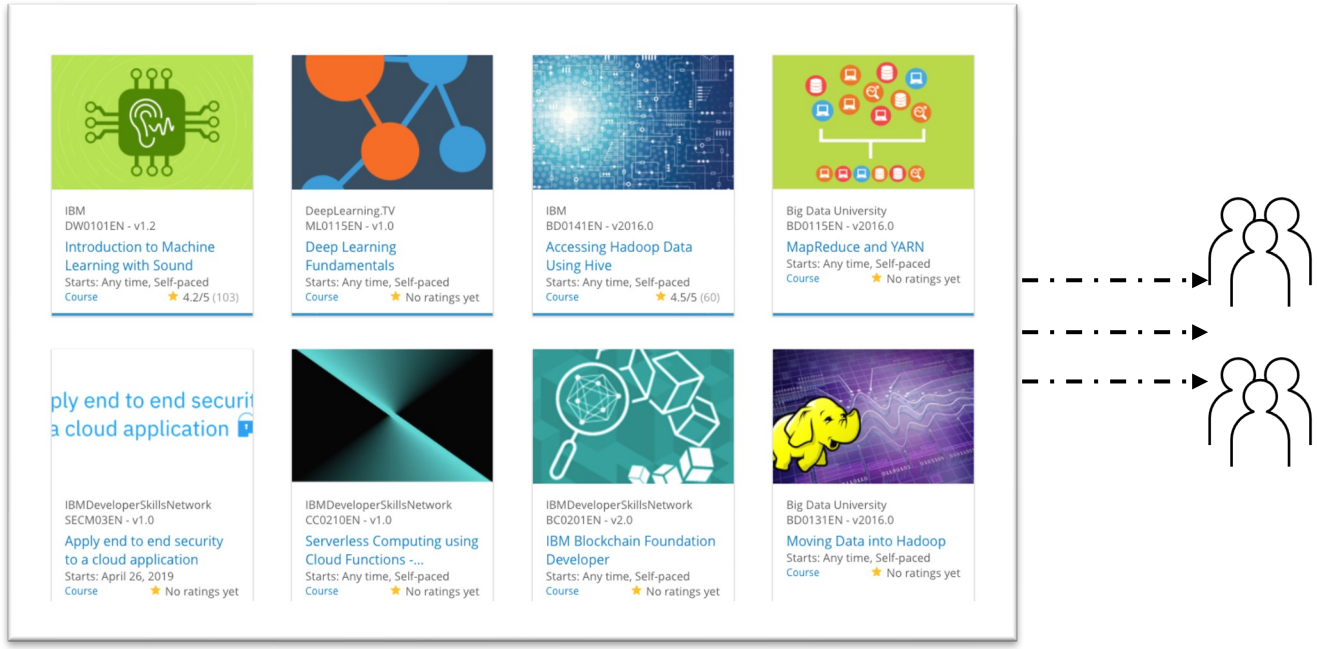
Build a Personalized Online Course Recommender System with Machine Learning

BK

May 22, 2023



Outline

- Introduction and Background
- Exploratory Data Analysis
- Content-based Recommender System using Unsupervised Learning
- Collaborative-filtering based Recommender System using Supervised learning
- Conclusion
- Appendix

Introduction

- Project background and context

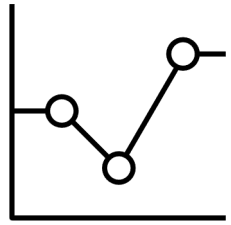
  AI Training Room is a Massive Open Online Courses (MOOCs) startup for learners across the world. The course catalogue provides various subjects to learn leading technologies. The demand grows rapidly and reached millions of customers in a very short time. A central concern of the company is to find new interesting courses for students to support their learning paths. For that reason, a Proof of Concept (PoC) for a recommender system (RS) is launched to improve the students' learning experience and increase the interaction with more courses. As a side effect of an established RS, the AI Training Room's revenue may be increase over time.

- Problem states
  - Which model is the best for our RS?
  - How much time does the training take?
  - Which model is the most economical for our RS?

- Hypothesis

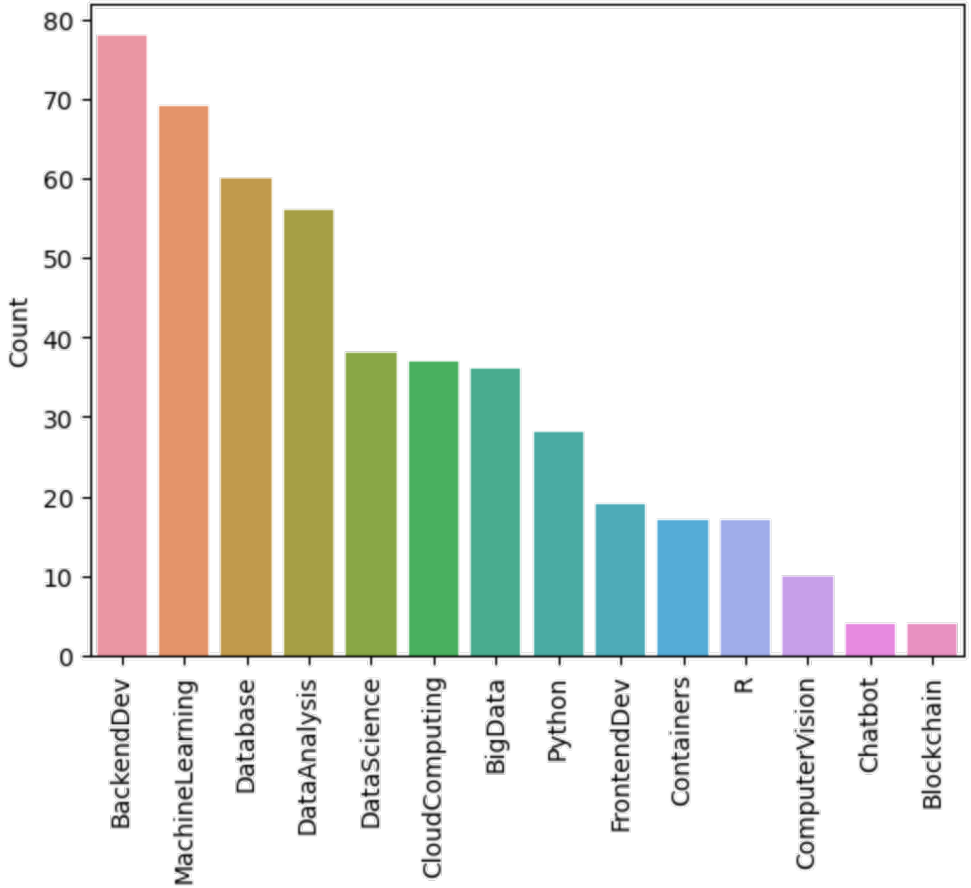
  Using enrollment data and
  course properties will provide sufficient information to build
  a recommender system to evaluate new courses for our students.

Exploratory Data Analysis



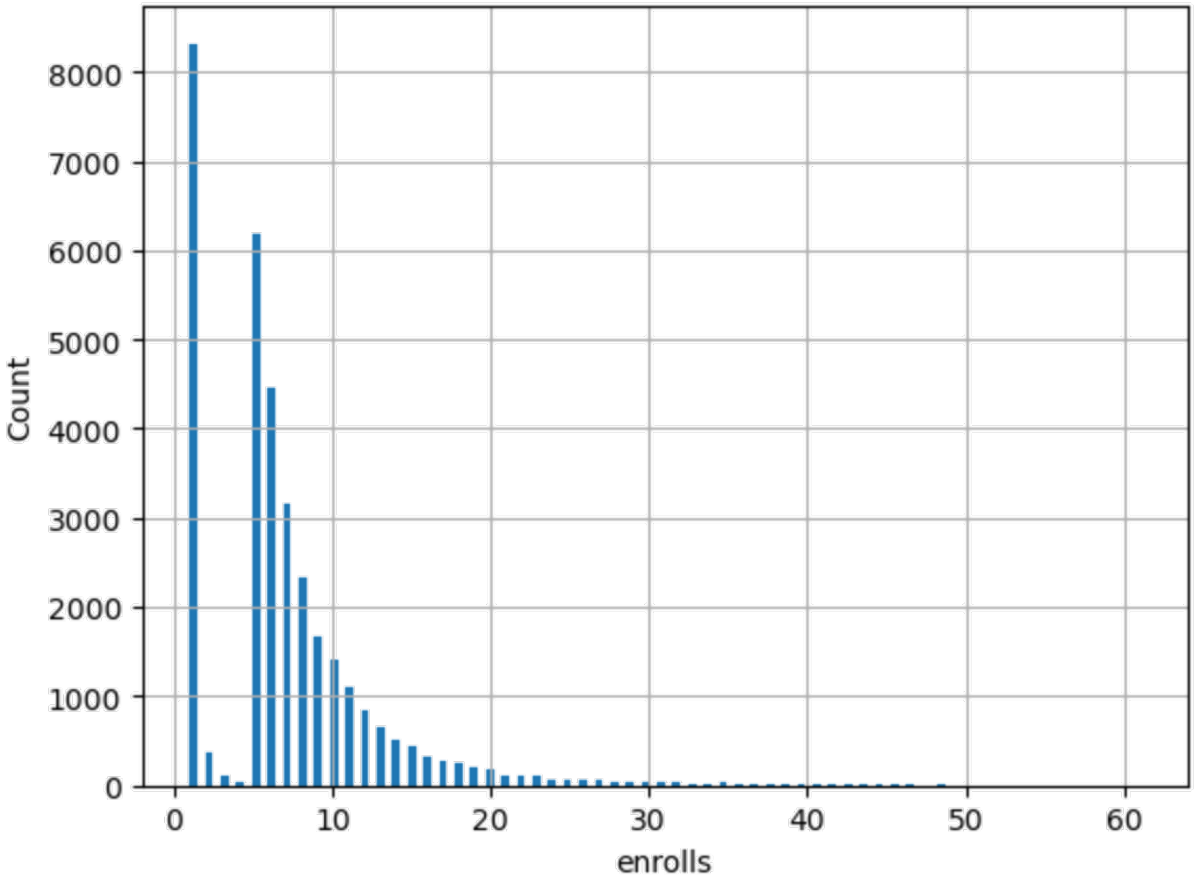
Course counts per genre

- 14 genres are offered.
- Most courses are backend development, machine learning anddatabases.
- Only two genres about programming languages.
- Very little courses about chatbots and blockchain.



