Recommender systems with TensorFlow

Martin Jakomin
Jan Hartman

About us

Data scientists

Outbrain

Dr. Martin Jakomin

Jan Hartman

What do we do?

Outbrain Slovenia

- We develop and maintain the “brains” behind the purchasing of online ad space
- Choosing the right ad <-> recommender system!
- We use TensorFlow for real-time ML predictions (1 billion predictions per second)
- Involved in many other interesting things (conversion, bid win prediction, bid price control…)

J. Hartman, D. Kopič - Scaling TensorFlow to 300 Million Predictions per Second, RecSys '21.
J. Hartman, D. Kopič - Exploration with Model Uncertainty at Extreme Scale in Real-Time Bidding, RecSys '22.

Agenda, part 1

- Recommender systems paradigms and algorithms
    - Content-based filtering:
        - Item feature extraction
        - Similarity measures and distances
    - Collaborative filtering:
        - Memory based CF (user-user, item-item, hybrid)
        - Basic memory based algorithms (nearest neighbours, ...)
        - Model based CF - latent factors
        - Matrix Factorization
        - Factorization Machines
    - Deep learning for RS:
        - Deep Neural CF
        - Autoencoders & Deep autoencoders
        - DeepFM
- Recommender systems evaluation and metrics
- A short case study - YouTube recommendations

Agenda, part 2

- **TensorFlow**: basic concepts, tensors, autodiff
- Keras high-level API: layers, models, fitting & evaluation
- Matrix factorization implementation
- Deep autoencoder implementation
- Bonus challenge

Repo link: github.com/janhartman/recsystf

Recommender Systems
An Overview

Introduction

- We often make choices in life without sufficient personal experiences, thus we heavily rely on recommendations.
- Recommender systems (RS) are tools that assist and augment this natural decision making process.

Introduction

- RS are large-scale machine learning and knowledge discovery tools aimed at providing **personalized** recommendations.
- Examples: videos, movies and songs, web pages, articles, ads, books, social media posts, products, services ...
- In terms of **machine learning** problems:
  - estimation of user ratings (matrix completion or regression),
  - picking topN items (ranking),
  - picking new unfamiliar items (novelty, diversity).

Paradigms And Algorithms

Typically we split RS into three categories:

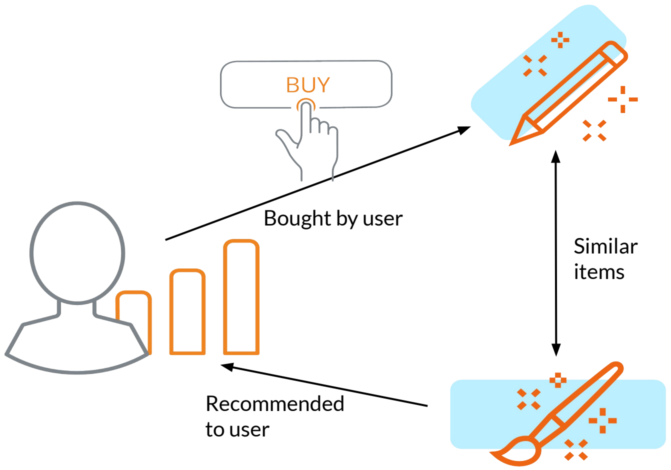
- ***Content-based filtering*** (where the user is recommended items similar to the ones he preferred in the past),
- ***Collaborative filtering*** (where the user is recommended items that people with similar tastes and preferences liked in the past),
- ***Hybrid approaches*** (that combine collaborative and content-based methods).

Bobadilla, Jesús, et al. "Recommender systems survey." *Knowledge-based systems* 46 (2013): 109-132.

Content Based Filtering

Content-based Filtering

- Recommendations are based on user choices made in the past (e.g. previous purchases), combined with rated items **descriptions**.
- The main idea: if you like a particular item in the past you will also like a **similar** item in the future.



Content-based Filtering

- **Similarity** between objects is therefore the basis for recommending new items.
- We can view this as a user-specific classification problem of user's likes and dislikes based on an item's features.
- CBF is best suited to situations where there is abundant data on items, but not for the users.

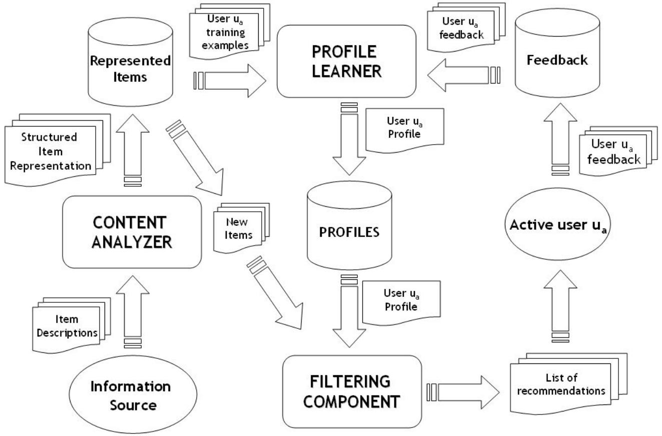
Content-based Filtering

★ Easy to implement
★ Transparent, Explainable
★ User independent (no user data needed)
★ Scalable
★ No item cold-start

⬇️ Difficult information extraction
⬇️ Limited content analysis
⬇️ Overspecialization (only recommending similar things)
⬇️ User cold-start

Content-based Filtering

- The recommendation process is usually performed in 3 steps:
  - Content Analysis (extracting features),
  - Profile learning (extracting user preferences),
  - Filtering (extract relevant items).



Ricci, Francesco, Lior Rokach, and Bracha Shapira. *Recommender systems handbook*. Springer, Boston, MA, 2011.

CBF - Item Similarity

- Item representation:
  - Structured (predefined sets of attributes and values),
  - Unstructured (raw text) - vector space models, e.g. **TF-IDF**, word embeddings, e.g. **word2vec**
  - Mixed.

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$ = number of occurrences of i in j
df_i = number of documents containing i
N = total number of documents

CBF - Similarity Measures

- Euclidean distance:

$$\sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}.$$

- Manhattan distance:

$$\sum_{i=1}^{n}|p_i - q_i|,$$

- Minkowski distance

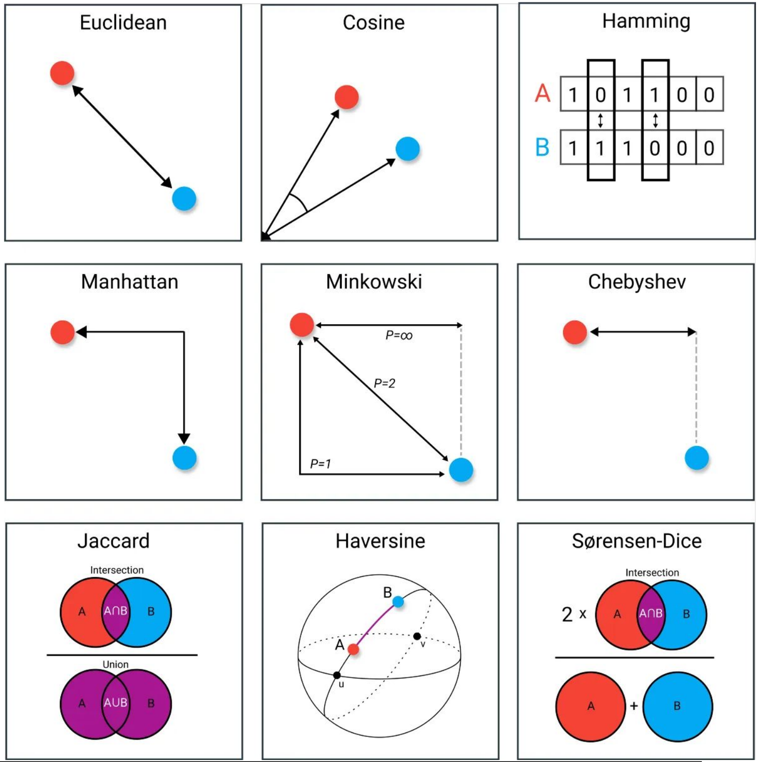
$$D(X,Y) = \left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{\frac{1}{p}}$$

