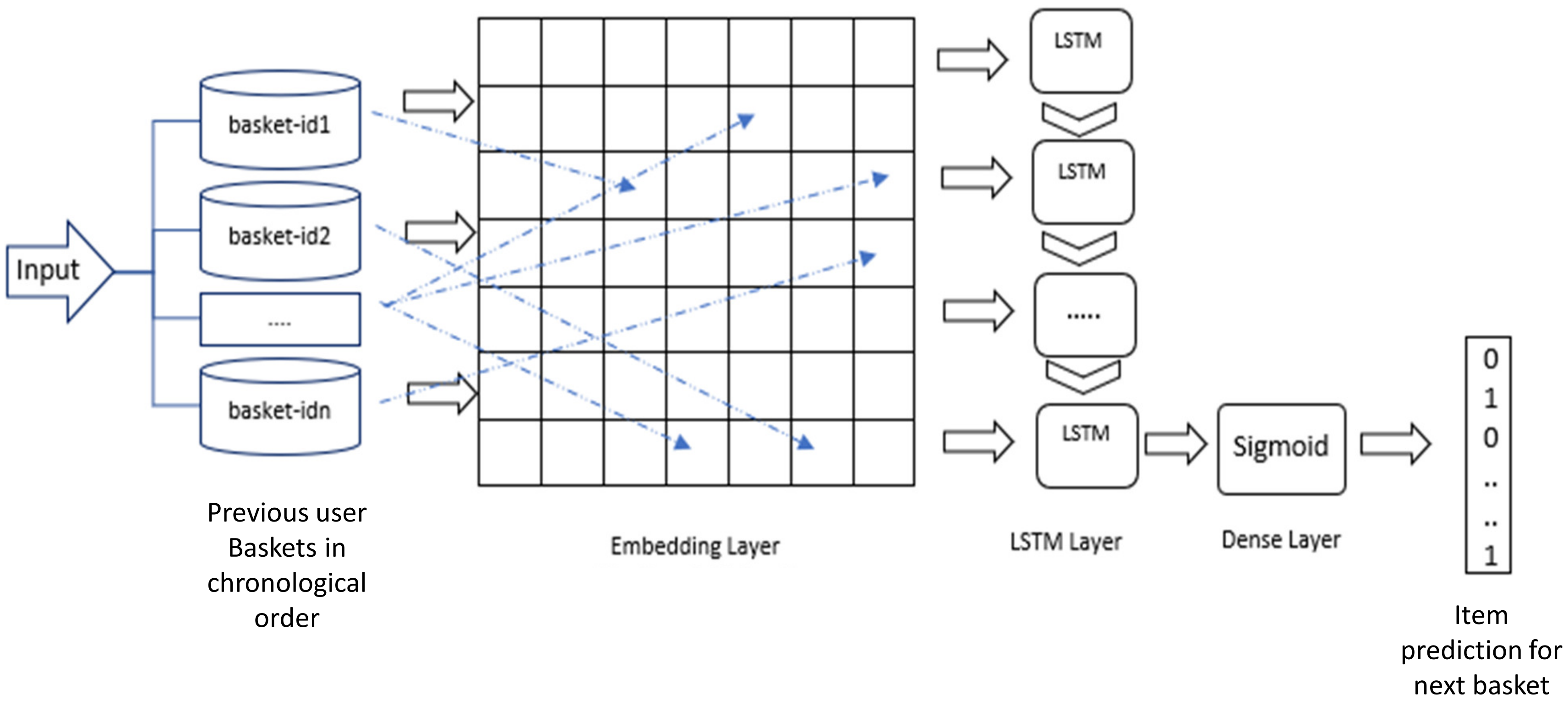
Evaluation Criteria

- **MRR:** Average 1/r, where r is the order of the selected item in an ordered recommendation list. If the user does not choose any item then r=∞
- **F1@k:** F1 score when recommending k items
- **Click Through Rate:** Number of recommended items previewed by the user over the number of item impressions
- **Conversion Rate:** Number of items added to cart by user divided by number of item impressions

Physical retail shop

- Requirements:
  - ✓Physical shop with loyalty card per customer
  - ✓We know the purchase history of the client

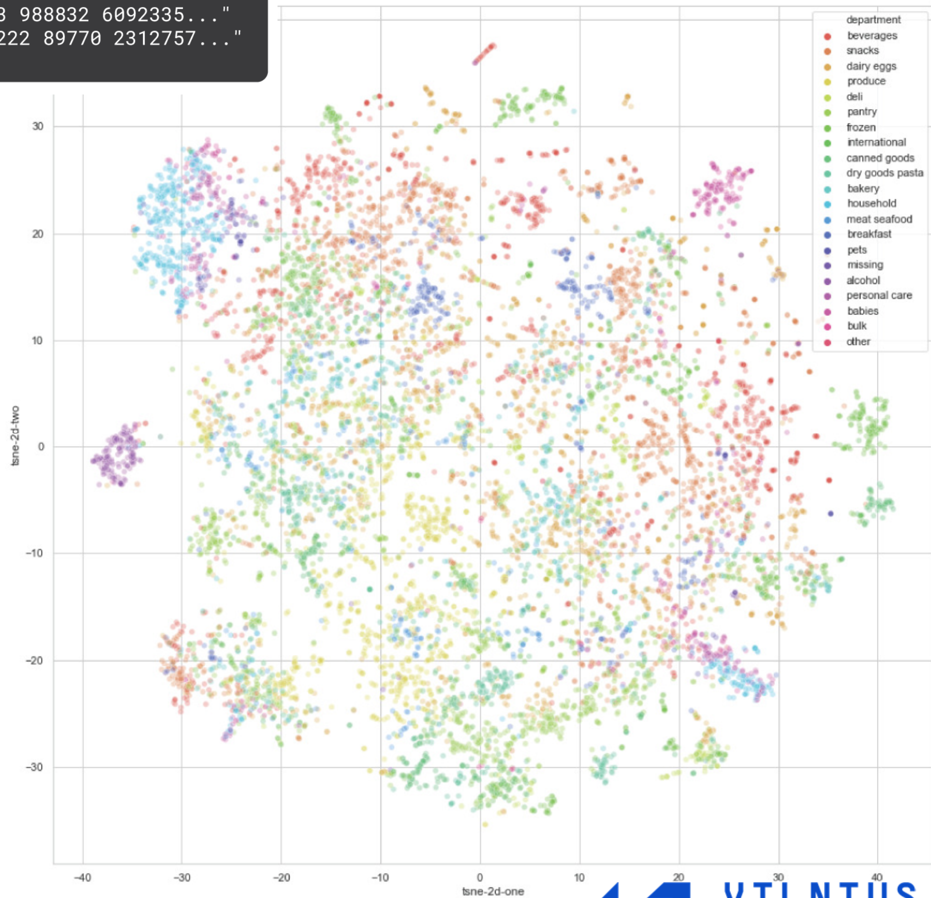
Physical retail store: Recurrent Neural Networks



Physical retail store: Item2Vec

corpus

```
Order ID        |          Product ID (order-text)
----------------|------------------------------------------------------
43532422        | "121774 78433 324400 980034 896953 988832 6092335..."
64432223        | "234437 855620 7002533 621333 564222 89770 2312757..."
```