Course enrollment distribution

- A bimodal distribution.
- Most students enrolled only one course.
- Little students enrolled two, three or four courses.
- Another peak at five enrolls.
- From that one the student's interest for courses dropped.



20 most popular courses

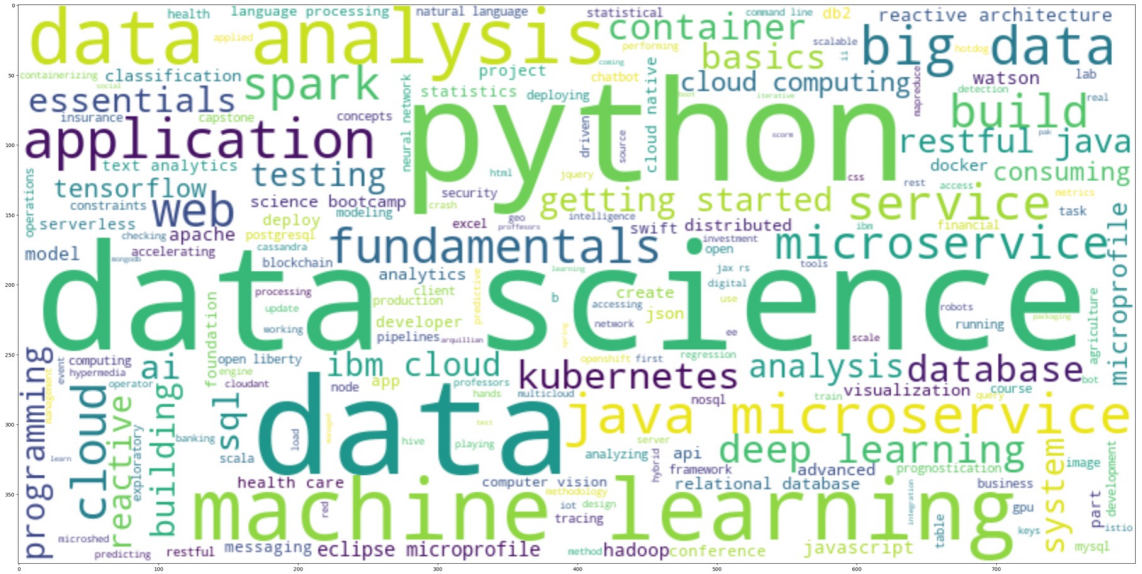
- Most courses are entry level.
- Overbalanced on data science.
- Only two programming languages.
  - Weighted to Python.
  - #1 is data science subject.
- Top rating on big data & hadoop.
- Machine learning starts at #7.
  - First course is intermediate level.

	TITLE	Ratings
0	python for data science	14936
1	introduction to data science	14477
2	big data 101	13291
3	hadoop 101	10599
4	data analysis with python	8303
5	data science methodology	7719
6	machine learning with python	7644
7	spark fundamentals i	7551
8	data science hands on with open source tools	7199
9	blockchain essentials	6719
10	data visualization with python	6709
11	deep learning 101	6323
12	build your own chatbot	5512
13	r for data science	5237
14	statistics 101	5015
15	introduction to cloud	4983
16	docker essentials a developer introduction	4480
17	sql and relational databases 101	3697
18	mapreduce and yarn	3670
19	data privacy fundamentals	3624

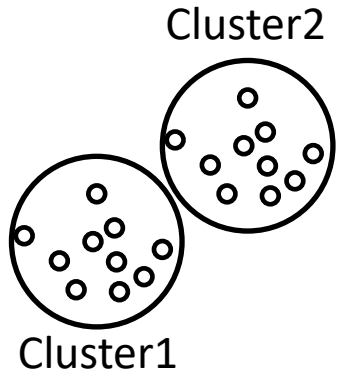
Word cloud of course titles

- The most frequent buzzwords used for course titles are data, data science and python.
- There seems a relationship between the frequency of these buzzwords used for course titles and the most popular courses.

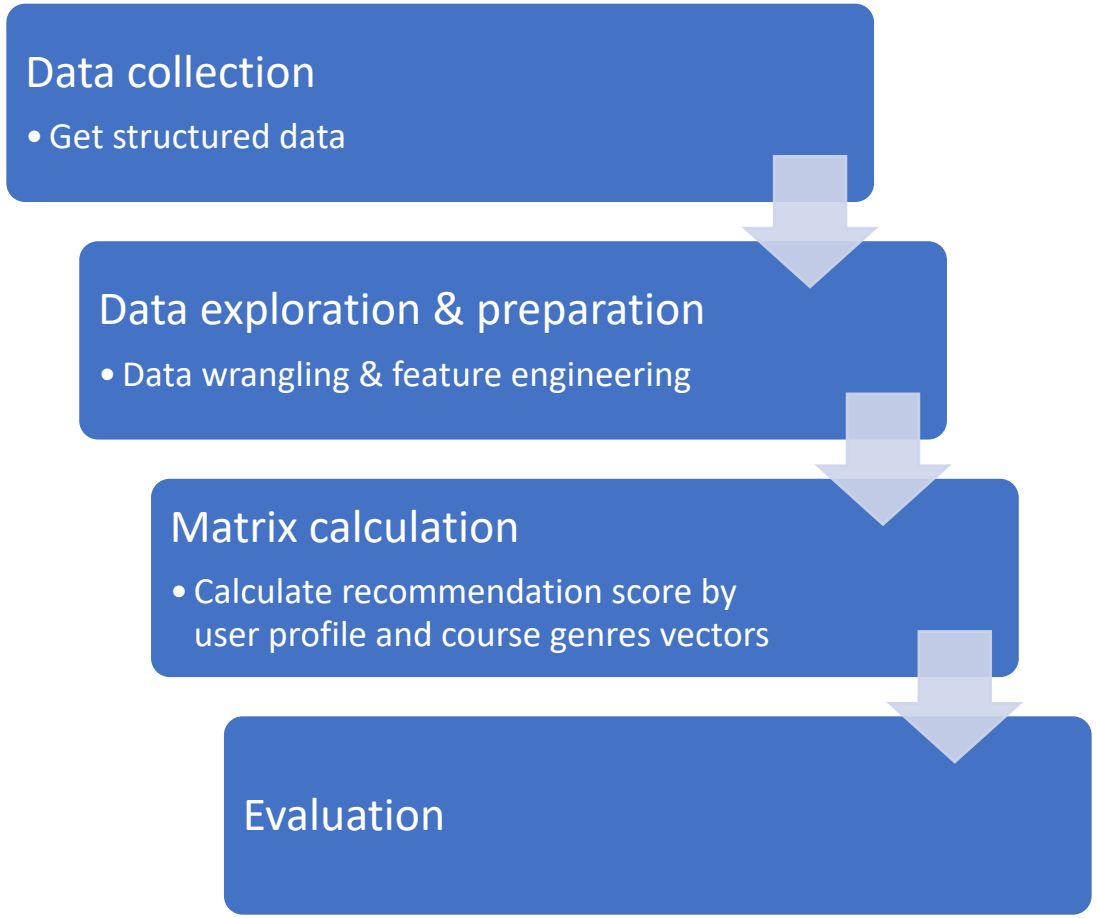
	TITLE	Ratings
0	python for data science	14936
1	introduction to data science	14477



Content-based Recommender System using Unsupervised Learning



Flowchart of content-based recommender system using user profile and course genres

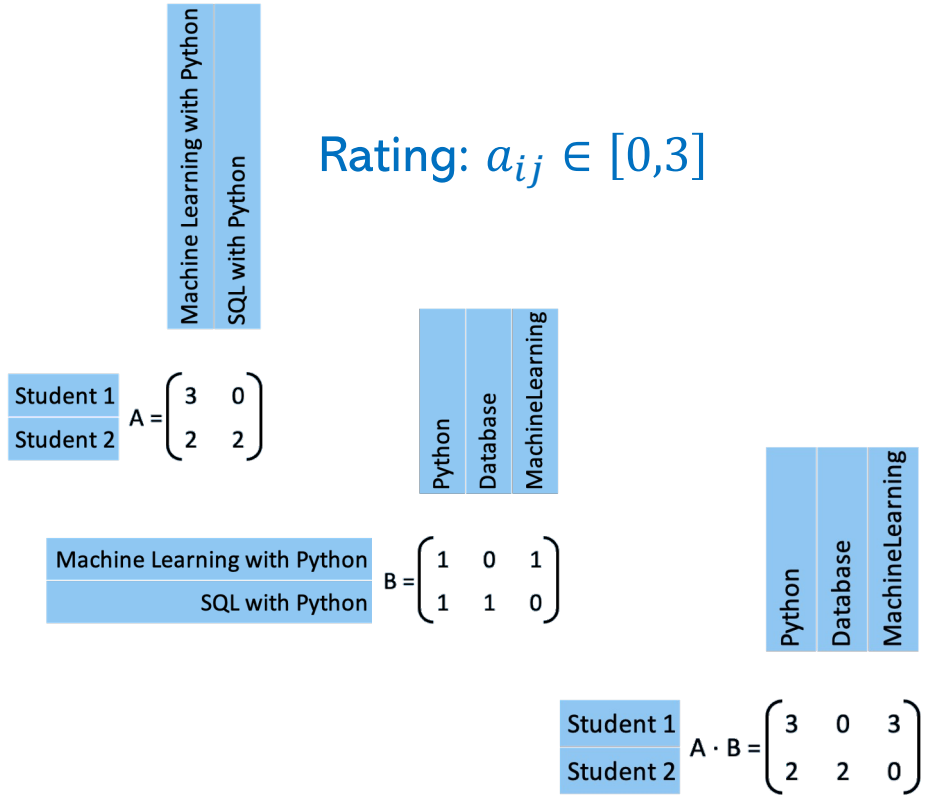


Matrix calculation

Let A be a $m \times n$ matrix with m students and n courses where each element denotes a rating of the student i about the course j within the interval $[0,3]$. A zero means that the student i has no interaction with the course j, a one means that the student i just browsed the course j, a two means that the student i just audited the course j without completing it and a three means that the student i completed the course j and earned a certificate.

