Neural Collaborative Filtering and Side Information

STAT3009 Recommender Systems

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» Recall: Neural Networks

Using TF2.0 to Implement Your Own Model

- M Define your Model mathematically
  - Motivation, EDA, input/output, parameters/hyperparameters, etc.
- T Translate your model into a neural network
- F Loss function, regularization
- OPT Optimizer, cross-validation, early stopping, etc.

Implementation

- Build Define the model using **Keras**
  - Layers and path from input to output
- Compile Compile your model with keras.losses, keras.optimizers, and keras.metrics
- Fit Train your model with data and hyperparameters
- Pred Make predictions using model.predict

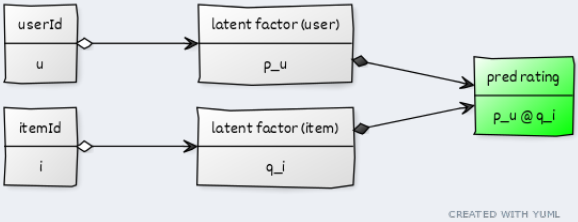
Can we reformulate MF as a neural network?

» Steps: MF to NN

- **MF model:**

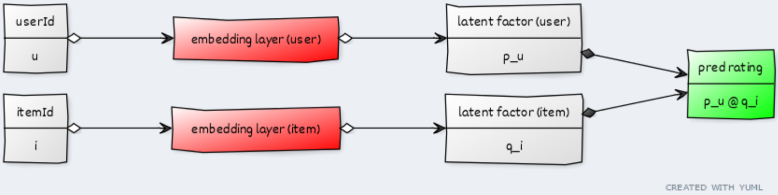
$$\widehat{r}_{ui} = \mathbf{p}_u^\intercal \mathbf{q}_i$$

  - Input user-item pair: $(u, i) \to$ Output inner product: $\mathbf{p}_u^\intercal \mathbf{q}_i$
- **Translate** your model to a neural network



The key is to map userId/itemId to latent factors. Do we have a layer to perform this mapping? YES!

» What: Embedding Layer



We can incorporate **MF** by introducing embedding layers into the network.

An embedding layer:

Input A categorical feature $j \in \{1, \cdots, J\}$

Output A latent factor for the input $\mathbf{w}_j \in \mathbb{R}^r$

Example **userId** $u \to$ **latent factor** $\mathbf{p}_u$

» What: Embedding Layer

```
tf.keras.layers.Embedding(
   input_dim,
   output_dim,
   embeddings_regularizer=None,
   activity_regularizer=None,
   embeddings_constraint=None,
   **kwargs)
```

Key Arguments:

input_dim J - Integer. Size of the vocabulary, i.e., maximum integer index + 1.

output_dim r - Integer. Dimension of the dense embedding.

» How: Embedding Layer

Steps for the embedding layer:

One-hot Encode cate_feat as one-hot encoding (a binary dummy vector)

$$j \rightarrow \mathbf{e}_{J,j} = (0, \cdots, \underbrace{1}_{j\text{th}}, \cdots, 0)^\intercal \in \{0,1\}^J,$$

Mapping Map one-hot encoding to a latent factor using the embedding matrix

$$j \rightarrow \mathbf{w}_j = \mathbf{e}_{J,j}^\intercal \mathbf{W},$$

Essentially, embedding is the same as latent factors; they are just different names.

» NCF: Embedding Layer

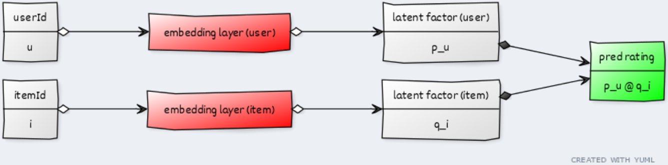
Let's summarize the Embedding Layer...