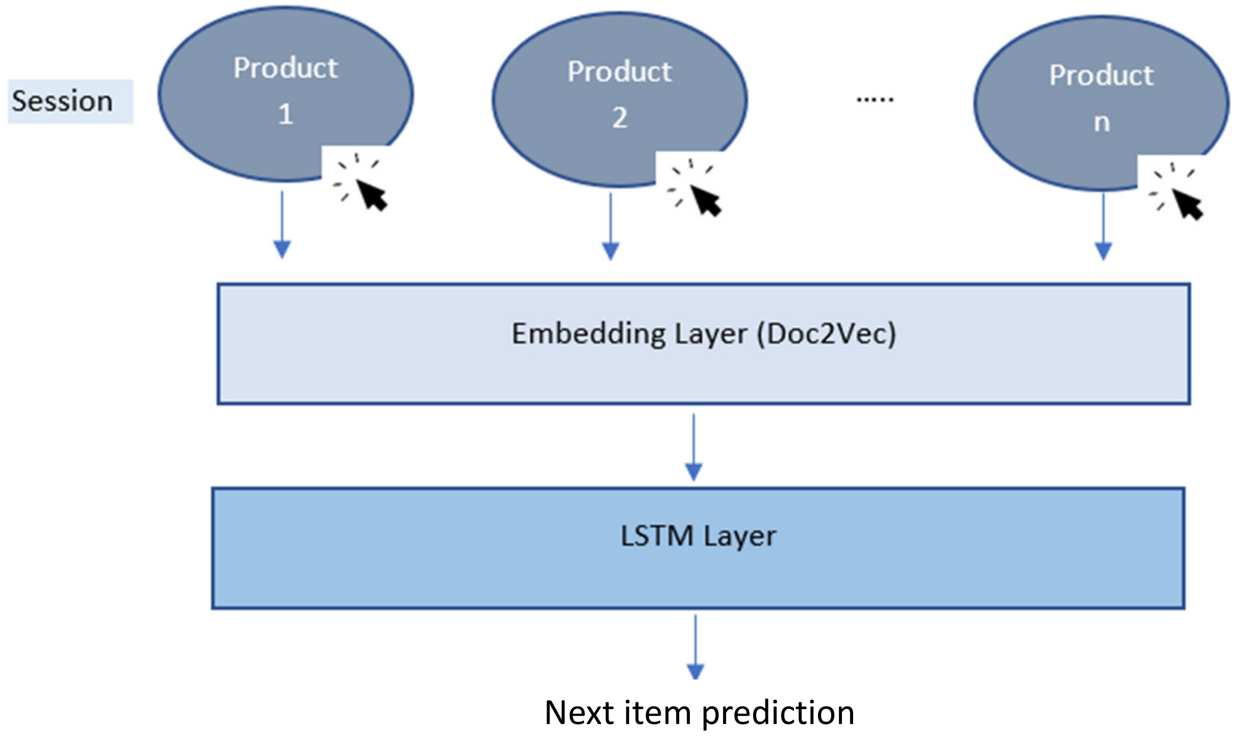


product
embeddings

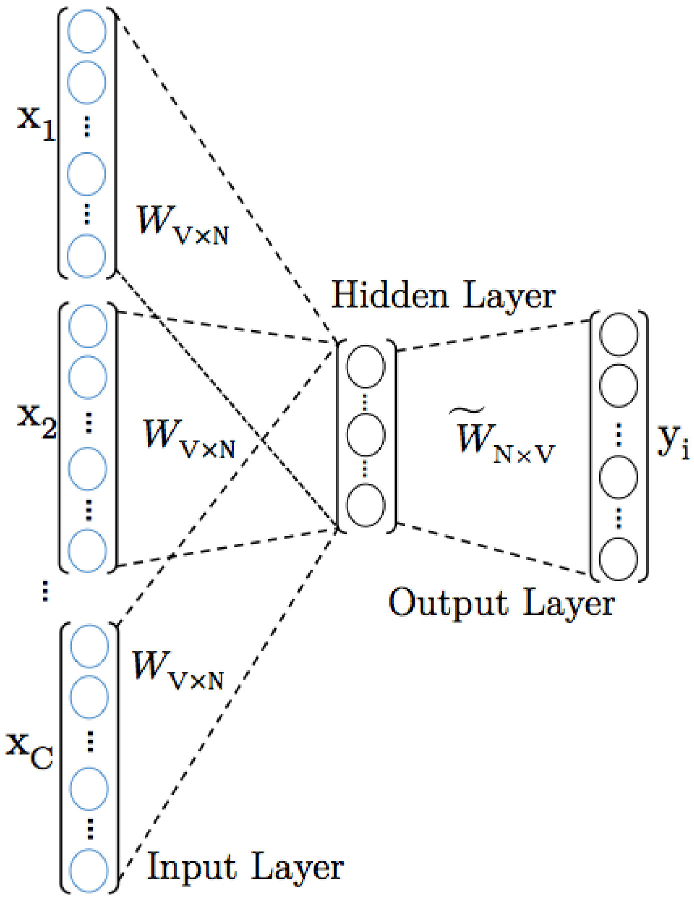
E-shop

- Requirements
  - ✓ Session-based recommendations: sequence of clicks
  - ✓ No prior info about the user

