A Survey on Neural Recommendation : From Collaborative Filtering to Content and Context Enriched Recommendation

Contents

What is Recommender system?

→ Serves as an effective solution to alleviate the information overload issue, to facilitate users seeking desired information, and to increase the traffic and revenue of service providers.

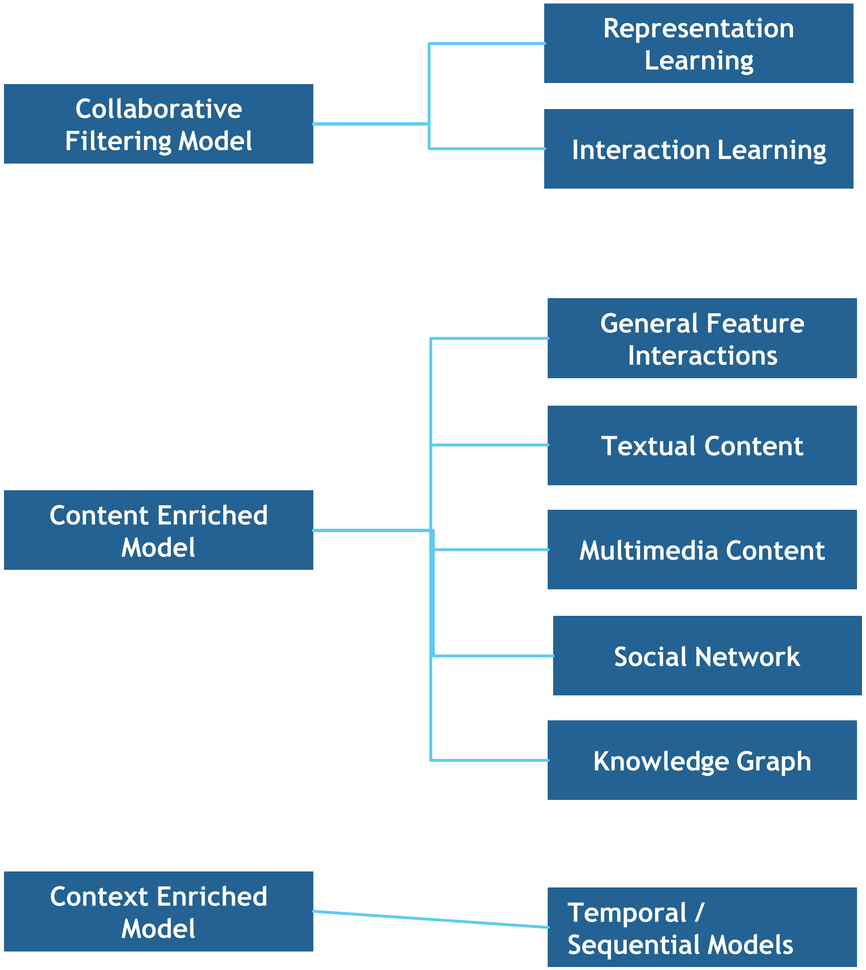
History

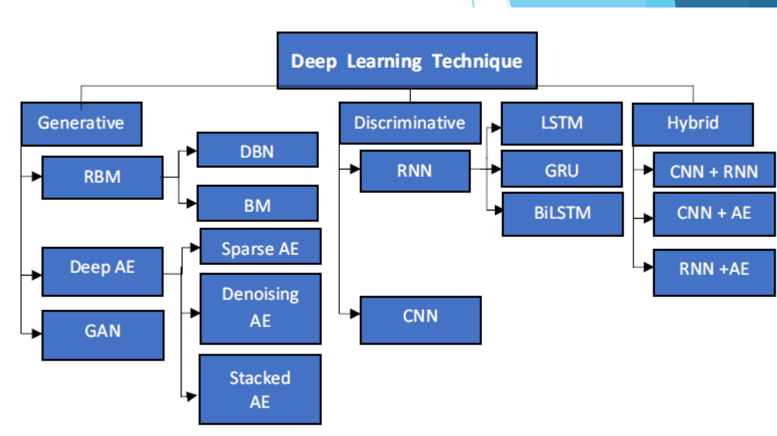
- Dated back to the 1990s when many “heuristics” for content-based and Collaborative Filtering (CF)
- From 2008 to 2016, Matrix Factorization (MF) later becomes the mainstream (Netflix Challenge)
  → less effective when dealing with large and complex data.
- Emergence of deep learning and neural network allow to process large data with complicate patterns.
  → brings advance of recommendation technologies .