- Jaccard distance

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}.$$

- Cosine distance

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$



Simranjeet Singh. Choosing the Best Distance Metric for Your ML Problem: A Comprehensive Guide with Examples. https://generativeai.pub/choosing-the-right-distance-metric-for-your-machine-learning-problem-a-comprehensive-guide-with-15415c27f99

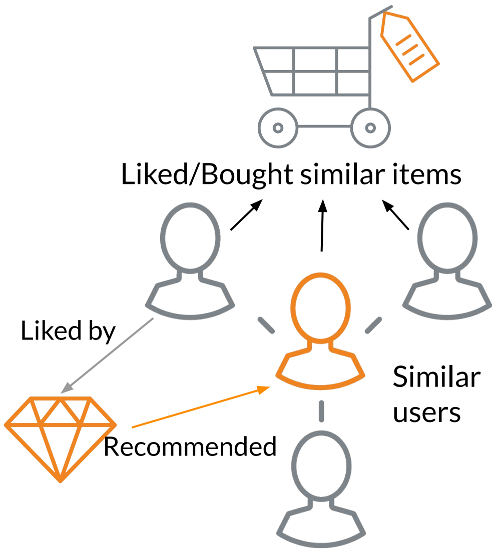
CBF - Recommending

- Recommend simply by returning similar items to those which the user has rated in the past.
- Weighting can be applied in case of real-number ratings.
- More sophisticated approaches can use Bayesian Classifiers, cluster analysis, decision trees, and neural networks in order to estimate the probability that the user is going to like the item.

Collaborative Filtering

Collaborative Filtering

- Recommendations are usually based on user's **neighbours** choices made in the past (of similar items).
- The main idea: people who agreed in the past will **agree** in the future and will like similar kinds of items.



Collaborative Filtering

- Oppose to CBF, in collaborative filtering (CF) we generally only use past **rating** information (though, other information/context can be incorporated into the models).
- No “feature extraction” needed, models can learn abstract (latent) features on the fly.
- This allows for serendipitous recommendations (items can be completely different from what was seen and liked in the past).

Collaborative Filtering

- ★ Superior modelling and accuracy
- ★ Serendipity
- ★ Efficient and scalable
- ★ Justifiable and transparent*
- ★ Robust and stable
- ★ Doesn’t need item information

- ⬇️ Black box models*
- ⬇️ User and Item cold-start
- ⬇️ Can be biased

* Depends on the model

Collaborative Filtering

CF methods are usually grouped in two general classes:

- **Memory-based / Neighborhood-based / Heuristic-based**
  - Where user/item ratings stored in the system are directly used for prediction
- **Model-based / Latent factors**
  - Where user/item ratings are used to learn a predictive model

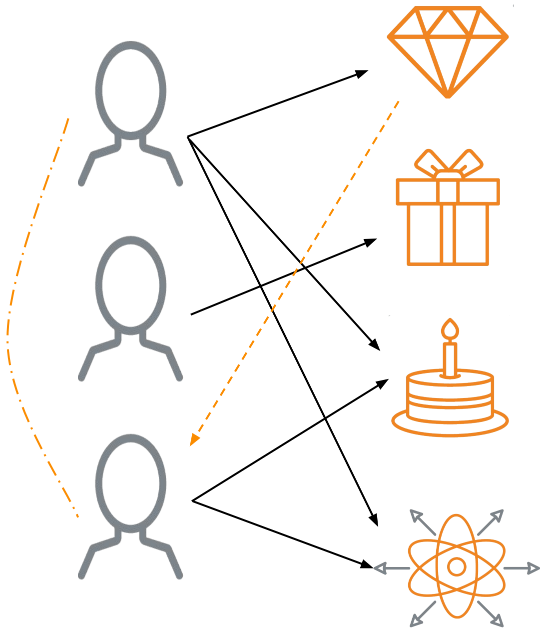
Memory-based CF

- Most basic approach where ratings are calculated using simple statistics and aggregations upon stored data.
- Very **simplistic**, but can often capture local associations in the data.
- Generally split into:
    - ***user-based*** (where users are recommended items from their neighbouring users with similar rating patterns),
    - ***item-based*** (where users are recommended items based on their ratings of the set of similar items).

Ricci, Francesco, Lior Rokach, and Bracha Shapira. *Recommender systems handbook*. Springer, Boston, MA, 2011.

(Memory) User-based CF

- Predict a rating for a user ***u*** for an item ***i*** using the ratings for the item ***i*** by users most similar to ***u***.
- Weighted kNN (regression or classification).



$$\hat{r}_{ui} = \frac{\sum\limits_{v \in \mathcal{N}_i(u)} w_{uv} \, r_{vi}}{\sum\limits_{v \in \mathcal{N}_i(u)} |w_{uv}|}$$

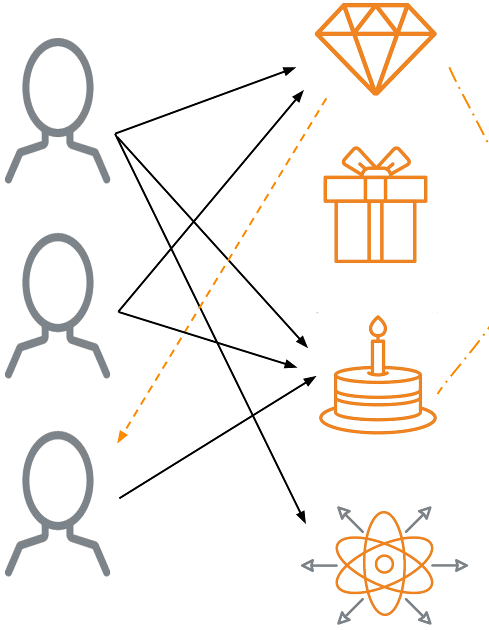
Where N denotes the neighboring users that rated the item, w the user similarity (weight) and r the rating.

(Memory) Item-based CF

- Predict a rating for a user ***u*** for an item ***i*** using the ratings by the user ***u*** for items most similar to ***i***.
- Weighted kNN (regression or classification).

$$\hat{r}_{ui} = \frac{\sum_{j \in \mathcal{N}_u(i)} w_{ij} r_{uj}}{\sum_{j \in \mathcal{N}_u(i)} |w_{ij}|}$$

Where N denotes the neighboring items that were rated by the user, w the item similarity (weight) and r the rating.



Memory-based CF

- Memory-based CF methods are **simplistic**, transparent (explainable), efficient and allow for serendipitous predictions.
- We can further extend MCF with various normalization (centering and biases), choosing different similarity metrics (Euclidean, Cosine, ...) or by applying various pre-filtering and post-filtering stages (neighbourhood selection), speedups (locality-sensitive hashing), ...
- Finally, we can combine user-based and item-based approaches using Hybrid models.