E-shop: Recurrent NN



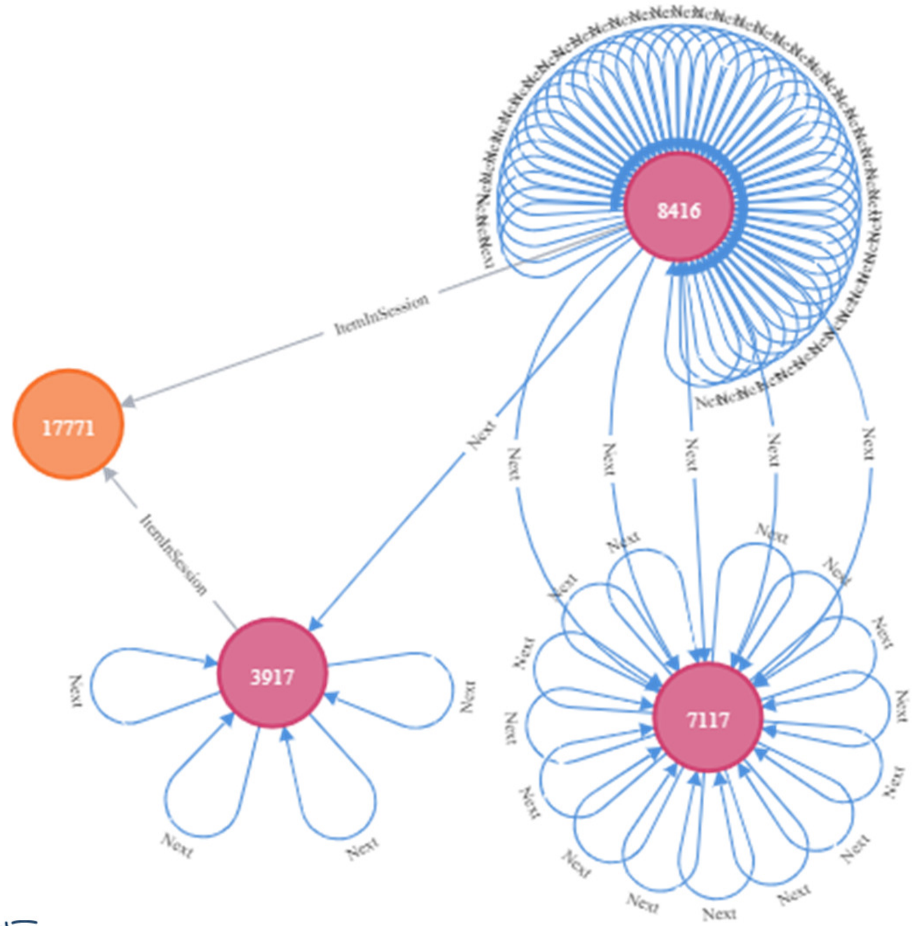
E-shop: Item2Vec



Retail and E-shop results

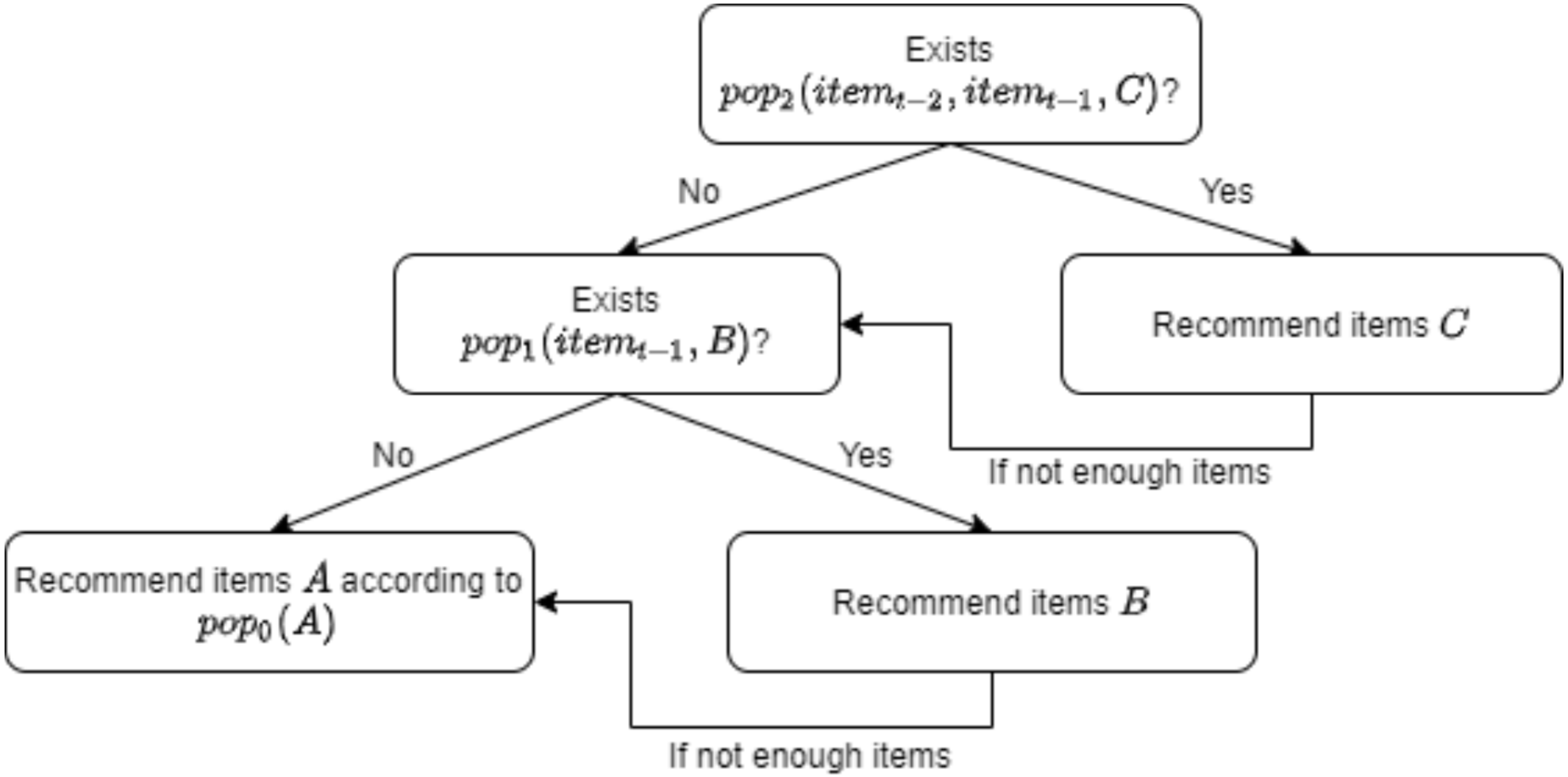
	Next-Item Recommendation (e-Commerce Site)		Next-Basket Recommendation Task (Almapet)	
Method	MRR/last	MRR/all	F1@2/7	F1@2/all *
Doc2Vec	0.101	0.062	0.154	0.114
Doc2Vec + reranking	0.123	0.079	0.143	0.105
Item2Vec	0.087	0.079	0.221	0.167
Item2Vec + reranking	0.111	0.093	0.182	0.148
Fusion method	0.112	0.078	0.216	0.167
Fusion method + reranking	0.126	0.089	0.184	0.151
LSTM (random init)	-	0.265	0.208	0.205
LSTM (Doc2Vec init)	-	0.268	0.218	0.219

Graph-based method: Hierarchical sequence popularity (HSP)



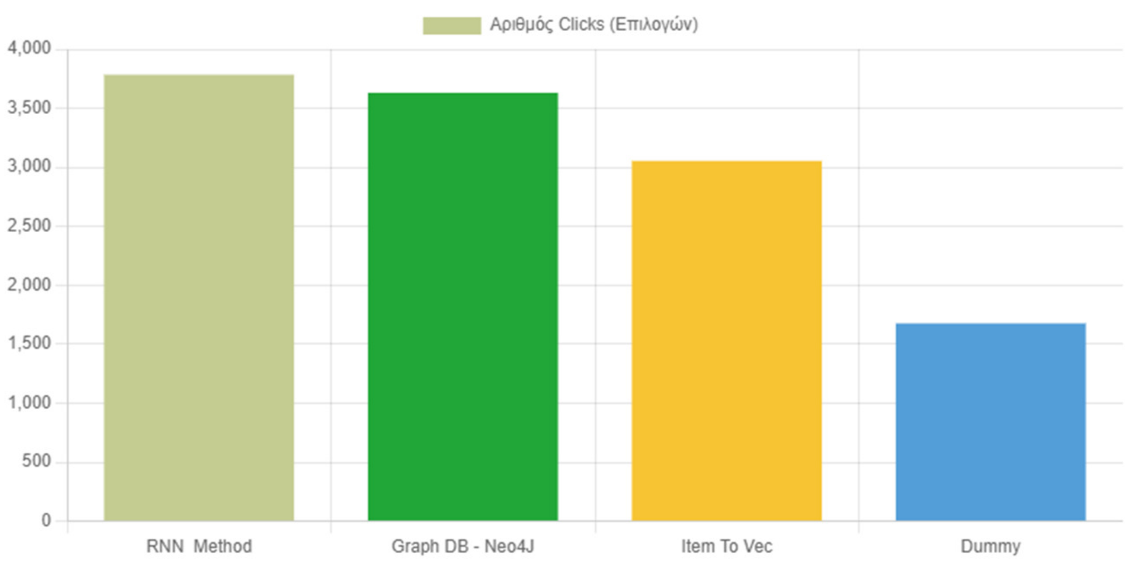
- Nodes:
  - Session
  - Items
- Relationships:
  - ItemInSession
  - Next