Let B be a $n \times p$ matrix with n courses and p genres where each element denotes that course i belongs to genre j if and only if the value is 1.

Then $A \cdot B$ is the product matrix of the size $m \times p$ with m students and p genres where each element denotes a rating of the student i about the genre j within the same interval as the elements of the matrix A.



Matrix calculation and recommendation score

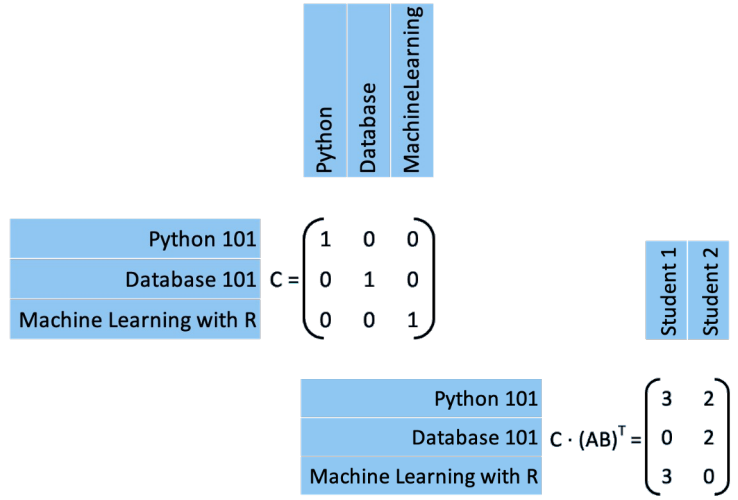
Let C be a $p \times q$ matrix with m unseen or unselected courses and n genres where each element denotes that the unseen or unselected course i belongs to genre j if and only if the value is 1.

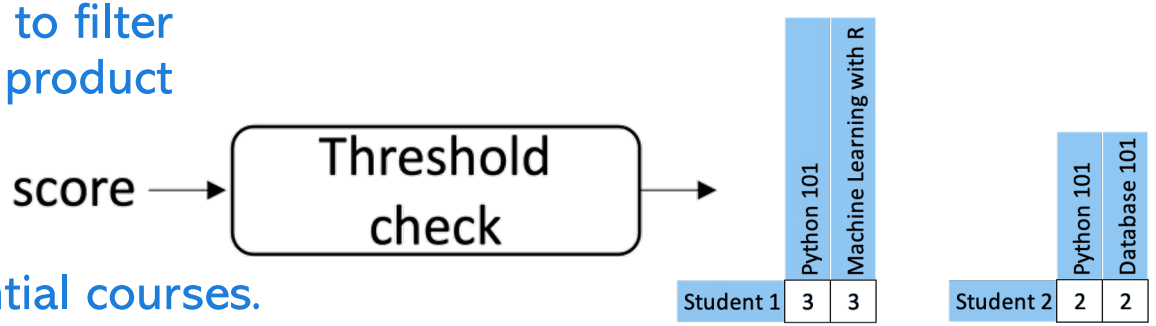
Then $C \cdot (AB)^T$ is the product matrix of the size $p \times m$ with p unseen or unselected courses and m students where each element denotes a rating of the unseen or unselected course i by the student j within the same interval as the elements of the matrix A.

A recommendation score threshold can be used to filter all unseen or unselected courses from the product matrix

$$C \cdot (AB)^T$$

to make appropriate recommendations to potential courses.





Evaluation results of user profile-based recommender system

Using a `score_threshold = 10`, the average new courses recommended per student (in percentage) is

```
len(res_df) / len(res_df['USER'].unique())
```

```
61.81828703703704
```

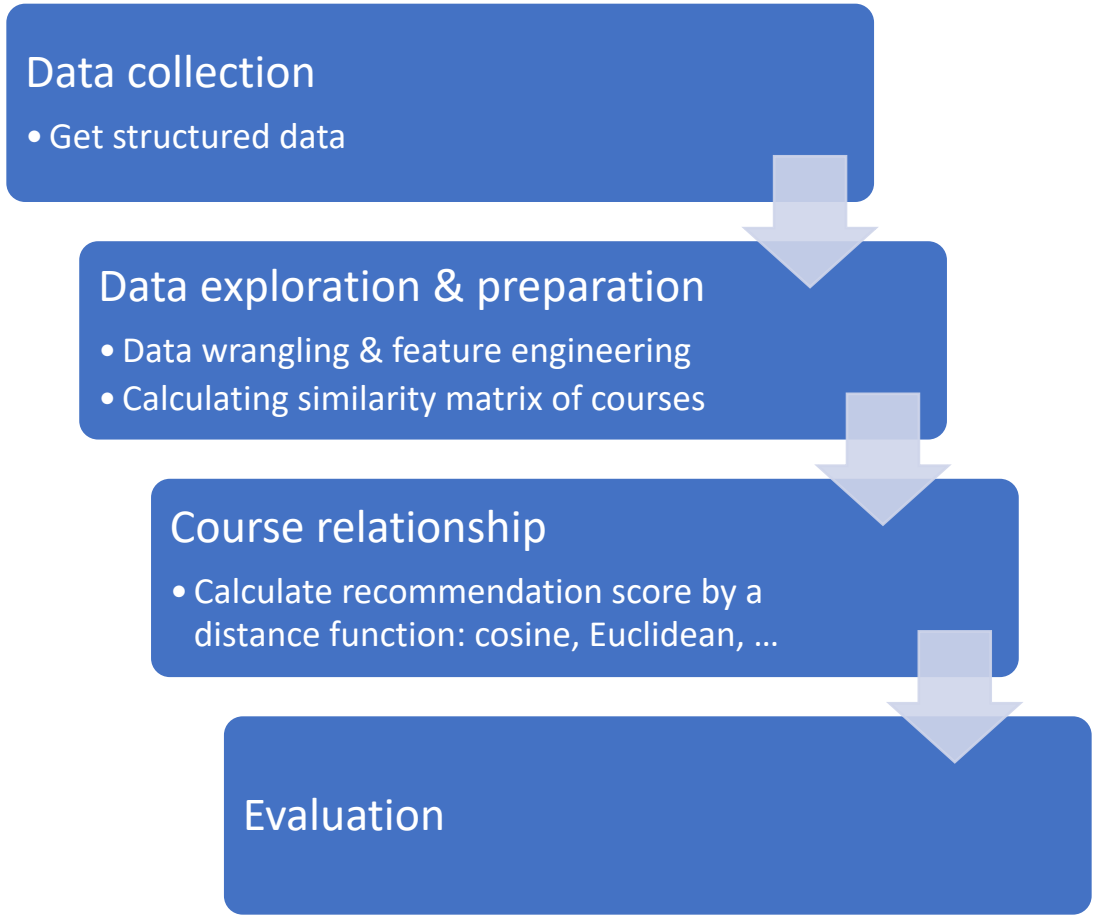
	USER	COURSE_ID	SCORE
0	37465	RP0105EN	27.0
1	37465	GPXX06RFEN	12.0
2	37465	CC0271EN	15.0
3	37465	BD0145EN	24.0
4	37465	DE0205EN	15.0
...	...	...	...
53406	2087663	excourse88	15.0
53407	2087663	excourse89	15.0
53408	2087663	excourse90	15.0
53409	2087663	excourse92	15.0
53410	2087663	excourse93	15.0

Evaluation results of user profile-based recommender system

The top-10 commonly recommended courses across all test users.

	TITLE	COURSE_ID	SCORE
0	analyzing big data with sql	excourse73	14386.0
1	foundations for big data analysis with sql	excourse72	14386.0
2	getting started with the data apache spark ma...	TMP0105EN	14182.0
3	analyzing big data in r using apache spark	RP0105EN	13347.0
4	cloud computing applications part 2 big data...	excourse31	13036.0
5	text analytics at scale	TA0106EN	12910.0
6	spark overview for scala analytics	SC0103EN	12853.0
7	introduction to data science in python	excourse22	11875.0
8	applied machine learning in python	excourse21	11875.0
9	accelerating deep learning with gpu	ML0122EN	11785.0

Flowchart of content-based recommender system using course similarity



Course relationship

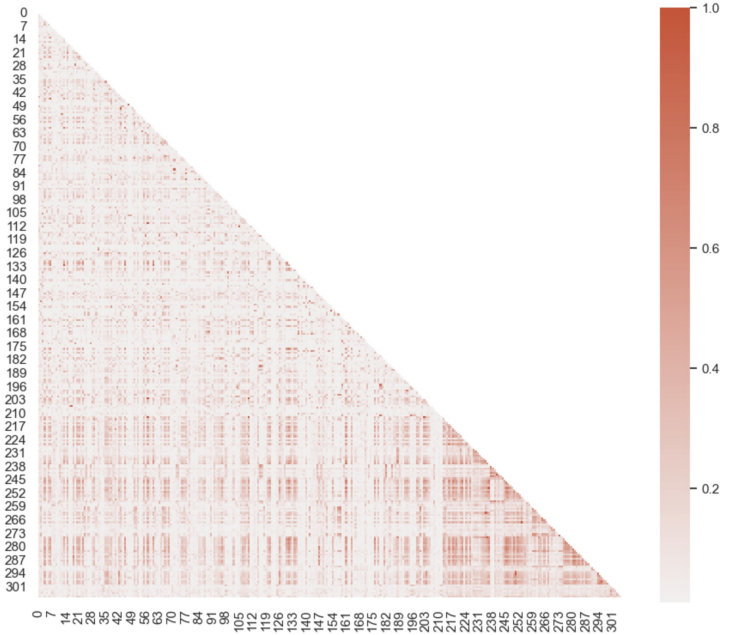
Let A be a $m \times n$ matrix with m courses and n courses where each element denotes the similarity of the course i and the course j within the interval $[0,1]$. A zero means no similarity between both courses a_{ij} and a value one means there is similarity.