Model-based CF

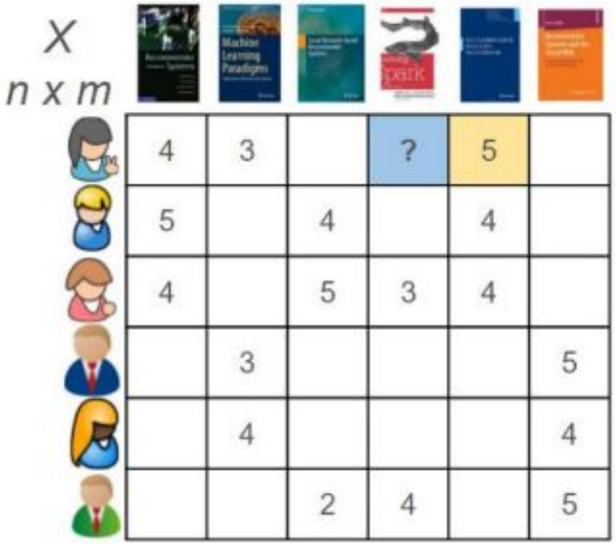
- Contrary, model-based approaches rather use ratings in order to learn a **predictive model** (which is then used to make new predictions).
- Goal of modelling user-item interactions with factors representing their latent **characteristics**.
- These factors are inferred solely from the ratings and might represent obvious dimensions (e.g. movie genres) or something completely uninterpretable to us.

Matrix Factorization

- Essential tool in machine learning, broadly used for dimensionality reduction, compression, clustering, classification, ...
- Also, one of the most popular and most used CF model.
- Simple and efficient way to model explicit data and various other side information (implicit ratings, biases, temporal effects, etc.).

Matrix Factorization

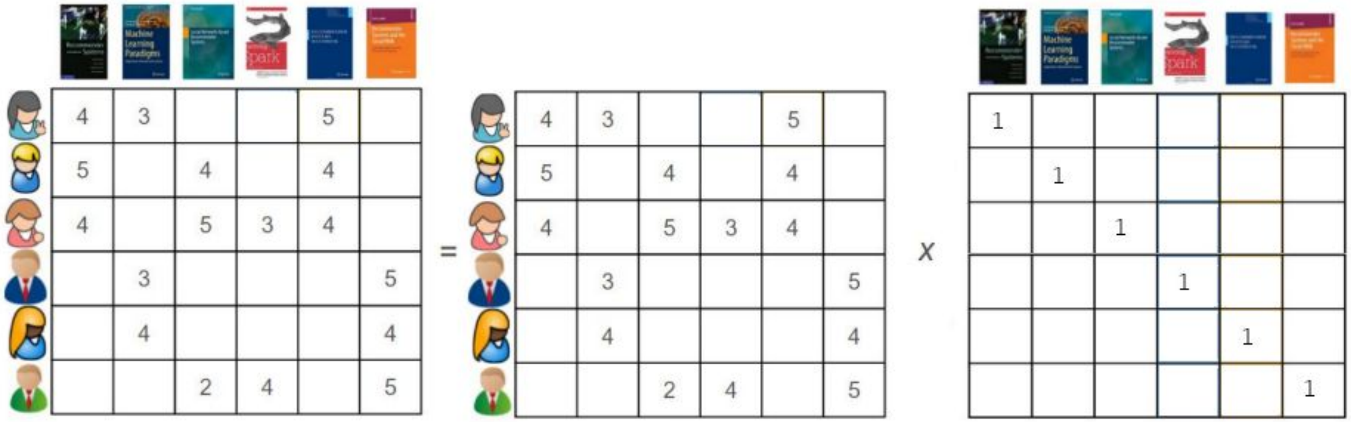
- User-Item ratings can be simply represented with a matrix.
- Recommendations now becomes a **matrix completion** problem.
- We can solve this by factorizing this matrix into a product of (two) smaller matrices.



Nikita Sharma. *Recommender Systems with Python*. https://heartbeat.fritz.ai/recommender-systems-with-python-part-iii-collaborative-filtering-singular-value-decomposition-5b5dcb3f242b