HSP


Exists
$pop_2(item_{t-2}, item_{t-1}, C)$?
No
Yes
Exists
$pop_1(item_{t-1}, B)$?
Recommend items C
No
Yes
If not enough items
Recommend items A according to $pop_0(A)$
Recommend items B
If not enough items

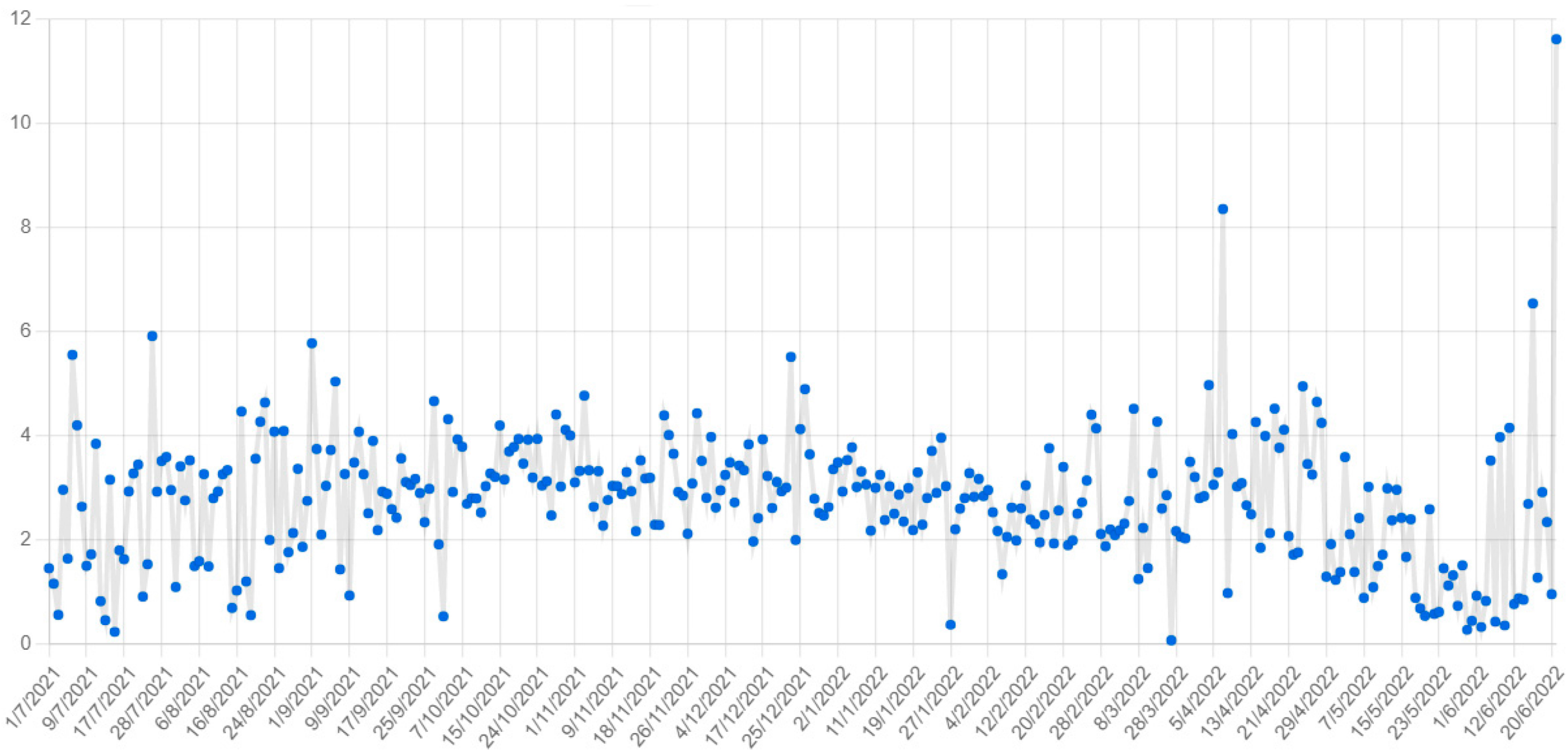
E-shop - Number of clicks

Algorithms from which we obtained clicks



RNN Method	**3784** clicks
Graph DB - Neo4J	**3631** clicks
Item To Vec	**3055** clicks
Dummy	**1676** clicks

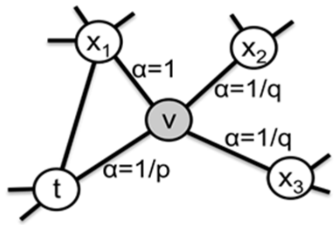
E-shop – click through rate



Web service

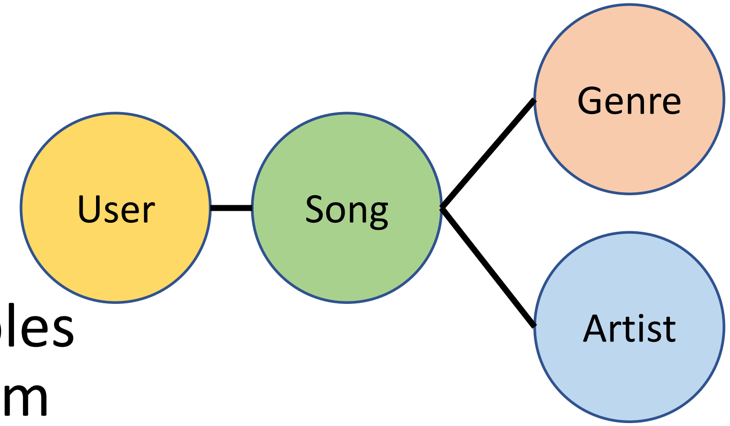
- Requirements:
  - ✓Know previous user history
  - ✓No demographics
  - ✓Know basic features of the items
- Example application: Ring Tone service
  - ✓Song title, Artist and Genre

Ring Tones: Graph-Based Recommendations



- Node2vec method
- Create random 2nd order paths from each node
- Path input in word2vec algorithm (skip-gram)
- Objects with similar characteristics acquire similar representations through this process.
- The final recommendation is obtained by comparing the final numerical representations of each node based on some distance metric, usually cosine similarity.