Aim of this survey

- To give a overview of recommender models that use neural networks
- Distinct from existing surveys that categorize existing methods based on the taxonomy of deep learning techniques, this survey instead summarizes the field from the perspective of recommendation modeling.

Neural Recommender Categorization





*Categorization based on Deep Learning Techniques

Collaborative Filtering Models

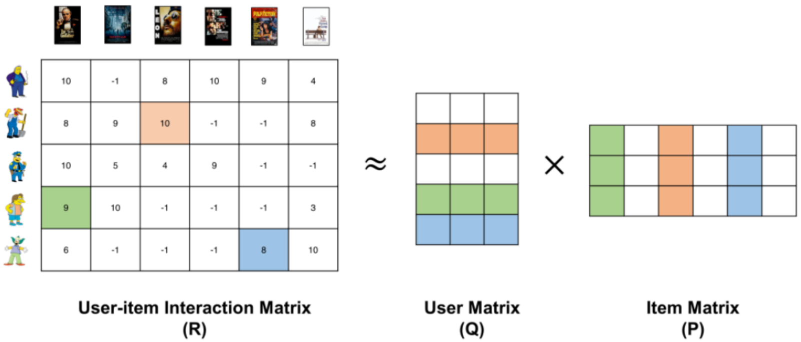
- Leverage the collaborative behaviors of all users for predicting the behavior of the target user
- Early model : user-based CF / item-based CF / MF (Matrix Factorization)

  → limited prediction power due to its simply linear modeling ability
- Categorized into representation learning, interaction modeling

※ Why Neural?

Early MF model → Simple and Linear

Hard to catch non-linear relations and complex patterns of interaction between user and item



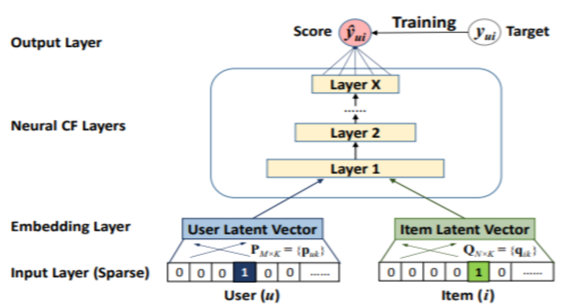


Figure 2: Neural collaborative filtering framework

Collaborative Filtering Models

1. Representation Learning

The objective of representation learning in CF is to find the accurate user-item interaction behavior matrix

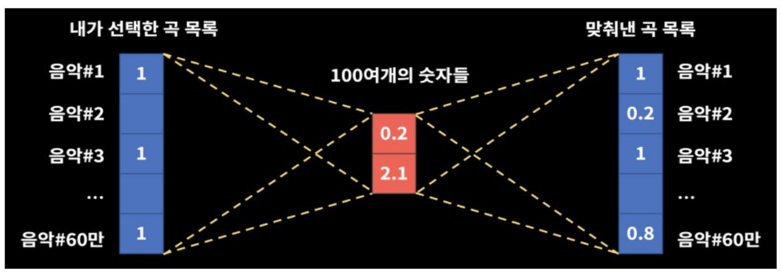
- History behavior aggregation enhanced models

- Borrowing users' historical behavior for better user representation modeling

Attentive Collaborative Filtering (ACF)	Neural Attentive Item Similarity (NAIS)
Assign item with attentive weight	Consider the historical item to user representation