Similarity: $a_{ij} \in [0,1]$

	Machine learning with R	Machine learning with Python	Predicting financial performance of a company
Machine learning with R	1	0.7	0.3
Machine learning with Python	0.7	1	0.3
Predicting financial performance of a company	0.3	0.3	1

$$A = \begin{pmatrix} 1 & 0.7 & 0.3 \\ 0.7 & 1 & 0.3 \\ 0.3 & 0.3 & 1 \end{pmatrix}$$

Visualisation of a pre-made similarity matrix A that contains 306 courses. The similarities of the courses are highlighted by a heat map.



Evaluation results of course similarity based recommender system

Using a `score_threshold = 10`, the average new/unseen courses recommended per student (in percentage) is

```
len(res_df) / len(res_df['USER'].unique())
```

```
20.733
```

The used distance function is **`cosine`**.

	USER	COURSE_ID	SCORE
0	37465	DS0101EN	1.000000
1	37465	BD0111EN	1.000000
2	37465	BD0101EN	1.000000
3	37465	BD0211EN	1.000000
4	37465	SC0101EN	1.000000
...	...	...	...
20728	2087663	excourse28	0.623754
20729	2087663	BD0145EN	0.623544
20730	2087663	excourse68	0.616759
20731	2087663	excourse60	0.615568
20732	2087663	excourse25	0.600535

Evaluation results of course similarity based recommender system

The top-10 commonly recommended courses across all test users.

	TITLE	COURSE_ID	SCORE
0	python for data science	PY0101EN	579.000000
1	introduction to data science	DS0101EN	553.931764
2	big data 101	BD0101EN	546.482523
3	data science with open data	DS0110EN	429.676691
4	hadoop 101	BD0111EN	420.000000
5	a crash course in data science	excourse63	385.920850
6	introduction to big data	excourse67	381.727268
7	introduction to data science in python	excourse22	374.903425
8	introduction to data science in python	excourse62	374.903425
9	foundations for big data analysis with sql	excourse72	361.846936

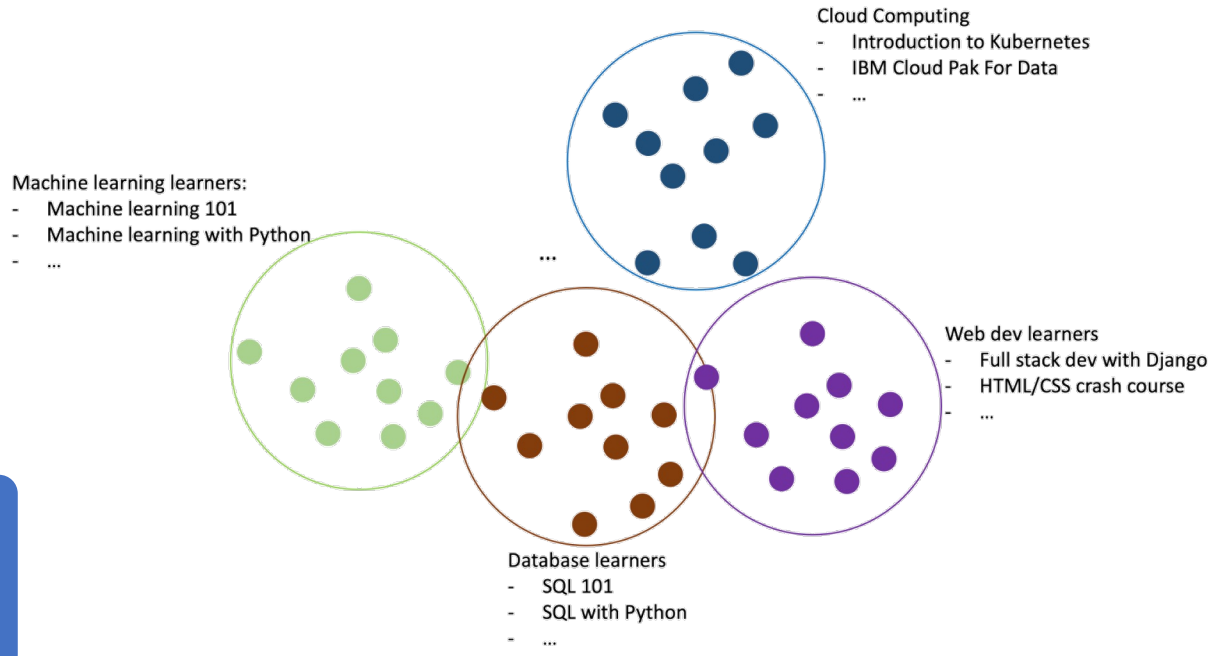
Flowchart of clustering-based recommender system

Data collection
- Get structured data

Data exploration & preparation
- Data wrangling & feature engineering
- Incl. normalisation by **StandardScaler**

Modeling
- Principal Component Analysis (PCA)
- Recommendation score by k-means

Evaluation

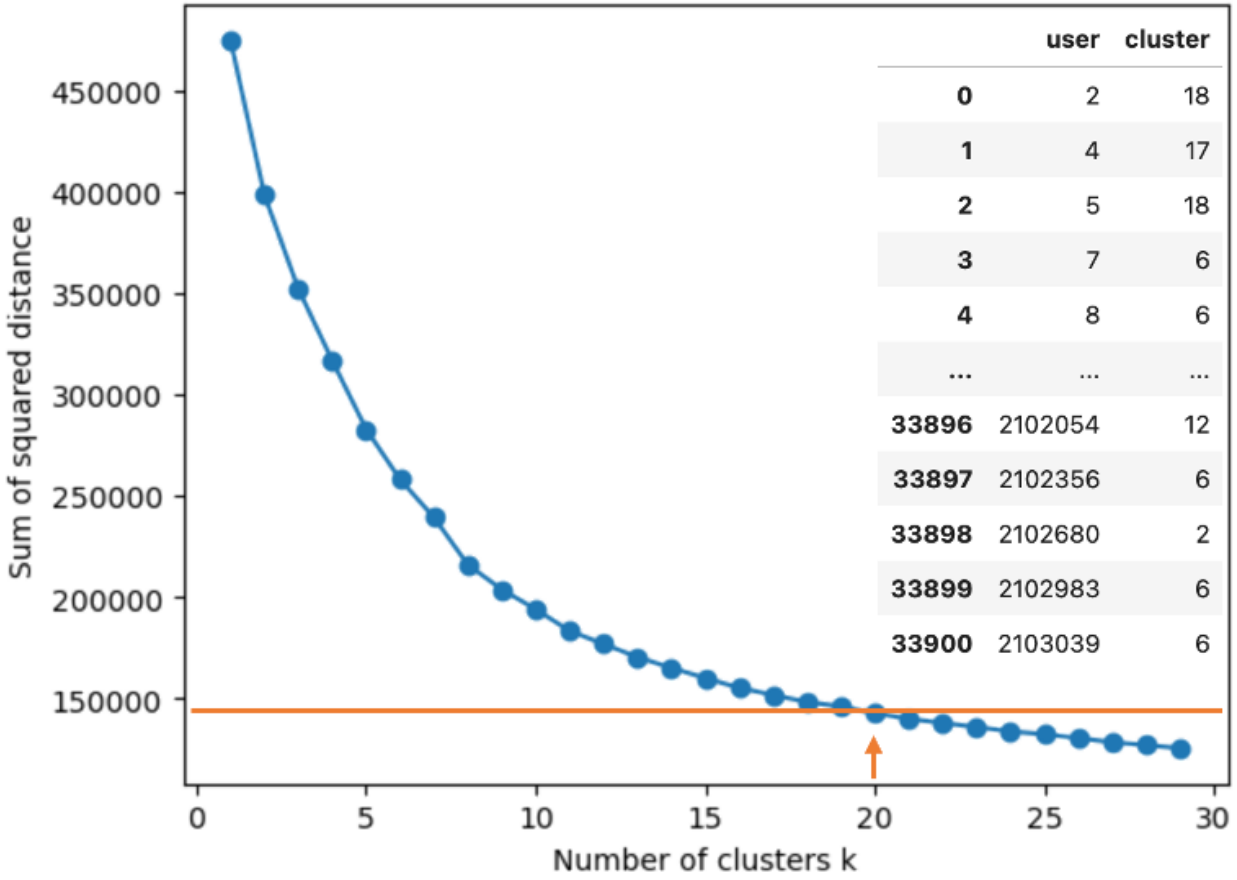


Modeling

- On the right, an elbow plot after grid search to optimize the KMeans hypterparameter:

  `n_cluster`

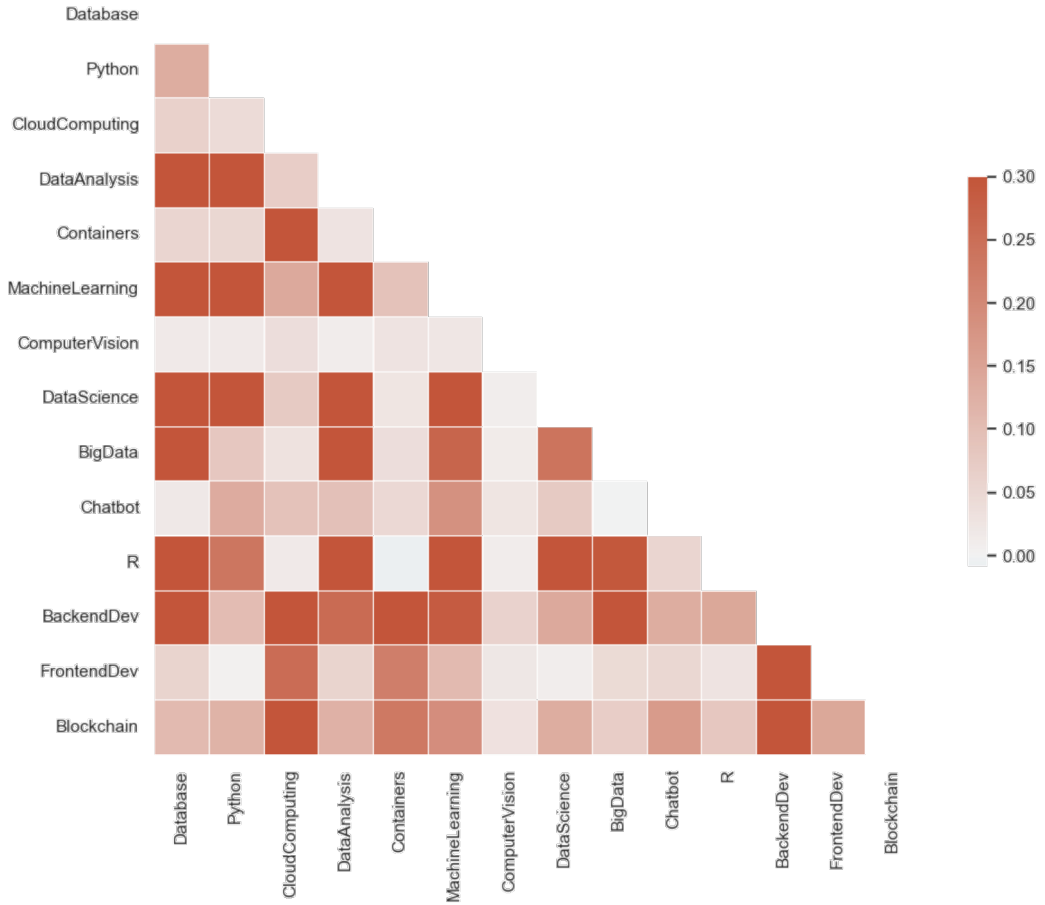
- A value of twenty seems to be a good choice to train our model.



	user	cluster
0	2	18
1	4	17
2	5	18
3	7	6
4	8	6
...	...	...
33896	2102054	12
33897	2102356	6
33898	2102680	2
33899	2102983	6
33900	2103039	6

Principal Component Analysis (PCA)

- A covariance matrix of the user profile feature vectors with 14 features to recognize which features are correlated.
- We can use PCA technique to reduce dimensionality at our 14 features to keep only only the independent main components.

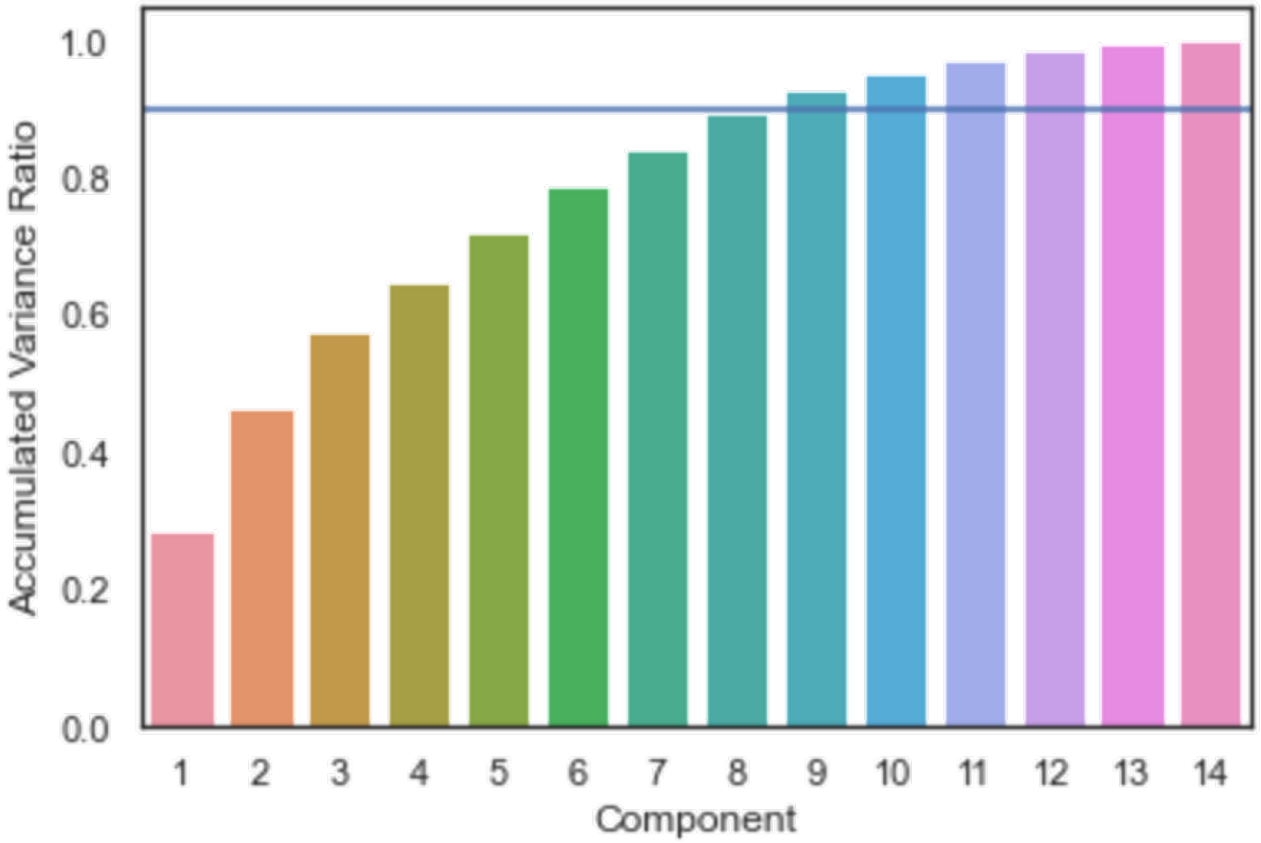


Principal Component Analysis (PCA)

- On the right, a visualization after grid search to optimize the PCA hyperparameter:

  `n_components`

- We see that eight features are below the accumulated variance ratio threshold of 90%.
- Hence, we can reduce the data's dimensionality to eight features.

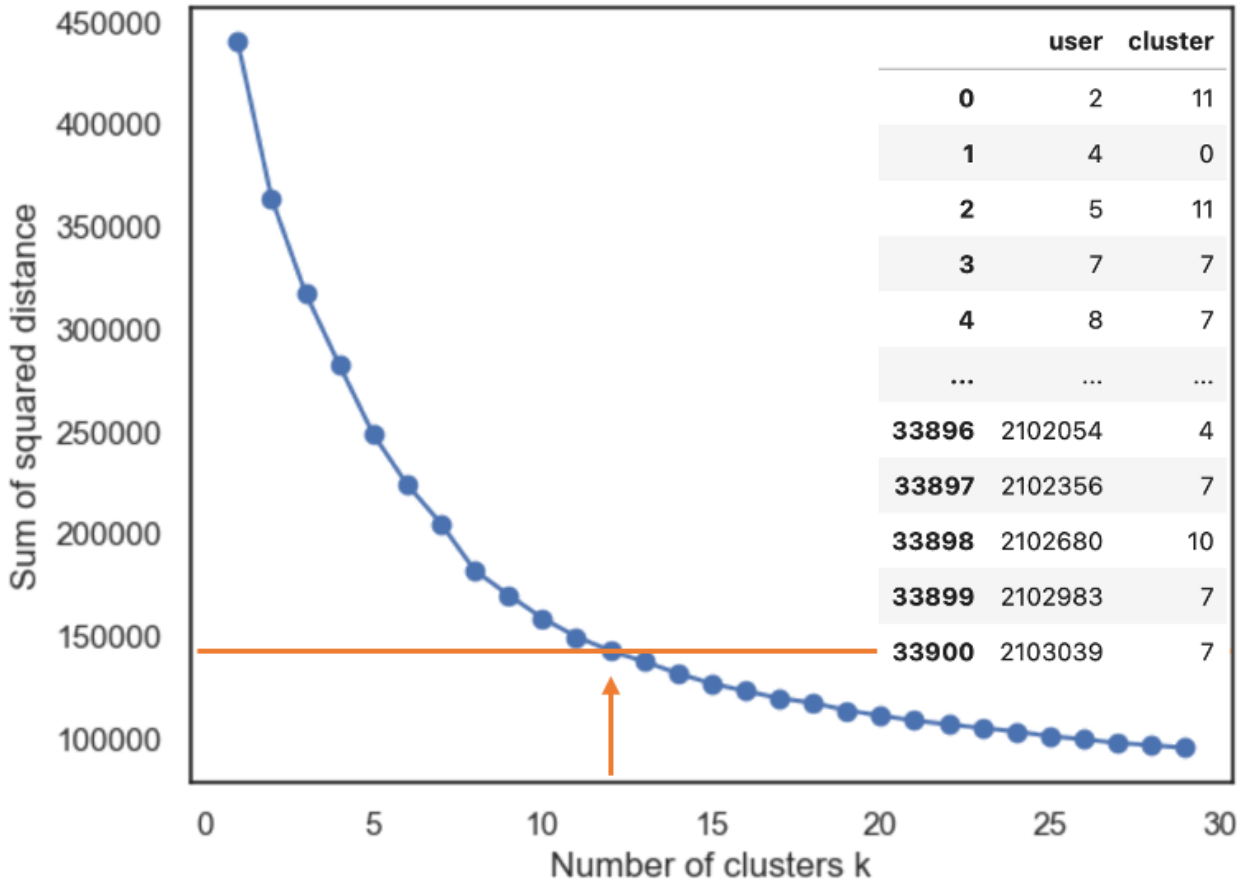


Modeling by PCA

- On the right, an elbow plot after grid search on the PCA transformed features to optimize the KMeans hypterparameter:

  `n_cluster`

- PCA enabled us to reduce the value of the same sum square error (SSE) from twenty clusters to twelve clusters.



	user	cluster
0	2	11
1	4	0
2	5	11
3	7	7
4	8	7
...	...	...
33896	2102054	4
33897	2102356	7
33898	2102680	10
33899	2102983	7
33900	2103039	7

Evaluation results of clustering-based recommender system

Using a `score_threshold = 10`,
the average new/unseen courses
recommended per student (in percentage) is

```
len(res_df) / len(res_df['USER'].unique())
```

```
22.21181262729124
```

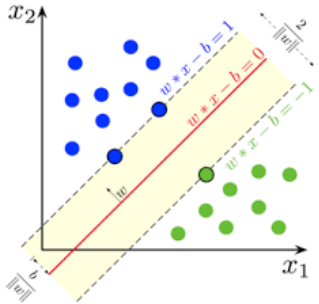
	USER	COURSE_ID
0	1502801	PY0101EN
1	1502801	DS0105EN
2	1502801	DS0103EN
3	1502801	DS0101EN
4	1502801	BD0143EN
...	...	...
11553	630511	ST0101EN
11554	630511	ML0103EN
11555	630511	WA0101EN
11556	630511	DA0101EN
11557	630511	ML0101ENv3

Evaluation results of clustering-based recommender system

The top-10 commonly recommended courses across all test users.

	TITLE	COURSE_ID	USER
0	statistics 101	ST0101EN	760
1	sql and relational databases 101	DB0101EN	717
2	watson analytics 101	WA0101EN	703
3	deep learning 101	ML0115EN	694
4	docker essentials a developer introduction	CO0101EN	682
5	spark fundamentals i	BD0211EN	671
6	data science methodology	DS0103EN	660
7	data analysis with python	DA0101EN	644
8	ibm cloud essentials	CL0101EN	625
9	blockchain essentials	BC0101EN	621

Collaborative-filtering Recommender System using Supervised Learning



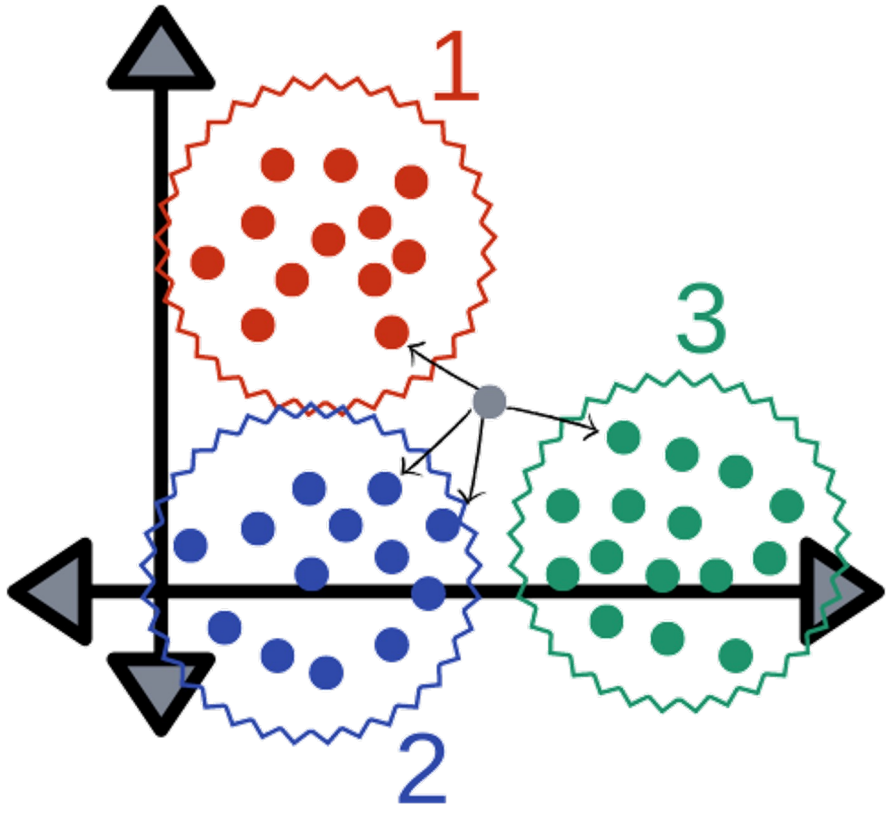
Flowchart of KNN based recommender system

Data collection
- Get structured data

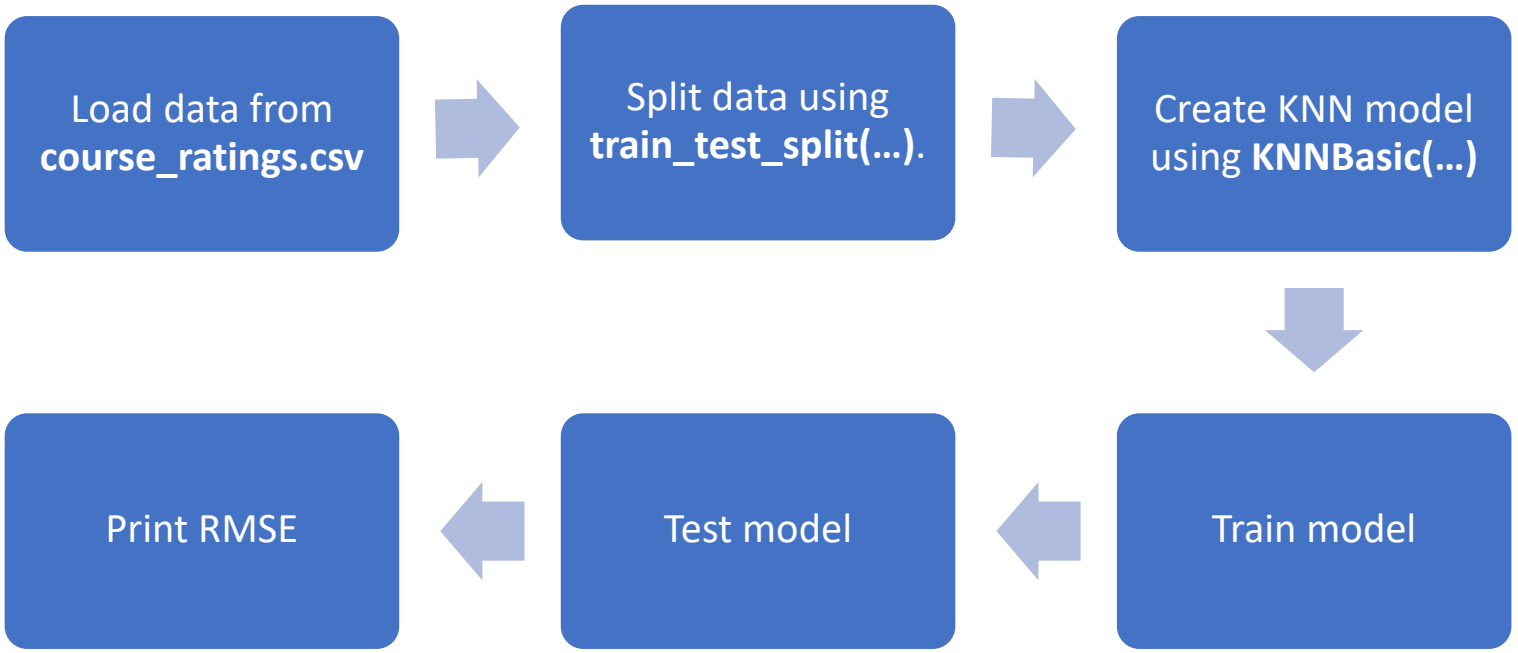
Data exploration & preparation
- Using Surprise API

Modeling
- Using Surprise API

Evaluation
- Calculate the root mean square error



Surprise API



	user	item	rating
0	1889878	CC0101EN	3.0
1	1342067	CL0101EN	3.0
2	1990814	ML0120ENv3	3.0
3	380098	BD0211EN	3.0
4	779563	DS0101EN	3.0

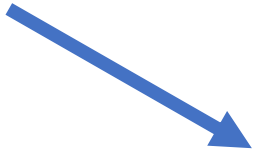
KNN Hyperparameters:

- `min_k = 3`
- `min_k = 12`
- `cosine` similarity

Sparse matrix

Notice that the Surprise API does the transformaton job for our us. On the right, you see an example how the data is transformed from a dense matrix to a sparse matrix.

user	item	rating
Student 1	Machine learning 101	3
Student 1	Machine learning capstone	3
Student 1	SQL with Python	3
Student 2	Machine learning 101	3
Student 2	Machine learning capstone	3
Student 2	SQL with Python	2
Student 3	Machine learning 101	3
Student 3	Machine learning capstone	2
Student 3	SQL with Python	2



	Machine learning 101	Machine learning capstone	SQL with Python
Student 1	3	3	3
Student 2	3	3	2
Student 3	3	2	2

$A =$

Evaluation results of KNN based recommender system

The result of the **user-based** collaborative filtering is a root mean square error (RMSE) of 0.2042. The predicted rating of user u to item i is given by the formula

$$\hat{r}_{ui} = \frac{\sum_{v \in N_i^k(u)} \text{similarity}(u, v) \cdot r_{vi}}{\sum_{v \in N_i^k(u)} \text{similarity}(u, v)}$$

The result of **item-based** collaborative filtering is a root mean square error (RMSE) of 0.2048. The predicted rating of user u to item i is given by the formula

$$\hat{r}_{ui} = \frac{\sum_{j \in N_u^k(i)} \text{similarity}(i, j) \cdot r_{uj}}{\sum_{j \in N_u^k(i)} \text{similarity}(i, j)}$$

The user-based collaborative filtering has a little better accuracy.