Ring Tones: Graph-Based Recommendations



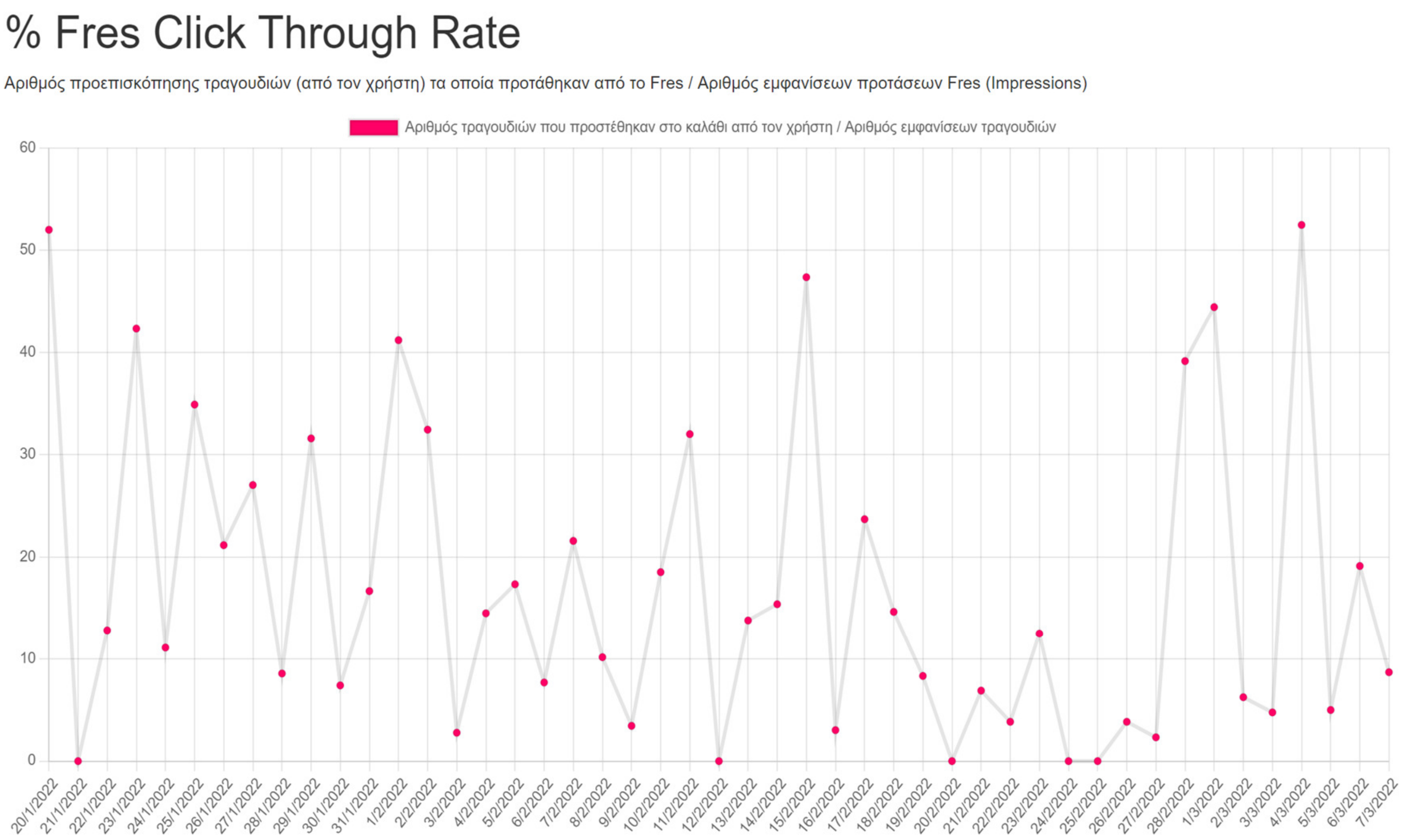
Nodes: **Songs** / Users / Artists / Genre

Original Dataset: 570.000 UserPack samples – The last interaction with each user's item is used as a test set (91,000 samples)

Results:

MRR	Length of Recommendation List	Empty results (total 91161)
0.017	1k	19080
0.020	2k	7652
0.022	3k	4015
0.026	5k	1429
0.030	10k	183

Ring tones recommendation performance



Conclusions

- LSTMs outperform embedding approaches in session-based next-item recommendations, requiring less tuning and effectively modeling e-commerce browsing behaviors.
- LSTMs performed slightly less effectively than Item2Vec in predicting the last basket, although they did surpass Word2Vec.
- Merging different recommendation approaches has yielded mixed results; custom, pluggable systems that dynamically select the best method could be more effective.
- Category-based re-ranking might help when recommender systems underperform.
- Efficiency and scalability, particularly with incremental training, remain challenging in large-scale applications and are subjects for future research.
- A key functional requirement for session-based recommendation systems (SBRS) in e-commerce is to integrate management-imposed business rules.

Recommending educational material

What is an Education Recommendation system?

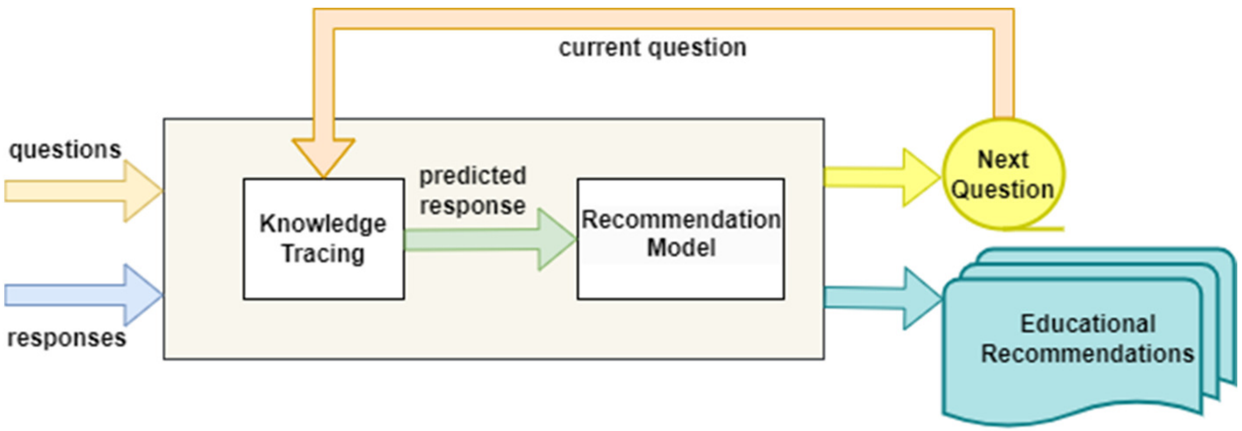
- An education recommendation system is a software tool designed to suggest educational content, such as courses, materials, videos, and problems, to learners based on various criteria.
- Data: user's past behavior, performance, preferences, and sometimes demographic information
- Primary objective: to enhance learning outcomes by making the educational experience more relevant and effective.