Mapping $u \rightarrow \mathbf{p}_u$, or cate_feat $\rightarrow$ dense representation

Params Embedding matrix: #Users (or #Items) $\times$ #LatentFactors

hp #LatentFactors or embedding size

M The model becomes



F The formulation becomes:

$$\hat{f}_\theta = \underset{f_\theta}{\text{argmin}} \ \frac{1}{|\Omega|} \sum_{(u,i)\in\Omega} (r_{ui} - f_{\boldsymbol{\theta}}(u,i))^2 + \lambda \text{Reg}(\boldsymbol{\theta})$$

code Demo in Colab

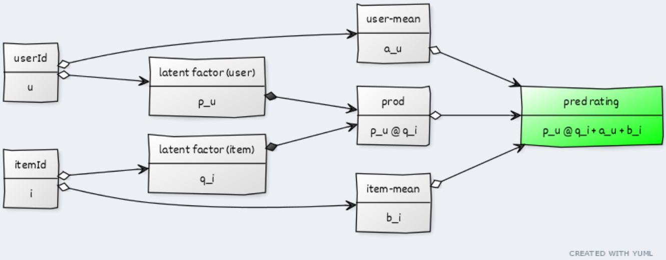
» In-Class Practice

In-class practice:

M MF-mean Model:

$$\widehat{r}_{ui} = \mathbf{p}_u^\intercal \mathbf{q}_i + a_u + b_i$$

NN-view From a neural network perspective:



» NCF: Nonlinear Interaction

Incorporating neural networks to model **high-order** interactions between users and items.

M Model:

Input User-item pair $(u, i) \in \{1, \ldots, n\} \times \{1, \ldots, m\}$

Output Predicted rating

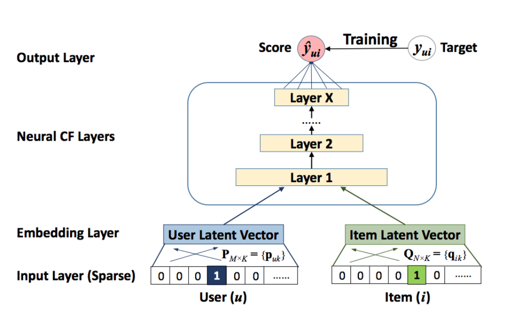
Math

$$\widehat{r}_{ui} = \phi(\mathbf{p}_u, \mathbf{q}_i),$$

where $\phi(\cdot)$ is a nonlinear function

» NCF: RS Formulation

Model The NCF model is illustrated as:



[1]

Params All parameters in the network include: (i) two embedding matrices in the embedding layers and (ii) weights in the other layers

hp Embedding size and network architecture

[1] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., and Chua, T. S. (2017, April). Neural collaborative filtering. In Proceedings of the 26th International Conference on World Wide Web (pp. 173-182).

» NCF: Implementation

Data $(u, i) \rightarrow r_{ui}$

Loss Mean Squared Error (MSE)

Metrics RMSE, MAE, etc.

Opt SGD/Adam

InClass demo: Neural Collaborative Filtering #1 in Colab

» ANCF: Additional Formulation

Motivation (from additive semi-parametric model)
The main effect is captured by first-order MF interaction; we then introduce additional latent factors to model higher-order interactions.

Model We aim to retain the MF terms in the model:

$$\widehat{r}_{ui} = \mathbf{p}_u^\intercal \mathbf{q}_i + \phi\left([\mathbf{s}_u, \mathbf{t}_i]\right)$$

» ANCF: Additional Formulation

Model We aim to retain the MF terms in the model:

$$\widehat{r}_{ui} = \mathbf{p}_u^\intercal \mathbf{q}_i + f([\mathbf{s}_u, \mathbf{t}_i])$$

Parameters All parameters in the network include: (i) **two** embedding matrices in the embedding layers and (ii) **weights** in the other layers.

rparameters Embedding size and network architecture

InClass demo: Neural Collaborative Filtering #2

» Neural-NCF: Neural Formulation (Optional)

More general operators based on MF terms:

* Without assuming a **additive** structure
* Interaction between first-order and higher-order interactions