Flowchart of NMF based recommender system

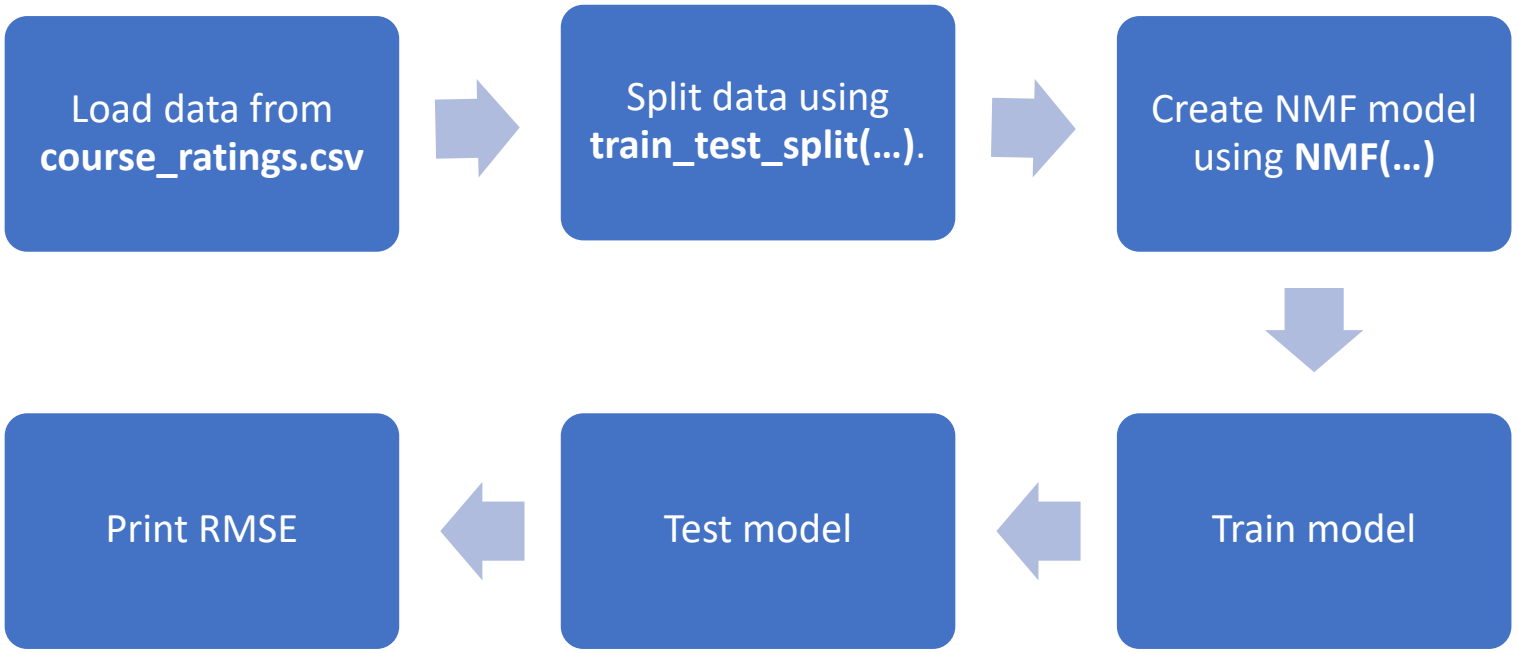
Data collection
- Get structured data

Data exploration & preparation
- Using Surprise API

Modeling
- Using Surprise API

Evaluation
- Calculate the root mean square error

Surprise API



	user	item	rating
0	1889878	CC0101EN	3.0
1	1342067	CL0101EN	3.0
2	1990814	ML0120ENv3	3.0
3	380098	BD0211EN	3.0
4	779563	DS0101EN	3.0

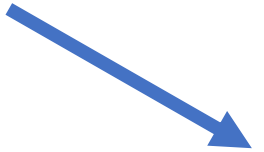
NMF Hyperparameters:

- `init_low = ½`
- `init_high= 5`
- `factors = 32`

Sparse matrix

Notice that the Surprise API does the transformaton job for our us. On the right, you see an example how the data is transformed from a dense matrix to a sparse matrix.

user	item	rating
Student 1	Machine learning 101	3
Student 1	Machine learning capstone	3
Student 1	SQL with Python	3
Student 2	Machine learning 101	3
Student 2	Machine learning capstone	3
Student 2	SQL with Python	2
Student 3	Machine learning 101	3
Student 3	Machine learning capstone	2
Student 3	SQL with Python	2

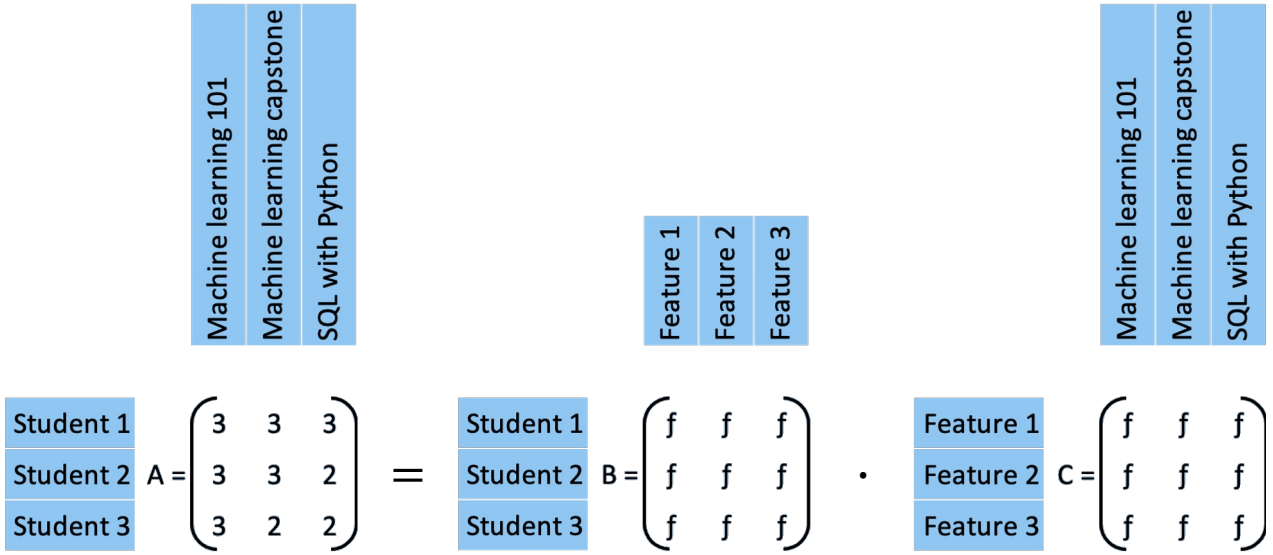


	Machine learning 101	Machine learning capstone	SQL with Python
Student 1	3	3	3
Student 2	3	3	2
Student 3	3	2	2

$A =$

Non-negative matrix factorization

For dimensionality reduction, the sparse matrix A is decomposed into two smaller and dense matrices, B and C.



Evaluation results of NMF based recommender system

The result of the NMF-based collaborative filtering is a root mean square error (RMSE) of 0.1912.
The accuracy is a little better than the KNN models.