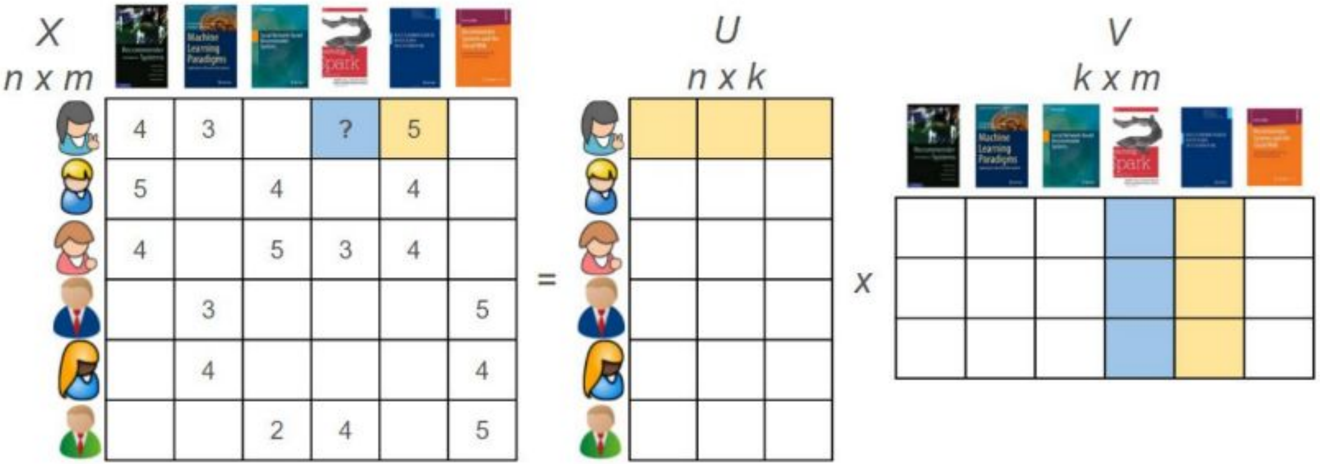
Matrix Factorization - Intuition

- A trivial factorization: ***X = X * I***

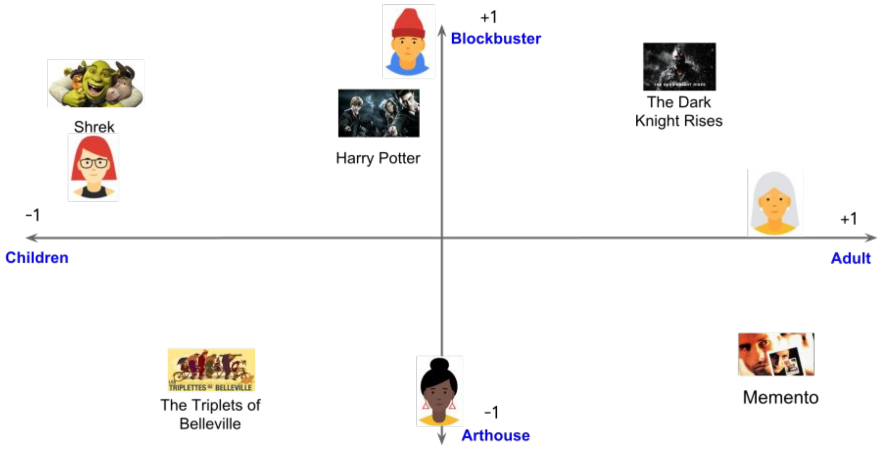


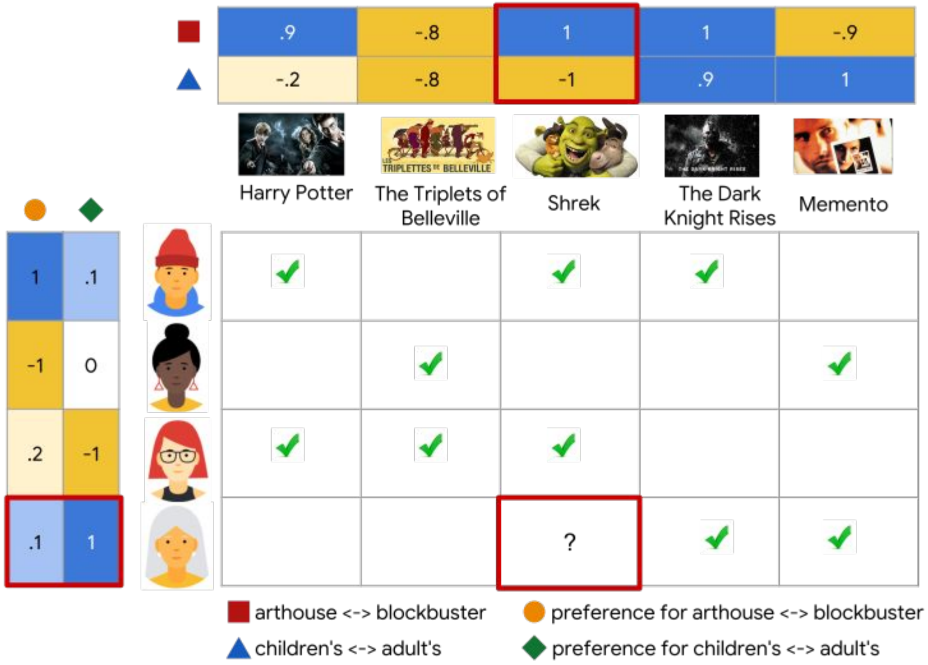
Matrix Factorization

- Low-Rank factorization: ***X = U * V***



Matrix Factorization





https://developers.google.com/machine-learning/recommendation/

Matrix Factorization

≈

.9	-1	1	1	-.9
-.2	-.8	-1	.9	1

1	.1
-1	0
.2	-1
.1	1

.88	-1.08	0.9	1.09	-0.8
-0.9	1.0	-1.0	-1.0	0.9
0.38	0.6	1.2	-0.7	-1.18
-0.11	-0.9	-0.9	1.0	0.91

Matrix Factorization

- **Solve** matrix factorization problem: $X \approx \hat{X} = UV^T$
- **Predict** with dot product (linear combinations) between latent user matrix and latent item matrix.
- There are (infinitely) many possible factorizations - how to find the best one?
- Define the matrix completion as an **optimization problem**.

Matrix Factorization

- Define the objective (loss) function, based on your needs.
- One of the most common is the squared loss (Frobenius norm): $$||X - \hat{X}||_F^2 = ||X - UV^T||_F^2 = \sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij} - u_i v_j^T)^2$$

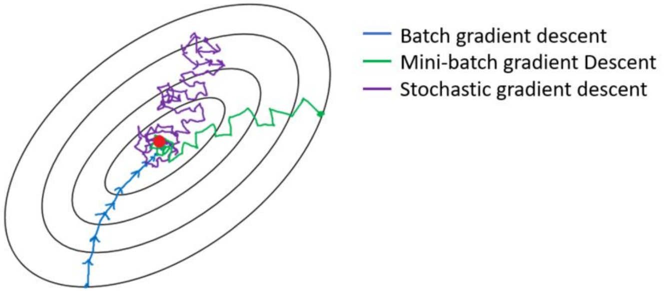
- Problem of huge **sparsity** (typically over 99%).
- We can use weighted (masked) matrix factorization:

$$\mathbb{W} \circ X \approx \mathbb{W} \circ \hat{X} = \mathbb{W} \circ (UV^T)$$

Ricci, Francesco, Lior Rokach, and Bracha Shapira. *Recommender systems handbook*. Springer, Boston, MA, 2011.

Matrix Factorization

- This kind of optimization problems are usually solved using various gradient descent methods: GD, SGD, MUR, PGD, CD ...
- Alternatively, we can use ALS (convex optimization).
- With SGD we can **omit** the weighted part and optimize only on the **known** (non-zero) ratings and thus tackle the sparsity problem very efficiently.



Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer* 42.8 (2009): 30-37.

Matrix Factorization - SGD

$$L = \sum_{u,i} (r_{ui} - (\mu + b_u + b_i + \mathbf{x}_u^\top \cdot \mathbf{y}_i))^2 + \lambda_{xb} \sum_u \|b_u\|^2 + \lambda_{yb} \sum_i \|b_i\|^2 + \lambda_{xf} \sum_u \|\mathbf{x}_u\|^2 + \lambda_{yf} \sum_u \|\mathbf{y}_i\|^2$$

$$\frac{\partial L}{\partial b_u} = 2(r_{ui} - (\mu + b_u + b_i + \mathbf{x}_u^\top \cdot \mathbf{y}_i))(-1) + 2\lambda_{xb} b_u$$

$$\frac{\partial L}{\partial b_u} = 2(e_{ui})(-1) + 2\lambda_{xb} b_u$$

$$\frac{\partial L}{\partial b_u} = -e_{ui} + \lambda_{xb} b_u$$

$$b_u \leftarrow b_u + \eta\,(e_{ui} - \lambda_{xb} b_u)$$

$$b_i \leftarrow b_i + \eta\,(e_{ui} - \lambda_{yb} b_i)$$

$$\mathbf{x}_u \leftarrow \mathbf{x}_u + \eta\,(e_{ui}\mathbf{y}_i - \lambda_{xf}\mathbf{x}_u)$$

$$\mathbf{y}_i \leftarrow \mathbf{y}_i + \eta\,(e_{ui}\mathbf{x}_u - \lambda_{yf}\mathbf{y}_i)$$

Matrix Factorization

- MF allows for a simple inclusion of various **side information** (like implicit ratings, tags), **constraints** (penalties and rewards), **regularization**, **biases** and **temporal dynamics**.
- Contextual information about the rating process (circumstances) can also be incorporated - CARS:
  - Contextual pre-filtering, post-filtering and modelling
  - $R : User \times Item \times Context \rightarrow Rating$
  - Tensor factorization

Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer* 42.8 (2009): 30-37.
Adomavicius, Gediminas, and Alexander Tuzhilin. "Context-aware recommender systems." *Recommender systems handbook*. Springer, Boston, MA, 2011.

Matrix Factorization

- Constrained Matrix Factorization:
  - NMF (only additive linear combinations induce parts-based representation)
  - Sparse MF (constrained number of combinations)
  - Orthogonal MF (uniqueness, clustering)
- Data Fusion

$$\overset{\mathrm{R}}{\begin{bmatrix} * & \mathrm{R}_{12} & \ldots \mathrm{R}_{1r} \\ \mathrm{R}_{21} & * & \ldots \mathrm{R}_{2r} \\ \vdots & \vdots & \ddots \; \vdots \\ \mathrm{R}_{r1} & \mathrm{R}_{r2} & \ldots \; * \end{bmatrix}} \approx \overset{\mathrm{G}}{\begin{bmatrix} \mathrm{G}_1 & & & \\ & \mathrm{G}_2 & & \\ & & \ddots & \\ & & & \mathrm{G}_r \end{bmatrix}} \overset{\mathrm{S}}{\begin{bmatrix} * & \mathrm{S}_{12} & \ldots \mathrm{S}_{1r} \\ \mathrm{S}_{21} & * & \ldots \mathrm{S}_{2r} \\ \vdots & \vdots & \ddots \; \vdots \\ \mathrm{S}_{r1} & \mathrm{S}_{r2} & \ldots \; * \end{bmatrix}} \overset{\mathrm{G}^{\mathrm{T}}}{\begin{bmatrix} \mathrm{G}_1^{\mathrm{T}} & & & \\ & \mathrm{G}_2^{\mathrm{T}} & & \\ & & \ddots & \\ & & & \mathrm{G}_r^{\mathrm{T}} \end{bmatrix}}$$

Jakomin, Martin. *Incremental matrix factorization for simultaneous learning from parallel data streams*. Diss. University of Ljubljana 2019.