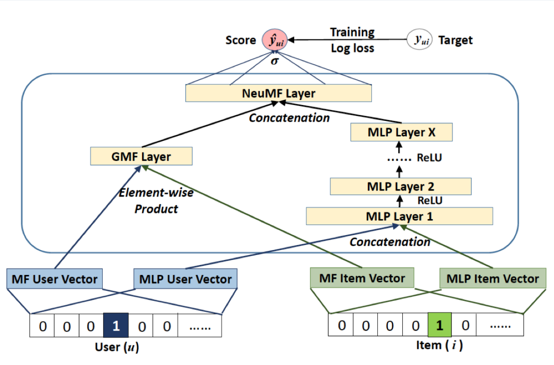
$$\widehat{r}_{ui} = \phi\left([\mathbf{p}_u \circ \mathbf{q}_i, \psi([\mathbf{s}_u, \mathbf{t}_i])]\right),$$

where ϕ and ψ are custom nonlinear functions.

» Neural-NCF: Neural Formulation (Optional)

* **Transform** the model into a neural network:

$$\widehat{r}_{ui} = \phi\left([\mathbf{p}_u \circ \mathbf{q}_i, \psi(\mathbf{s}_u, \mathbf{t}_i)]\right)$$



[2]

[2] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., and Chua, T. S. (2017, April). Neural Collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web (pp. 173-182).

» NCF: RS formulation (Optional)

Model The model becomes

$$\widehat{r}_{ui} = \phi\left([\mathbf{p}_u \circ \mathbf{q}_i, \psi(\mathbf{s}_u, \mathbf{t}_i)]\right)$$

Params All params in the network: (i) four embedding matrices in embedding layers and (ii) weights in the other layers

hp embedding size and network architecture

Data $(u, i) \to r_{ui}$

Loss MSE

Metrics RMSE, MAE, ...

Opt SGD/B-SGD

InClass demo: Neural collaborative filtering #3

» MF: Cold-Start Issue

Cold-Start Issue:

Problem Completely new users/items in recommender systems

Prediction Existing methods:

- User/Item-Average Unable to compute a meaningful average
- Correlation Cannot compute distance
- MF/SVD For example, if user u has no ratings in the system ($\mathcal{I}_u = \emptyset$):

Conclusion For cold-start users/items, most existing methods **fail** to provide a solution.
We NEED side information!

» MovieLens: Side Information

YES, we have side information.

For example, in the MovieLens dataset:

- User: USER_ID, AGE, GENDER, OCCUPATION, ZIP_CODE, RATING_MEAN, RATING_COUNT, RATING_QUANTILE, etc.
- Item: ITEM_ID, DATE, GENRE, RATING_MEAN, RATING_COUNT, RATING_QUANTILE, etc.
- Other: DATE

Key Message:

* Exploratory Data Analysis (EDA) in MovieLens indicates that side information is critical.
* Side information is promising for solving cold-start issues.
* How to incorporate side information to build a new recommender system.

» Conclusion from EDA (MovieLens)

Insights from EDA in MovieLens:

* **Side information** or user/item features are critical for predicting ratings: $f(\mathbf{x}_u, \mathbf{z}_i) \to r_{ui}$
* Personalization/itemization remains important even for users/items with similar features—MF terms are necessary: $f(\mathbf{x}_u, \mathbf{z}_i) + \mathbf{p}_u^\intercal \mathbf{q}_i \to r_{ui}$

→ **Joint effect** of features should be considered in recommender system modeling:

$$f\big(\mathbf{p}(u, \mathbf{x}_u), \mathbf{q}(i, \mathbf{z}_i)\big) \to r_{ui}$$

» MovieLens: Side Information

Update our setting:

Rating		[userID, itemID, rating]: (u, i, r_{ui})
Side Info	User	[continuous_features, categorical_features]
	Item	[continuous_features, categorical_features]
Examples	Continuous	[AGE, RATING_MEAN, RATING_COUNT, RATING_QUANTILE]
	Categorical	USER_ID + [GENDER, OCCUPATION, ZIPCODE]
Train		[userID, itemID, userFeatures, itemFeatures, rating]
Test		[userID, itemID, userFeatures, itemFeatures, ?]