Education RS vs. E-commerce RS

	Education RS	E-commerce RS
Objective	enhance learning outcomes by identifying and addressing knowledge gaps	maximizing sales and customer satisfaction
Data	test scores, quiz results, assignment grades	browsing history, purchase history, item ratings, user demographics
Impact	long-term implications for a learner's educational trajectory and knowledge acquisition	short-term, influencing immediate purchasing decisions and customer retention strategies
Adaptivity	Must adapt to the changing knowledge state of the learner	focus is less on user change over time and more on maximizing immediate sales opportunities

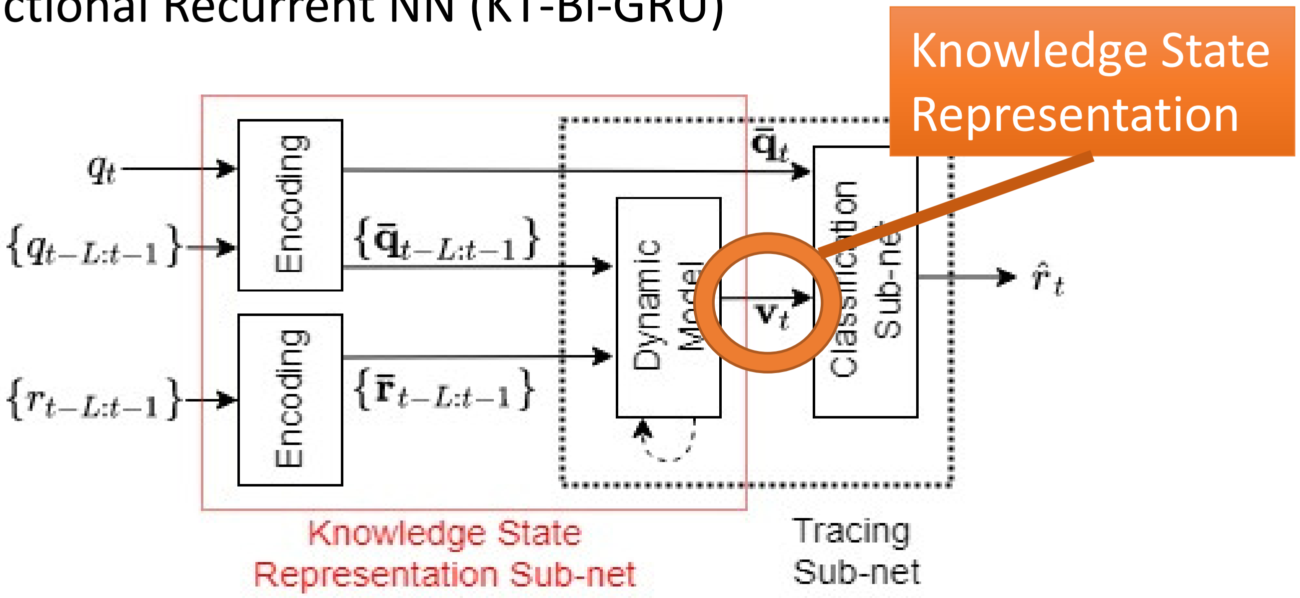
Introducing DK-PRACTICE

- "DK-PRACTICE" (Dynamic Knowledge Prediction and Educational Content Recommendation System) is an intelligent online platform that uses machine learning to offer personalized learning recommendations.
  - Students begin with a short, adaptive assessment on key concepts in a specific knowledge domain.
  - The system selects questions dynamically based on the accuracy of previous answers.



Knowledge tracing

- KT: The method used to model and track the knowledge state of learners over time as they interact with instructional content. Plays a critical role in adaptive learning systems and intelligent tutoring systems.
- KT using Bidirectional Recurrent NN (KT-Bi-GRU)

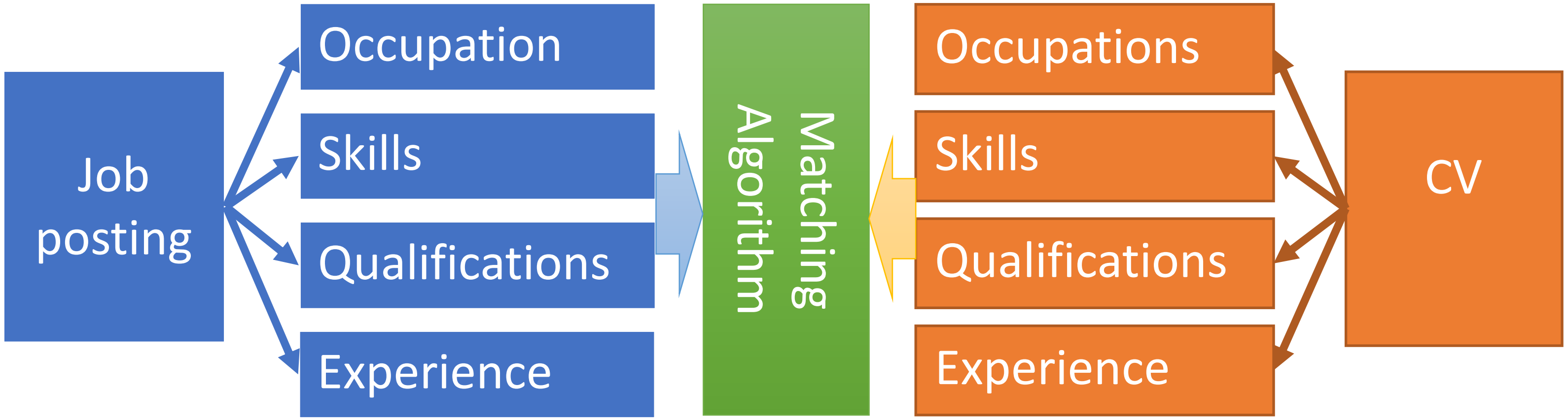


DK-PRACTICE

- **Personalization**
  - Post-assessment, DK-PRACTICE recommends tailored learning materials to address knowledge gaps.
  - Recommendations and question selections are powered by machine learning models trained on anonymized real-world data.
- **Self-Assessment and Monitoring**
  - Students can take pre- and post-teaching tests to monitor learning progress.
  - Detailed reports and visualizations of progress are provided after each test.
- **Benefits**
  - Promotes adaptive learning tailored to individual student needs.
  - Provides instructors with valuable insights into student knowledge levels.