Factorization Machines

- Factorization machines can be looked as a generalization of linear regression.
- Moreover, they are a generalization of support vector machines (SVM) with a polynomial kernel.
- Except, with FM we do **not** need to calculate every feature interaction (especially if they are sparse): **k<< n**.

1) Model Equation: The model equation for a factorization machine of degree $d = 2$ is defined as:

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i \, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \mathbf{v}_i, \mathbf{v}_j \rangle \, x_i \, x_j \tag{1}$$

where the model parameters that have to be estimated are:

$$w_0 \in \mathbb{R}, \quad \mathbf{w} \in \mathbb{R}^n, \quad \mathbf{V} \in \mathbb{R}^{n \times k} \tag{2}$$

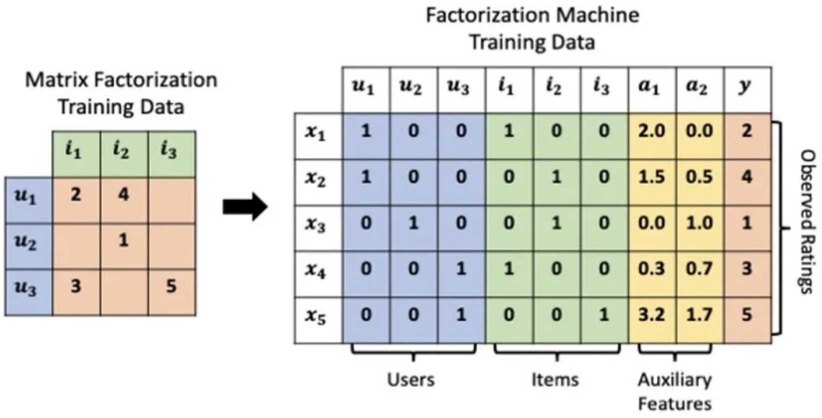
And $\langle \cdot, \cdot \rangle$ is the dot product of two vectors of size k:

$$\langle \mathbf{v}_i, \mathbf{v}_j \rangle := \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f} \tag{3}$$

Rendle, Steffen. "Factorization machines." *2010 IEEE International conference on data mining*. IEEE, 2010.

Factorization Machines

- Allows for **quadratic** (second-order) feature interactions or even higher (*d* hyperparameter) with variable number of **latent dimensions** (*k* hyperparamter).
- Designed to capture interactions between features within high dimensional **sparse** datasets
- Still very fast - can be trained in a **linear** time.



Rendle, Steffen. "Factorization machines." *2010 IEEE International conference on data mining*. IEEE, 2010.
https://towardsdatascience.com/factorization-machines-for-item-recommendation-with-implicit-feedback-data-5655a7c749db

Deep Learning For RS

Deep Learning for RS

- Nowadays, deep learning is everywhere - RS are not an exception.
- Data is becoming more abundant and available.
- Main Idea - the user/item interaction may be **non-linear**.
- Deep models and Hybrids are SOTA.

Zhang, Shuai, et al. "Deep learning based recommender system: A survey and new perspectives." *ACM Computing Surveys (CSUR)* 52.1 (2019)

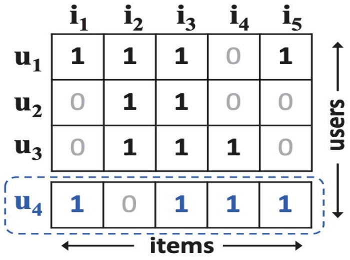
Deep RS

★ Non-linear transformations
★ Representation learning and better generalization
★ Sequence modelling (RNN)
★ Flexibility
★ Superior accuracy
★ Unified representation and data fusion

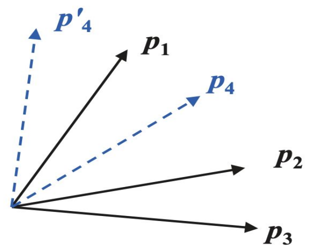
⬇️ Black box models - bad interpretability
⬇️ Data requirement and sparseness
⬇️ Extensive Hyperparameter tuning

Deep Neural CF

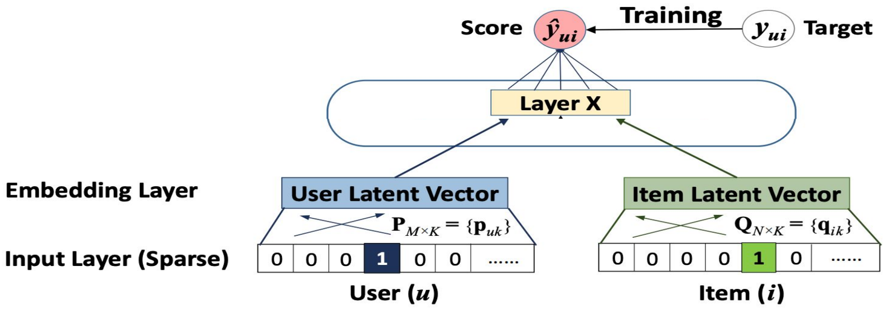
- User and Item embeddings (with one-hot input).
- Dense layers and single output.



(a) user–item matrix



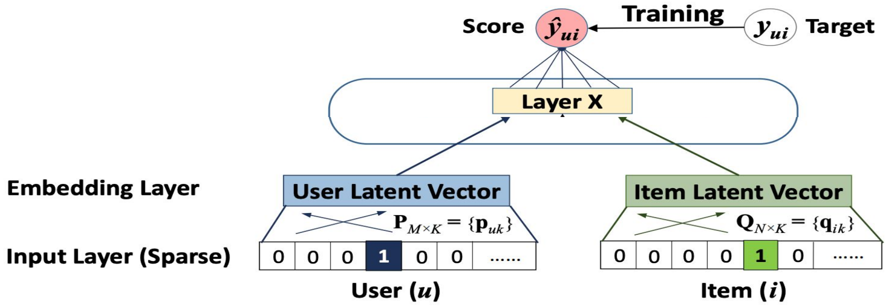
(b) user latent space



He, Xiangnan, et al. "Neural collaborative filtering." *Proceedings of the 26th international conference on world wide web*. 2017.

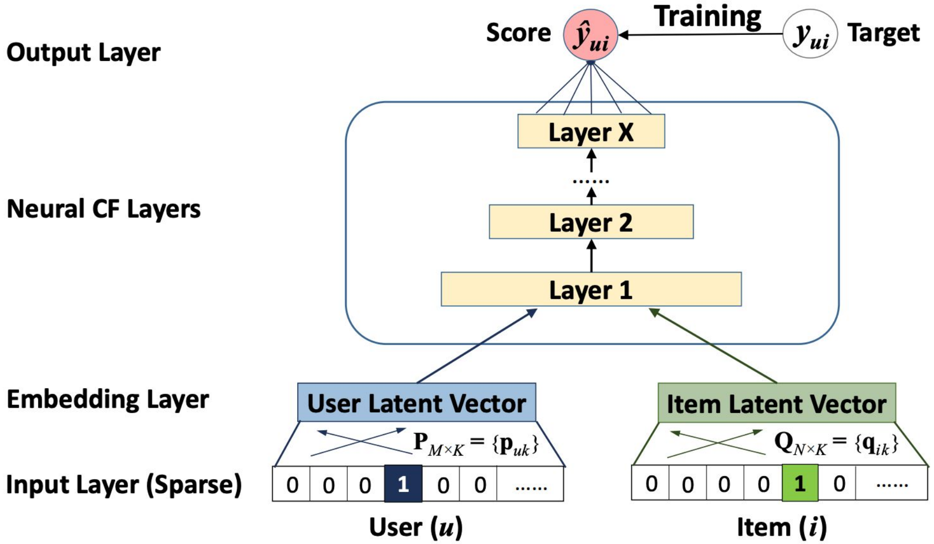
Deep Neural CF

- This is a generalization of the matrix factorization (by using the element-wise product layer).