» Pre-processing: Side Information

Cont **Continuous Features**

- Type → float
- Process Standardize features
- Python SKLEARN.PREPROCESSING.STANDARDSCALER

Cate **Categorical Features**

- Type → int
- Process Label encoding
- Python SKLEARN.PREPROCESSING.LABELENCODER

Cont/Cate **Can be continuous or categorical**

- Example "year" in item_feature
- EDA Use EDA to decide: continuous effect or group effect
- Both Or include in both

» Missing Data and Imputation (Optional)

	item_id	count	mean	gene	year	month
266	267	3	2.666667	unknown	NaN	NaN

Python Sklearn: Imputation of Missing Values[3]

Methods Approaches to impute missing values

Univariate Mean (continuous); Most frequent (categorical), etc.

Multivariate IterativeImputer, etc.

[3] https://scikit-learn.org/stable/modules/impute.html

» Continuous/Categorical Features

Cont Continuous features can be directly used as inputs.

Cate Utilizing categorical features;

Recall the concept of **Matrix Factorization (MF)**:

id USER_ID $\rightarrow \mathbf{p}_u$ ITEM_ID $\rightarrow \mathbf{q}_i$

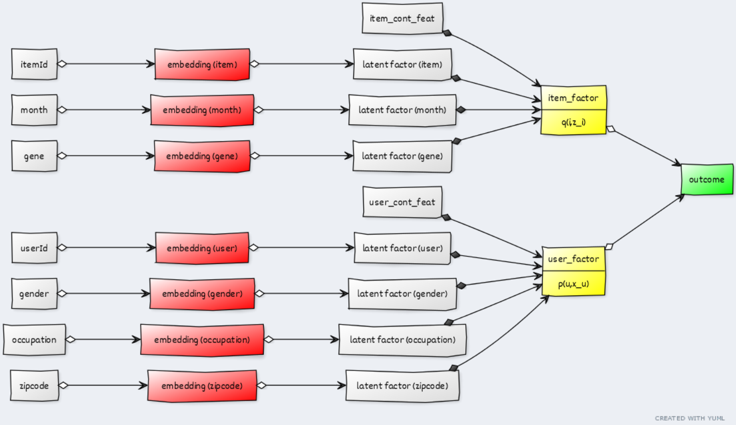
We can apply the **MF** approach to other categorical features, illustrated here with gender.

Encoding M $\rightarrow 0$, F $\rightarrow 1$
(SKLEARN.PREPROCESSING.LABELENCODER)

Embedding M $\rightarrow 0 \rightarrow \mathbf{w}_0$; F $\rightarrow 1 \rightarrow \mathbf{w}_1$

» LinearRS

Plot **Network:**



Code **Implementation in Colab**

» Two-tower neural nets: overview

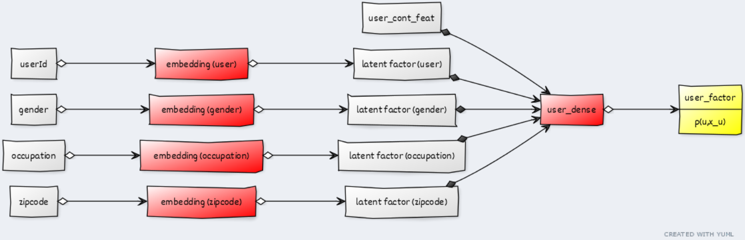
Motivation:

nl **nonlinear** modeling for features
within&btw user/item feats

effect **with-in** effects of user/item features:
E.g. (GENDER + OCCUPATION) @ ITEMID $\rightarrow$ rating