Recommending jobs

Job recommendations

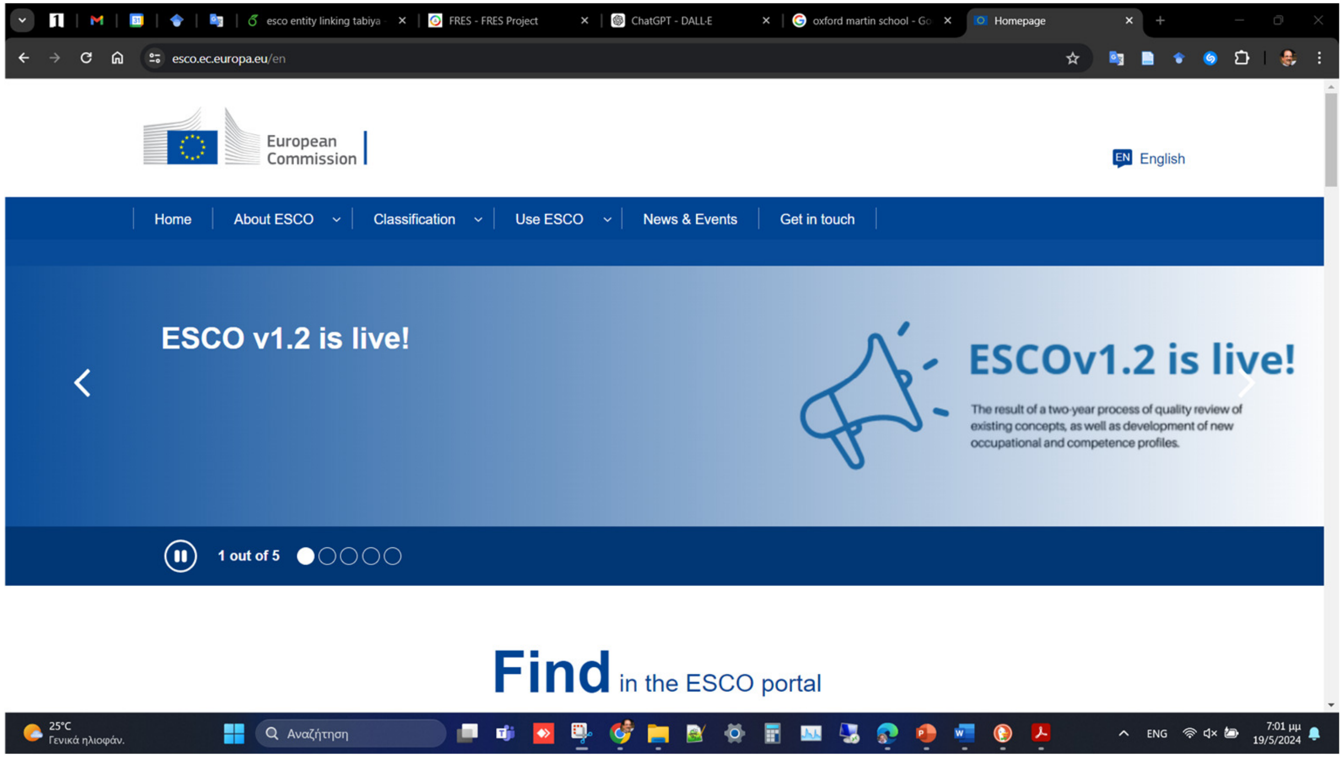


Job linking

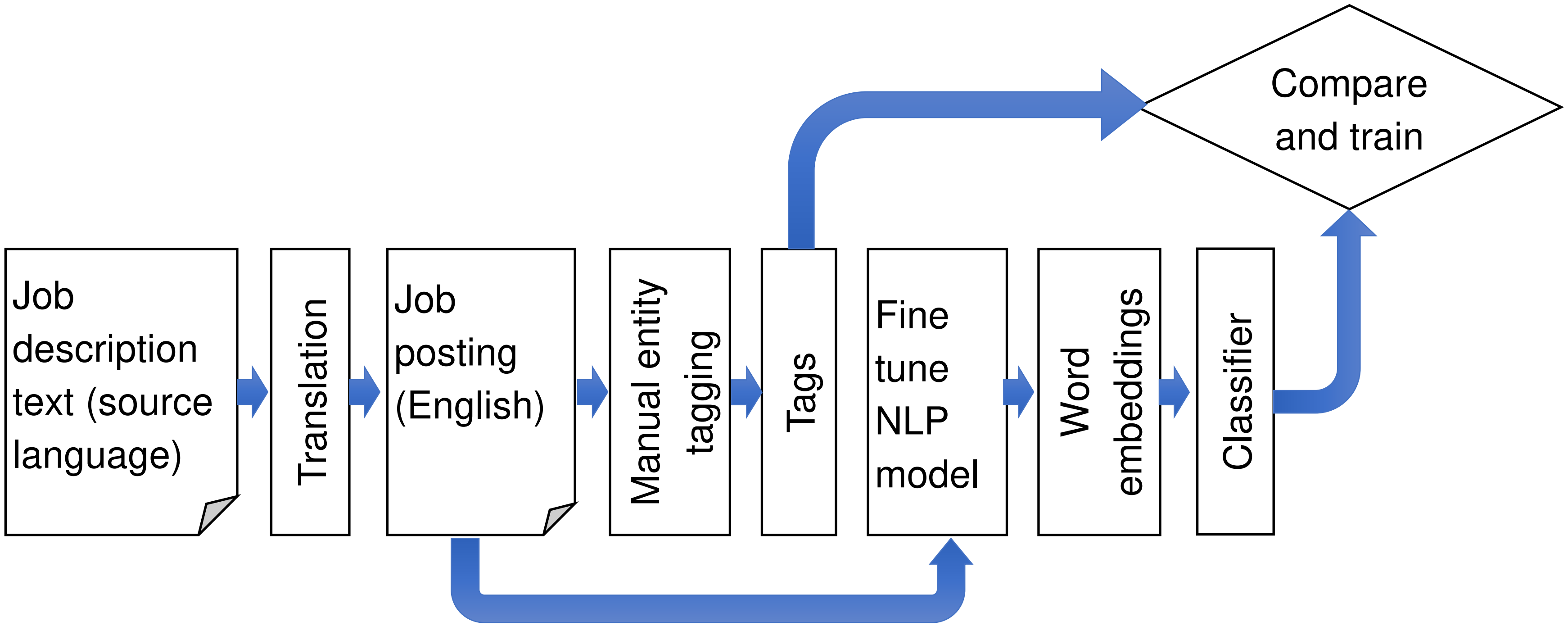
- Intelligent Platform for Job Analysis And Skill Matching
- Funded by OXFORD MARTIN SCHOOL
- Task: extract entities relating to Occupations, Skills and Qualifications from job description text and then assign them to corresponding taxonomies