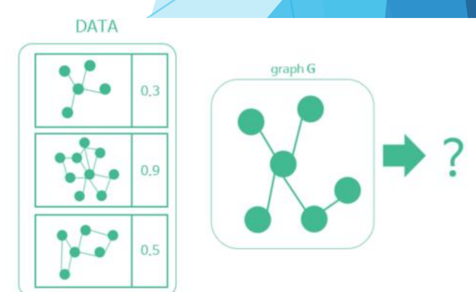
- Autoencoder based models

Incomplete user-item matrix (input) → Hidden representation (learn) → Reconstruct (prediction)



Melon music recommender system based on Autoencoder model

Graph Neural Network (GNN)
Neural models that capture the dependence of graphs via message passing between the nodes of graphs



- Graph learning approaches

- Use graph structure for better representation learning
- Graph Neural Networks (GNN) for modeling graph structure data

Collaborative Filtering Models

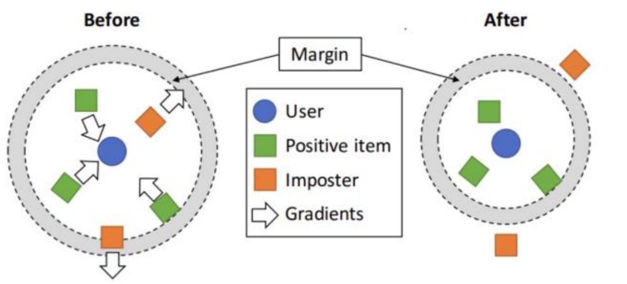
2. Interaction Modeling

- Classical inner product based approaches

  - Only encourage the representations of users and historical items to similar
  - Lack of considering similarity between user-user and item-item relationships
  - Linear models → fail to capture complex interactions

- Distance based Metrics

  - Use distance metric as the interaction function.
  - Collaborative Metric learning (CML)

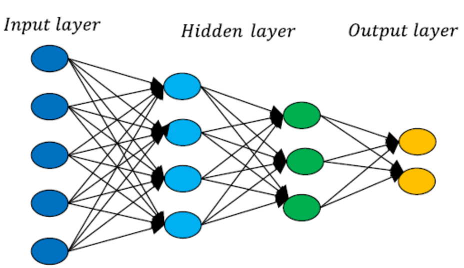


Collaborative Metric Learning (CML)

- Neural network based Metrics

  - Recent works adopt a diverse array of neural architectures to mine complex and non-linear patterns of user-item interactions (MLP, CNN, AE)

Fig. 7 A structural representation of the MLP model with two hidden layers



Multi Layer Perception (MLP)

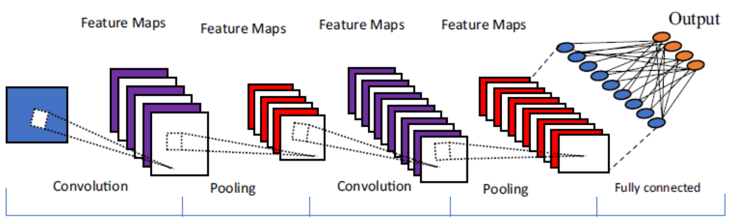


Fig. 5 The structure of the CNN architecture

Convolutional Neural Network (CNN)

Content-enriched Recommendation

Content based information	Context-aware data
Associated with user and items - General user and item features - Textual content ex) item tags, item textual descriptions and users' reviews for items) - Multimedia descriptions ex) images, videos and audio information - User social networks - knowledge graphs.	Shows environment when users make item decisions. Ex) time, location, and specific data that are collected from sensors(speed and weather), and so on.

General Feature Interactions | Textual Content | Multimedia Content | Social Network | Knowledge Graph

Content-enriched Recommendation

1. Modeling General Feature Interactions

→ Factorization Machine (FM) is most generally used but it faces complexity when features added

Feature vector **x** | Target y

	User				Movie					Other Movies rated					Time	Last Movie rated					Target y	
	A	B	C	...	TI	NH	SW	ST	...	TI	NH	SW	ST	...	Time	TI	NH	SW	ST	...		
$x^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$x^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$x^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(2)}$
$x^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(3)}$
$x^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(4)}$
$x^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(5)}$
$x^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$

To solve complexity →

- MLP based High Order Modeling : Multi-layer perception
- Cross Network for K-th Order Modeling
- Tree Enhanced Modeling

2. Modeling Textual Content

- Based on Natural Language Processing (NLP)
- Use content descriptions associated with items such as users' tags to items, or reviews for products.