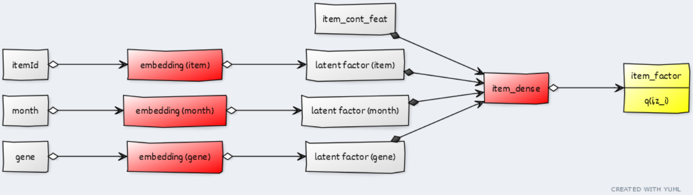
» Two-tower neural nets: user-tower

Plot **user-tower**



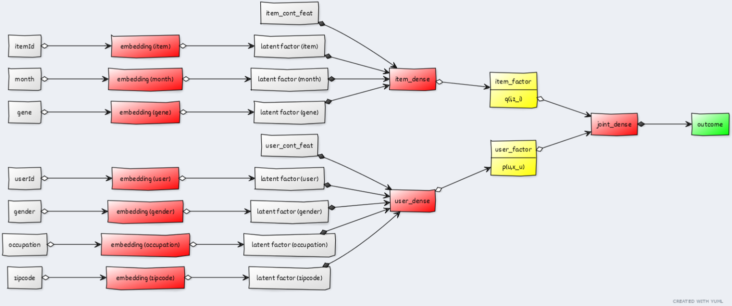
» Two-tower neural nets: item-tower

Plot **item-tower**



» Two-tower neural nets

Plot Dense layer to model the joint effect:



M The final formulation is given as:

$$\rho\left(\mathbf{p}(u, \mathbf{x}_u), \mathbf{q}(i, \mathbf{z}_i)\right) \to r_{ui}$$

» Side information in industry

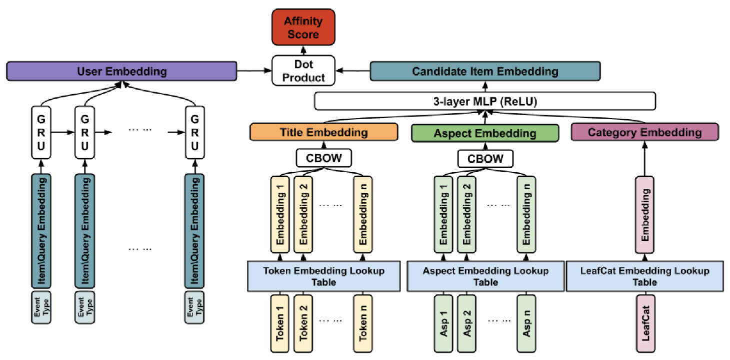
Text	Searching query; reviews; description; comments;
Image	profile for users; images for items;
Network	social network for users; item networks
Dynamic	behavior sequence; historical series

The general idea is mapping side information as numerical vectors, and feed into a two-tower based model.

Text	$\rightarrow$ embedding; Word2Vec; recurrent layers
Image	$\rightarrow$ convolutional layers
Network	$\rightarrow$ embedding; Node2Vec; graph convolutional layers

» Two-tower models in industry

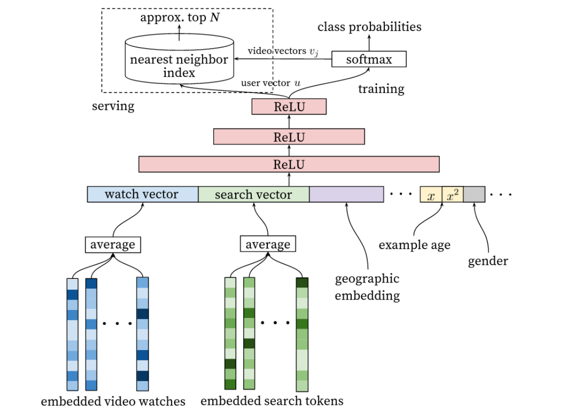
eBay **Model**



Ref Wang, T., Brovman, Y. M., & Madhvanath, S. (2021). *Personalized embedding-based e-commerce recommendations at ebay.*

» Two-tower models in industry

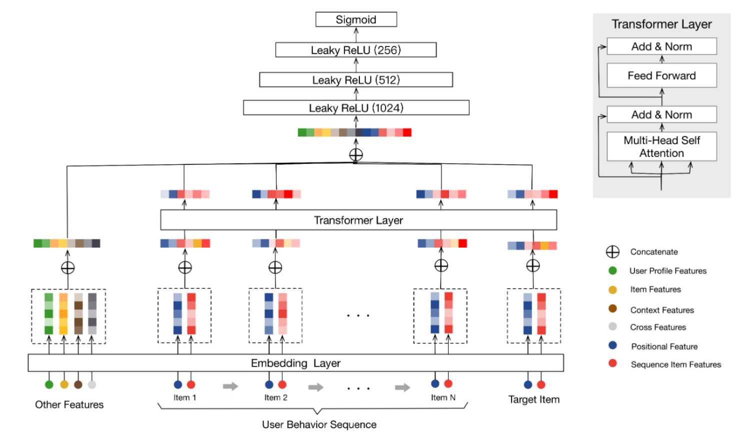
Youtube **Model**



Ref Covington, P., Adams, J., & Sargin, E. (2016). *Deep neural networks for youtube recommendations.*