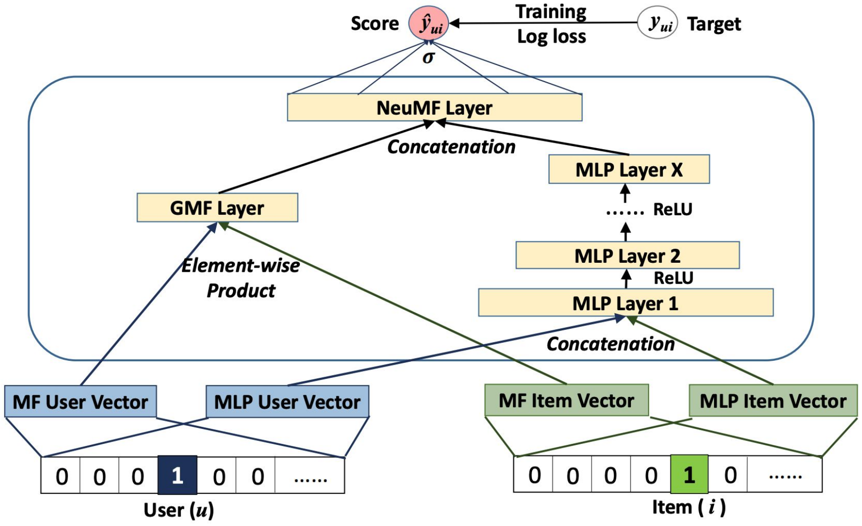
Deep Neural CF

- We can then add multiple dense layers.



Deep Neural CF

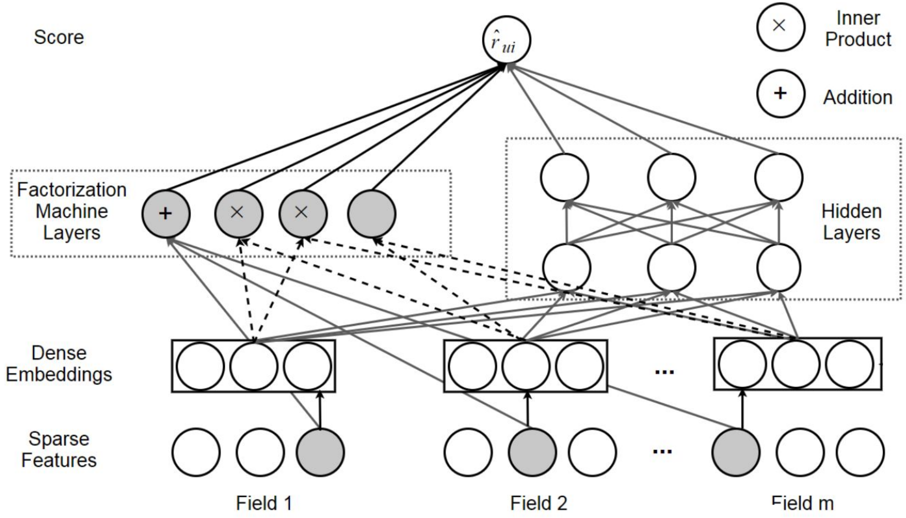
- Or combine both models - **Deep & Wide** architecture.



Deep Factorization Machines

- Main idea: Learn both, **low-order** (FM) **and high-order** (DNN) feature interactions.

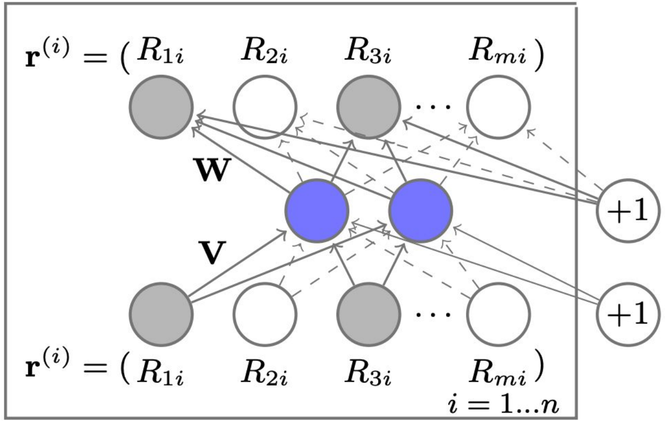
	User				Item				Categories				History				Quantity	
x^1	1	0	0	...	1	0	0	...	1	0	1	...	1	0	1	...	2	y^1
x^2	1	0	0	...	0	1	0	...	0	2	1	...	0	0	1	...	4	y^2
x^3	0	1	0	...	1	0	0	...	3	0	14	...	1	0	0	...	5	y^3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
x^n	0	0	0	...	0	0	1	...	0	1	5	...	0	0	1	...	1	y^n



Guo, Huifeng, et al. "DeepFM: a factorization-machine based neural network for CTR prediction." *arXiv preprint arXiv:1703.04247* (2017).
Rendle, Steffen. "Factorization machines." *2010 IEEE International Conference on Data Mining*. IEEE, 2010.
Zhang, Shuai, et al. "Deep learning based recommender system: A survey and new perspectives." *ACM Computing Surveys (CSUR)* 52.1 (2019).

Autoencoders & AutoRec

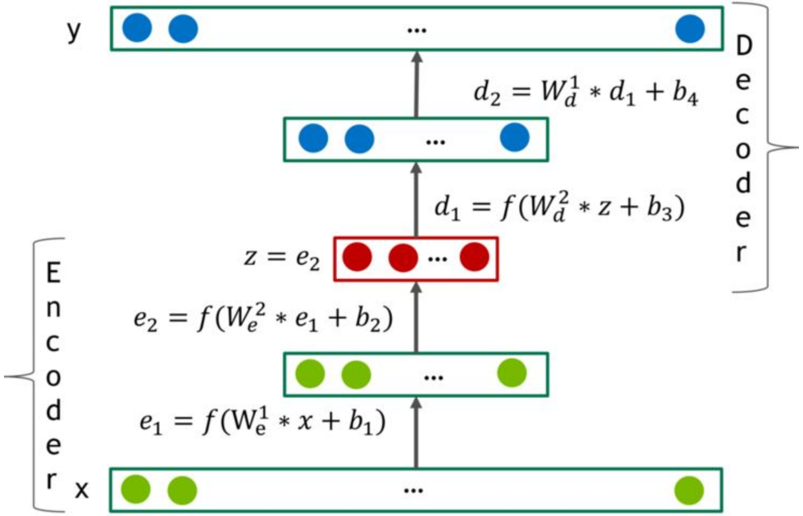
- Generalization of the PCA.
- Aims to reconstruct the input on the output level.
- Either User-based or Item-based (by passing in the partial vectors of either user ratings or item ratings).



Sedhain, Suvash, et al. "Autorec: Autoencoders meet collaborative filtering." *Proceedings of the 24th international conference on World Wide Web*. 2015.

Deep Autoencoders & DeepRec

- Either User-based or Item-based.
- Based on the AutoRec but much deeper with a high dropout rate.
- It uses iterative output re-feeding during the training for better results.



Kuchaiev, Oleksii, and Boris Ginsburg. "Training deep autoencoders for collaborative filtering." *arXiv preprint arXiv:1708.01715* (2017).