- Autoencoder based Models : Use autoencoders to learn the bottleneck hidden content representations of items.
- Word Embeddings : Leverage word embedding techniques for better content recommendation
- Attention Models : Assign attentive weights to different pieces of content.
- Text Explanations for Recommendation : Providing text explanations for recommendation.

Content-enriched Recommendation

3. Modeling Multimedia Content

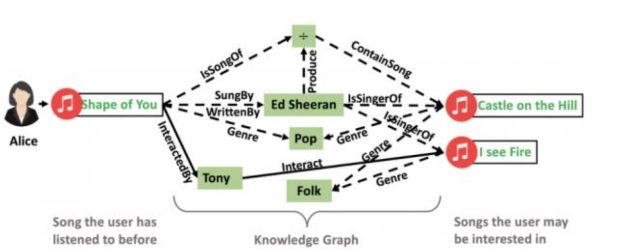
- Image Content based Models : Exploit visual signals for constructing item visual representations.
- Hybrid Recommendation Models : Use both the collaborative signals and the visual content for recommendation.
- Video Recommendation : content based video recommendation models

4. Modeling Social Network

- Social Correlation Enhancement and Regularization : With users' social behavior as social domain, item preference behavior as the item domain, this model try to fuse two behaviors from two domains in a unified representation.
- GNN Based Approaches : each user is influenced recursively by the global social network graph structure. GNN based models to better model the global social diffusion process for recommendation.

5. Modeling Knowledge Graph

- Path Based Models : find path that present high-order connectivity between users and items, then feed them into predictive models to directly infer user preferences.
- Regularization Based Models
- GNN Based Methods



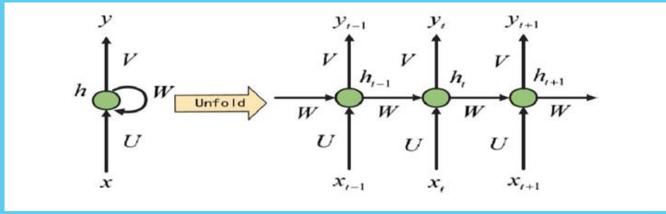
Temporal / Sequential Models

Focus on modeling users' dynamic preferences or sequential patterns over time.

1. Temporal based recommendation

- Focus on capturing the temporal evolution of users' preference over time.
- Recurrent Recommender Networks (RRN) is one of the representative works.

RNN ?
specifically used to model sequential data by simply incorporating temporal layers to capture sequential information



2. Session Based recommendation

- Deal with short session data from anonymous users. models the sequential item transition patters given many session records.

3. Temporal and session based recommendation

- Consider both temporal evolution and sequential item patterns

Metrics for RS Performance Evaluation

Rating prediction metrics	Classification accuracy metrics	Ranking Metrics
Measure the extent at which the RS can predict the rating of users towards items	Assess the extent at which the RS correctly classify items based on the user's interest	Measure the performance of RS in providing a recommendation of an ordered list of items to users in the case where the order of the items on the list is significant.
MSE (Mean Squared Error) RMSE (Root Mean Squared Error) MAE (Mean Absolute Error)	Recall Precision F1 score AUC (Area under the curve)	Normalized-discounted-cumulative gains (NDCG) Hit ratio (HR) Mean Reciprocals Ranks (MRR) Mean average precision (MAP)

Conclusion and Future Direction

Possible Directions for recommendation

- Basics : Recommendation Benchmarking
- Models : Graph Reasoning based Recommendation
- Conversational Recommendation
- Multi-Objective Goals for Social Good Recommendation

References

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[2] Da'u, A., & Salim, N. (2019). Recommendation system based on deep learning methods: A systematic review and new directions. *Artificial Intelligence Review*, *53*(4), 2709–2748.