» Two-tower models in industry

Alibaba **Model**



Ref Chen, Q., Zhao, H., Li, W., Huang, P., & Ou, W. (2019). *Behavior sequence transformer for e-commerce recommendation in alibaba.*

» Appendix: Embedding layers in NLP (Optional)

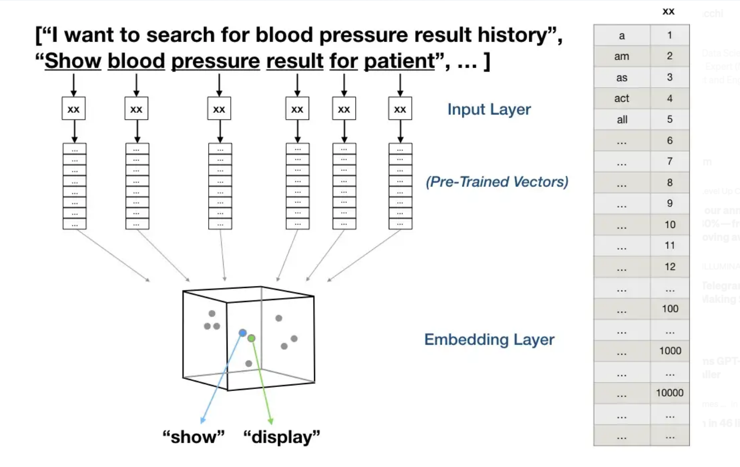
* **Embedding layers** is a fundamental tool for NLP tasks

Data Restaurant Review dataset

Training Examples	Labels
Simply loved it	Positive
Most disgusting food I have ever had	Negative
Stay away, very disgusting food!	Negative
Menu is absolutely perfect, loved it!	Positive
A really good value for money	Positive
This is a very good restaurant	Positive
Terrible experience!	Negative
This place has best food	Positive
This place has most pathetic serving food!	Negative

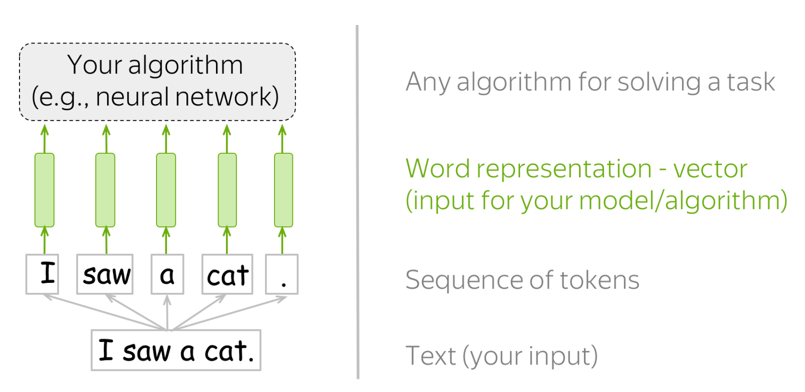
Goal Given textual reviews, can you provide a label to the review?

» Appendix: Embedding layers in NLP (Optional)



source: https://medium.com/@JMangia/coreml-with-glove-word-embedding-and-recursive-neural-network-part-2-ab238ca90970 tf.keras.Embedding(input_dim, output_dim, input_length)

- *input_dim* - #vocabulary: total number of words in dictionary
- *output_dim* - Embedding size: dimension of latent factors
- *input_length* - length of sentence/document
- All words share the same embedding layer



Embedding Using the embedding layer to convert Words to a Matrix; then mapping Matrix to a target Outcome

- Padding words with the same length
- Train and fit the model as a general network

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source: https://lena-voita.github.io/nlp_course/word_embeddings.html