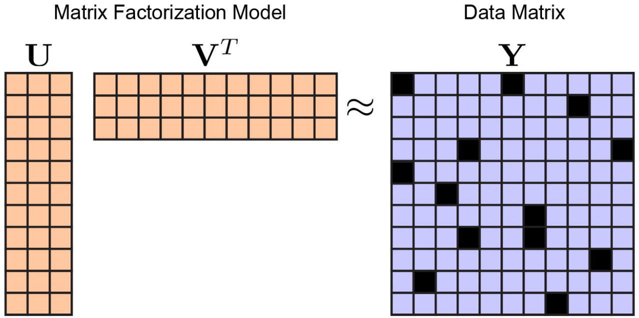
Evaluating RS

Evaluating Recommender Systems

- Inherently difficult, highy sparsity, bias and many outliers.
- How to measure success? User **satisfaction** is hard to define!
- How to optimize for novelty and serendipity?
- In general, we try to optimize the pre-defined loss function (which does not guarantee best predictions or best user satisfactions).
- Offline results do not guarantee the success in production environment.

Evaluating Recommender Systems

- We commonly use a offline holdout set (sub-matrix, random sample) on which we apply predictive accuracy metrics, such as RMSE, MAE, …
- For topN recommendations we typically use coverage measures, such as precision and recall (and F1).



Random Holdout

Alex Williams. *How to cross-validate PCA, clustering, and matrix decomposition models*. http://alexhwilliams.info/itsneuronalblog/2018/02/26/crossval/

YouTube - Case Study

YouTube - A short case study

- Largest platform for creating, sharing and discovering video content.
- And also one of the **largest** recommender system in industry!
- Main Goal: Maximize the **time** users spend on the platform (and thus maximize the number of served ads).
- Vast majority of views come from recommendations (more than 70 %).
- However, YouTube is not fully transparent how their algorithms work.

Spandana Singh. *Why Am I Seeing This?* https://www.newamerica.org/oti/reports/why-am-i-seeing-this/

History

- In the past YouTube recommended videos according to **click-rate**, but this incentivized users to create click-baity videos.
- YouTube then changed their strategy to recommend videos based on overall **watch time**.
- Emphasis on user satisfaction and quality watch time (hard to measure).
- Search results are also personalized.
- Offline metrics, such as precision, recall, ranking loss are widely used, however the most important metric is the live **A/B testing**.

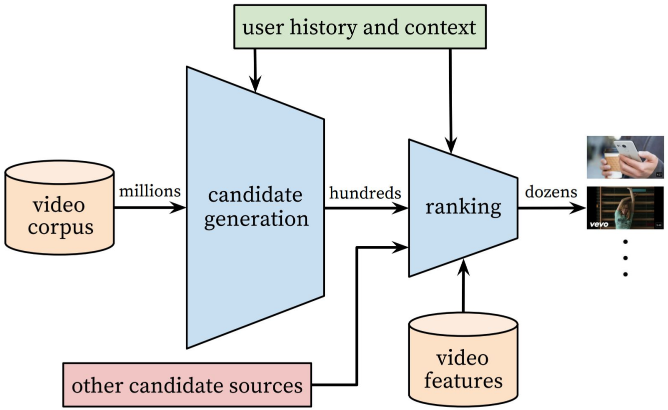
Deep Neural Networks for Youtube Recommendations

- Used matrix factorization in the past.
- One of first to use deep neural network for recommendations .
- Built upon TensorFlow.
- Two-stage design (with two deep neural networks), one for candidate generation and one for ranking.
- This two stage approach allows for recommendation from millions of different videos.

Covington, Paul, Jay Adams, and Emre Sargin. "Deep neural networks for youtube recommendations." *Proceedings of the 10th ACM conference on recommender systems*. 2016.

The two-stage design

- The candidate generation uses collaborative filtering in order to provide **broad personalization** (using various features) with a high precision.
- Ranking network scores each video according to the desired objective function and thus provides **fine-level representation** among candidates with a high recall.

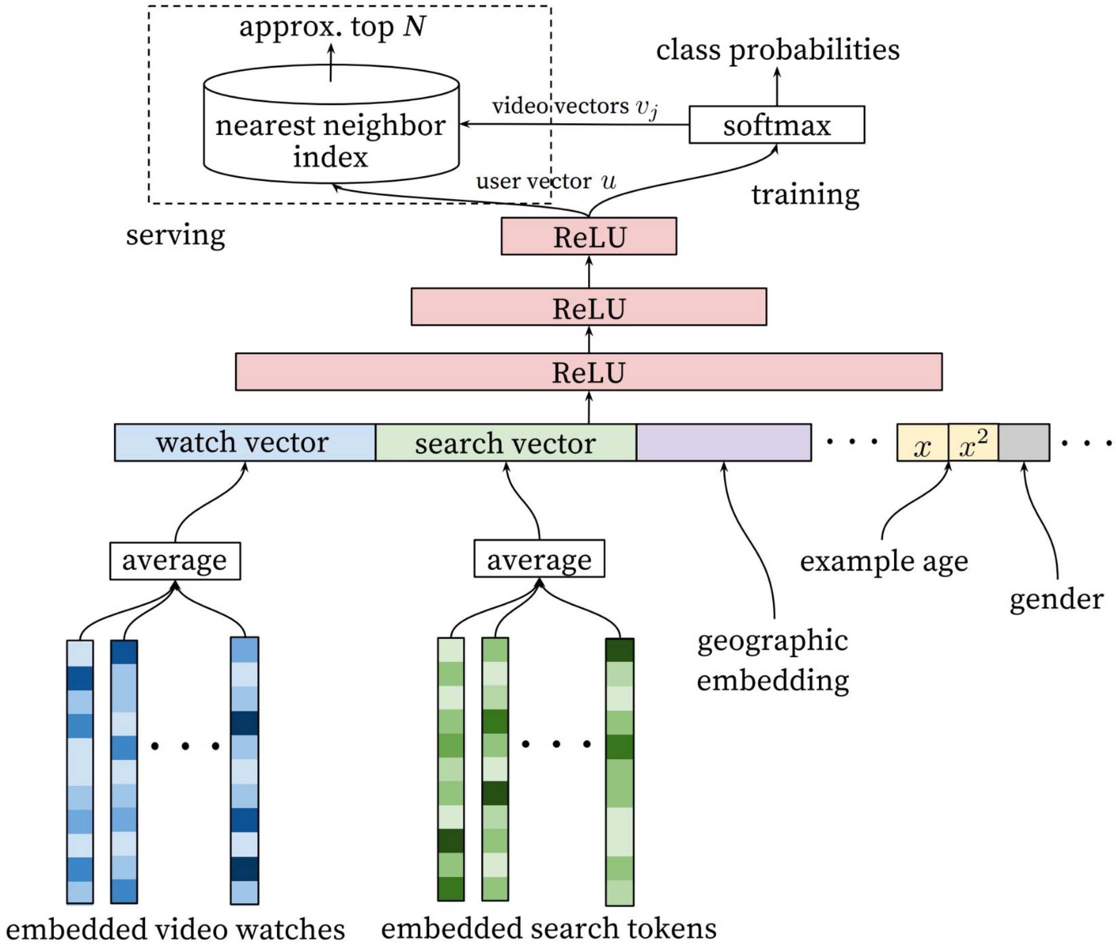


Candidate generation

- Neural networks as a generalization of matrix factorization (for embedding user's behaviours).
- Recommendation is viewed as an extreme multiclass (1M) classification.
- Explicit data is very sparse, but **implicit** (such as video views) is more abundant.
- User watch history is represented by a sequence of sparse video IDs (which is then embedded).
- Arbitrary continuous and categorical features can be easily added to the model.