ESCO taxonomy

- https://esco.ec.europa.eu/en



AI pipeline extracting entities



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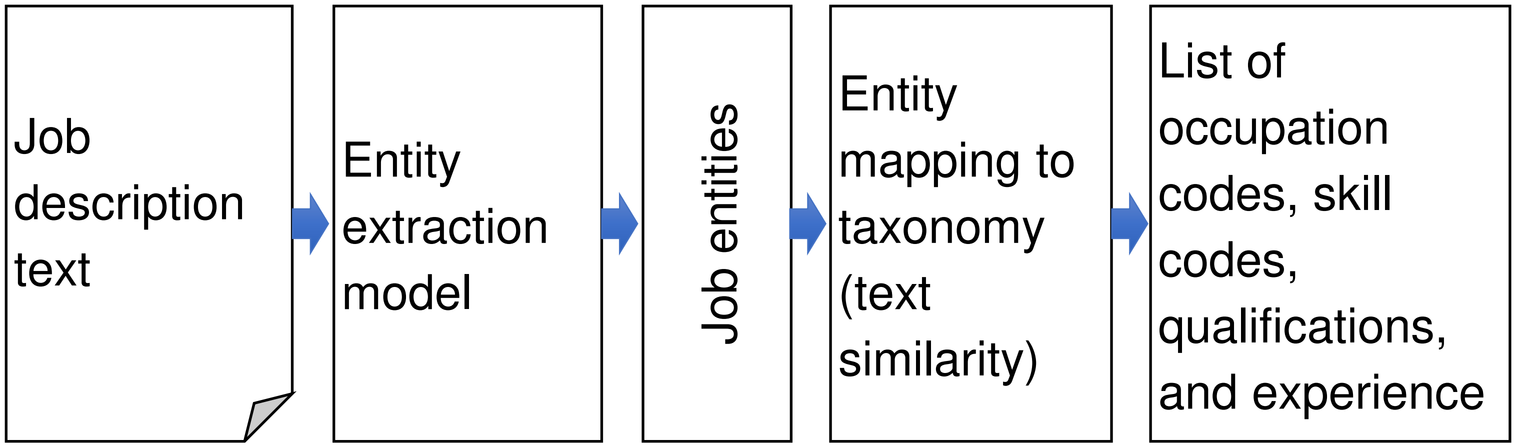
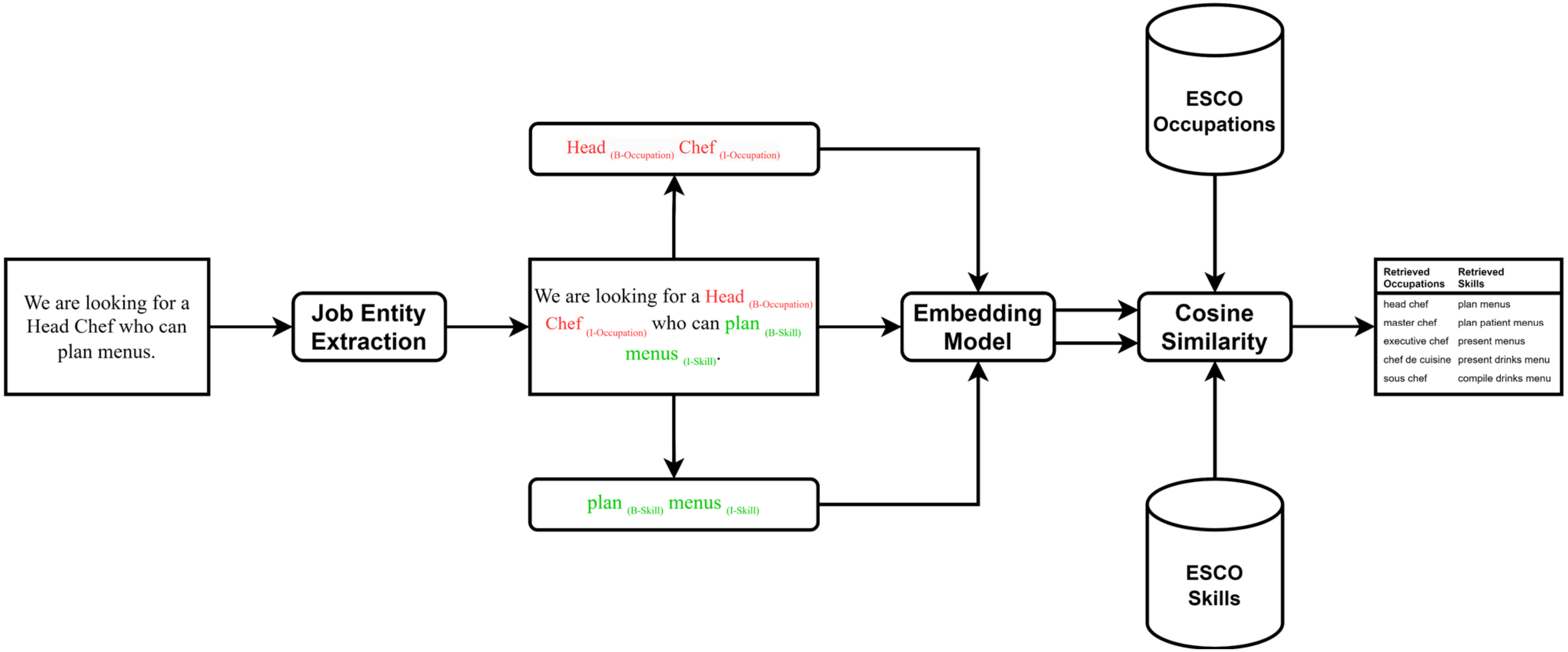


Entity Linker



Our contribution

- Provide a framework to analyze a job vacancy regarding the occupations, skills, and qualification information it contains
- Conducted a series of experiments in entity recognition for occupations, skills and qualifications based on the dataset released by Green et. al.
- Evaluated the performance of various BERT-based models on the entity recognition task
- Fine-tuned two specialized sentence transformer models to match occupation titles with the ESCO taxonomy. We provide the training and evaluation sets, which are based on the Ethiopian https://hahu.jobs/ platform
- Evaluate our methodology on the matching performance with respect to Occupations, Skills, and Qualifications.

	Entity Model	Similarity Model	MAP@1	MAP@5
Occupations	jjzha/jobbert-base-cased+CRF	all-MiniLM-L6-v2	0.373	0.231
	bert-base-cased+CRF	all-MiniLM-L6-v2	0.308	0.196
	roberta-large+CRF	all-MiniLM-L6-v2-FT	0.434	0.347
	roberta-base+CRF	all-MiniLM-L6-v2-FT	0.365	0.291
	roberta-large+CRF	all-mpnet-base-v2	0.369	0.235
	roberta-base+CRF	all-mpnet-base-v2	0.303	0.198
	roberta-large+CRF	all-mpnet-base-v2-FT	**0.467**	**0.390**
	roberta-base+CRF	all-mpnet-base-v2-FT	0.387	0.328
Skills	roberta-base+CRF	all-MiniLM-L6-v2	0.494	0.491
	jjzha/jobbert-base-cased+CRF	all-MiniLM-L6-v2	0.470	0.468
	deberta-base	all-MiniLM-L6-v2-FT	0.347	0.362
	deberta-base+CRF	all-MiniLM-L6-v2-FT	0.316	0.331
	roberta-base	all-mpnet-base-v2	**0.497**	**0.494**
	jjzha/jobbert-base-cased+CRF	all-mpnet-base-v2	0.474	0.466
	roberta-large+CRF	all-mpnet-base-v2-FT	0.330	0.345
	deberta-base	all-mpnet-base-v2-FT	0.295	0.312
Qualifications	jjzha/jobbert-base-cased+CRF	all-MiniLM-L6-v2	0.630	0.614
	roberta-base+CRF	all-MiniLM-L6-v2	0.618	0.606
	bert-large-cased	all-MiniLM-L6-v2-FT	0.582	0.556
	bert-large-cased+CRF	all-MiniLM-L6-v2-FT	0.567	0.537
	bert-large-cased	all-mpnet-base-v2	**0.640**	**0.630**
	roberta-base+CRF	all-mpnet-base-v2	0.623	0.615
	jjzha/jobbert-base-cased	all-mpnet-base-v2-FT	0.576	0.566
	bert-large-cased+CRF	all-mpnet-base-v2-FT	0.554	0.545

Demo – Entity linking

- file:///C:/Users/User/OneDrive%20-%20International%20Hellenic%20University/Code/NLPOxford_matching/client/client%20(2).html


THANK
YOU