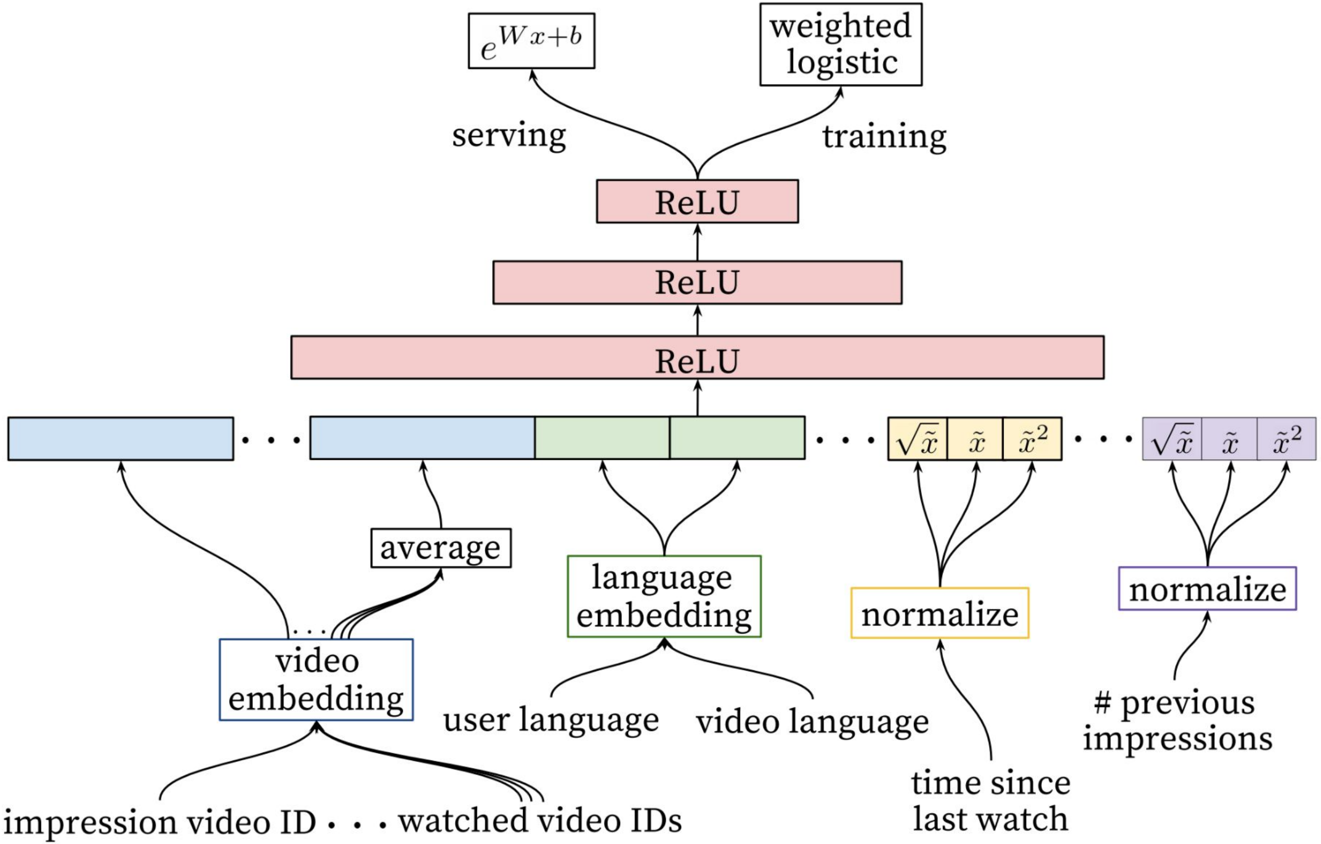
Candidate generation

- Age of the video is very important feature in order to recommend “fresh” examples.
- Candidates are found by nearest neighbour search from the last layer of the network.
- Limited number of training example per user (to avoid heavy raters).
- Adding features and layers significantly improves the accuracy.


approx. top N
nearest neighbor index
serving
video vectors v_j
softmax
class probabilities
user vector u
training
ReLU
ReLU
ReLU
watch vector
search vector
x
x^2
average
average
example age
gender
geographic embedding
embedded video watches
embedded search tokens

Ranking

- A similar deep neural network is used as for candidate selection.
- More video features (such as thumbnails, etc.) are used.
- **Feature engineering** is very important (although deep learning alleviates this problem).
- Shared embedding for similar features and normalization of continuous features.
- Adding features and layers significantly improves the accuracy.



e^{Wx+b}
weighted logistic
serving
training
ReLU
ReLU
ReLU
$\sqrt{\tilde{x}}$ $\tilde{x}$ $\tilde{x}^2$
$\sqrt{\tilde{x}}$ $\tilde{x}$ $\tilde{x}^2$
average
language embedding
normalize
normalize
video embedding
user language
video language
previous impressions
time since last watch
impression video ID • • • watched video IDs

Add-ons

- Such design is still not optimal (often only relevant/similar items are recommended and users can get bored).
- Google then introduced REINFORCE algorithm (reinforcement learning) with goal to maximize users' engagement over time by predicting which recommendations would expand their tastes.
- YouTube is **constantly updating** their machine learning algorithms and has multiple A/B tests in production.

Conclusion

Conclusion - Key Takeaways

- Offline metrics are a good indicator, but they **do not** always map perfectly to the online setting.
- A/B testing in production is a **must**.
- Continuous improvements and optimizations.
- Although deep networks help, manual **feature engineering** can still vastly improve the performance.
- Adding features and layers usually improve the accuracy (but has higher infrastructure costs and/or diminishing returns).
- Optimize for **user satisfaction.**

TensorFlow

What is TensorFlow?

- *"An end-to-end open source machine learning platform"*
- At its core: general purpose ML framework, focused on DL
- Core implemented in C / C++ / Python, wrappers for Java / Go / Swift
- Peripherals: TF Serving (microservice for serving models), TensorBoard (model visualization / profiling), etc.

Pros & cons of TF

+ A lot of implemented operations and models

+ Optimized for speed, CPU, GPU support

+ Ecosystem (users, libraries, end-to-end platform) - most widely used DL framework

- Complexity

- Poor documentation + awkward API in some places

Code time

- Repository: github.com/janhartman/recsystf
- Option 1: run the notebooks on Google Colab
  - Colab: https://colab.research.google.com/
  - Click GitHub and enter *janhartman/recsystf*
  - All dependencies are preinstalled
  - The colab notebooks are stored on your GDrive
- Option 2: run the notebooks locally
  - Clone the repo and open it
  - Create virtualenv and install dependencies
  - Run *jupyter-lab*

Stuff we left out

- Saving and loading models
- TF Serving, production usage
- TF in other programming languages
- Custom op creation
- Estimators and tf.data pipelines

Sources (TF part)

- TensorFlow guide
- Deep Learning With Keras: Recommender Systems
- Collaborative Filtering for Movie Recommendations
- NVIDIA/DeepRecommender: Deep learning for recommender systems
- An implementation of DeepRecommender in Tensorflow & Keras

Challenge

Data

- Data: Goodreads book ratings, filtered
- 84k train, 21k test examples
- *train.csv* & *test.csv*: user ID, book name & rating
- Bonus: additional book data in *books.csv* (match by book name) - try to find a way to add it to the model
- *books.csv*: authors, publish date, publisher, rating, number of reviews, number of pages

Challenge

- Goal: implement a recommender system in TF to accurately predict a user's rating of a book
- Use mean squared error as your loss function & a validation dataset
- Play around with different algorithms, add extra book data into the model...
- Try to achieve the lowest MSE on the test set (mine: 0.84)
- Make sure to use additional data from *books.csv*

Conclusion

We are hiring!

- Always looking for interesting candidates
- Various positions are open
- Hard and interesting problems
- Big data
- outbrain.com/careers

Thank you for your attention!

Martin Jakomin

mjakomin@outbrain.com

linkedin.com/in/martin-jakomin

Jan Hartman

jan.hartman7@gmail.com

linkedin.com/in/jan-hartman