Flowchart of Neural Network Embedding based recommender system

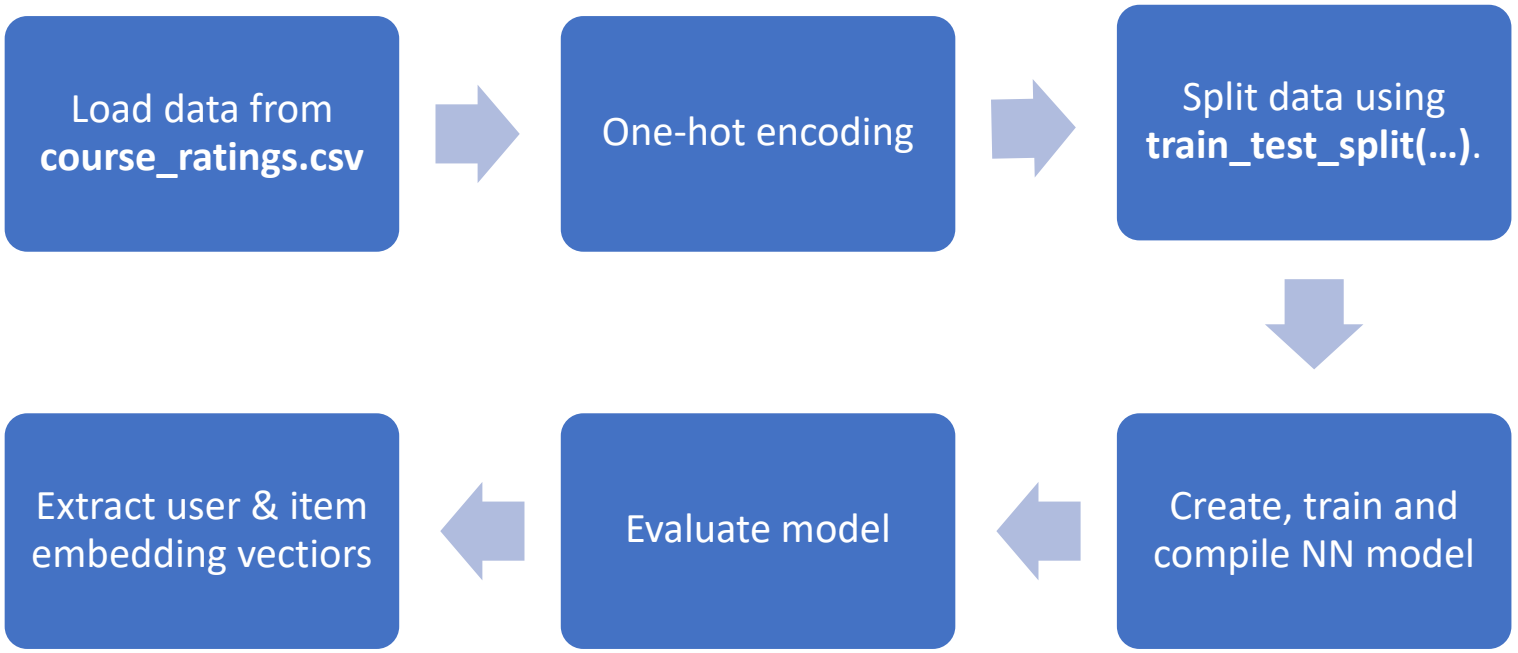
Data collection
- Get structured data

Data exploration & preparation
- Data wrangling & feature engineering
- Incl. creating one-hot encoding vectors

Modeling
- Using Keras API

Evaluation
- Calculate the root mean square error

Details



	user	item	rating
0	1889878	CC0101EN	3.0
1	1342067	CL0101EN	3.0
2	1990814	ML0120ENv3	3.0
3	380098	BD0211EN	3.0
4	779563	DS0101EN	3.0

Modeling

Our neuronal network (NN) model
is build by the customized function:

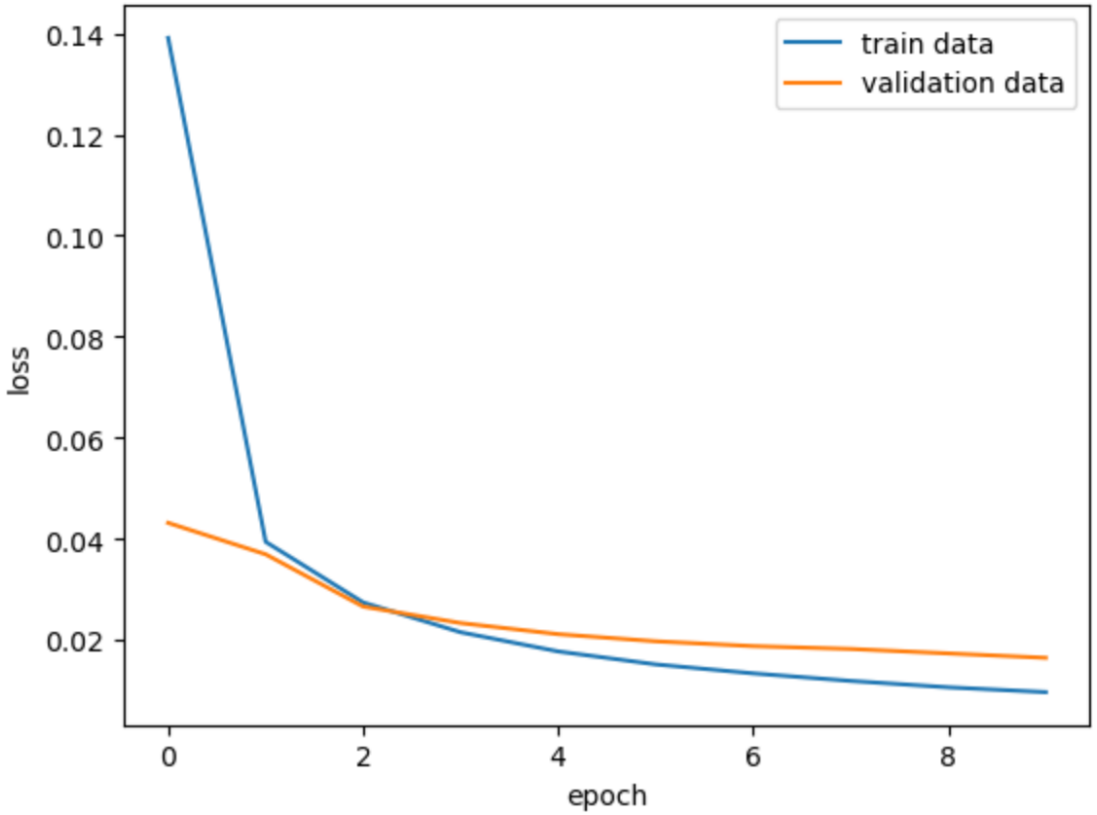
```
class RecommenderNet(keras.Model):

    def __init__(self, num_users, num_items, embedding_size=16, **kwargs):
        """
           Constructor
           :param int num_users: number of users
           :param int num_items: number of items
           :param int embedding_size: the size of embedding vector
        """
        super(RecommenderNet, self).__init__(**kwargs)
        self.num_users = num_users
        self.num_items = num_items
        self.embedding_size = embedding_size

        # Define a user_embedding vector
        # Input dimension is the num_users
        # Output dimension is the embedding size
        self.user_embedding_layer = layers.Embedding(
            input_dim=num_users,
            output_dim=embedding_size,
            name='user_embedding_layer',
            embeddings_initializer="he_normal",
            embeddings_regularizer=keras.regularizers.l2(1e-6),
        )
        # Define a user bias layer
        self.user_bias = layers.Embedding(
            input_dim=num_users,
            output_dim=1,
            name="user_bias")

        # Define an item_embedding vector
        # Input dimension is the num_items
        # Output dimension is the embedding size
        self.item_embedding_layer = layers.Embedding(
            input_dim=num_items,
            output_dim=embedding_size,
            name='item_embedding_layer',
            embeddings_initializer="he_normal",
            embeddings_regularizer=keras.regularizers.l2(1e-6),
        )
        # Define an item bias layer
        self.item_bias = layers.Embedding(
            input_dim=num_items,
            output_dim=1,
            name="item_bias")

    def call(self, inputs):
        """
           method to be called during model fitting

           :param inputs: user and item one-hot vectors
        """
        # Compute the user embedding vector
        user_vector = self.user_embedding_layer(inputs[:, 0])
        user_bias = self.user_bias(inputs[:, 0])
        item_vector = self.item_embedding_layer(inputs[:, 1])
        item_bias = self.item_bias(inputs[:, 1])
        dot_user_item = tf.tensordot(user_vector, item_vector, 2)
        # Add all the components (including bias)
        x = dot_user_item + user_bias + item_bias
        # Sigmoid output layer to output the probability
        return tf.nn.relu(x)
```

The `compile` parameters are

- `Optimizer = Adam`
- `loss = MeanSquaredError`
- `metrics = RootMeanSquaredError`

Modeling training

- At the first epochs, the validation data optimized better than the train data.
- After epoch two, the trainset outperformed.
- Finally, the spread between the sets kept stable but the optimization rate decelerated.



Evaluation results of Neural Network Embedding based recommender system

At the end, we evaluated our model on the testset and found:

- loss is 0.0159
- RMSE is 0.1190

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}}$$

Extract user & item embedding vectors

A summary of the model gives us the number of parameters on

- `user_embedding_layer`
- `item_embedding_layer`

```
model.summary()
```

```
Model: "recommender_net"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 user_embedding_layer (Embed  multiple                  542416
 ding)

 user_bias (Embedding)        multiple                  33901

 item_embedding_layer (Embed  multiple                  2016
 ding)

 item_bias (Embedding)        multiple                  126

=================================================================
Total params: 578,459
Trainable params: 578,459
Non-trainable params: 0
_________________________________________________________________
```

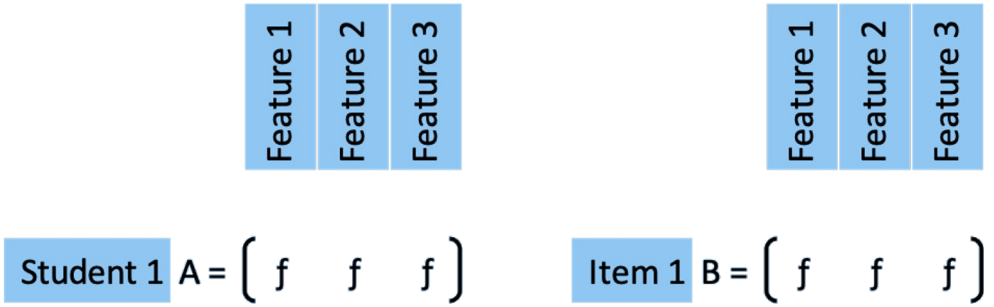
Extract user & item embedding vectors

Furthermore, the function `get_weights(...)` gives us the trained weights on both layers:

- user features shape: $(33901,16)$
- Item features shape: $(126,16)$

Each user or item has been tarnsformed into a $16x1$ latent feature vector used for prediction.

Illustration of two latent feature vectors of the size $3x1$:



Next, we will use both latent feature matrices for prediction.

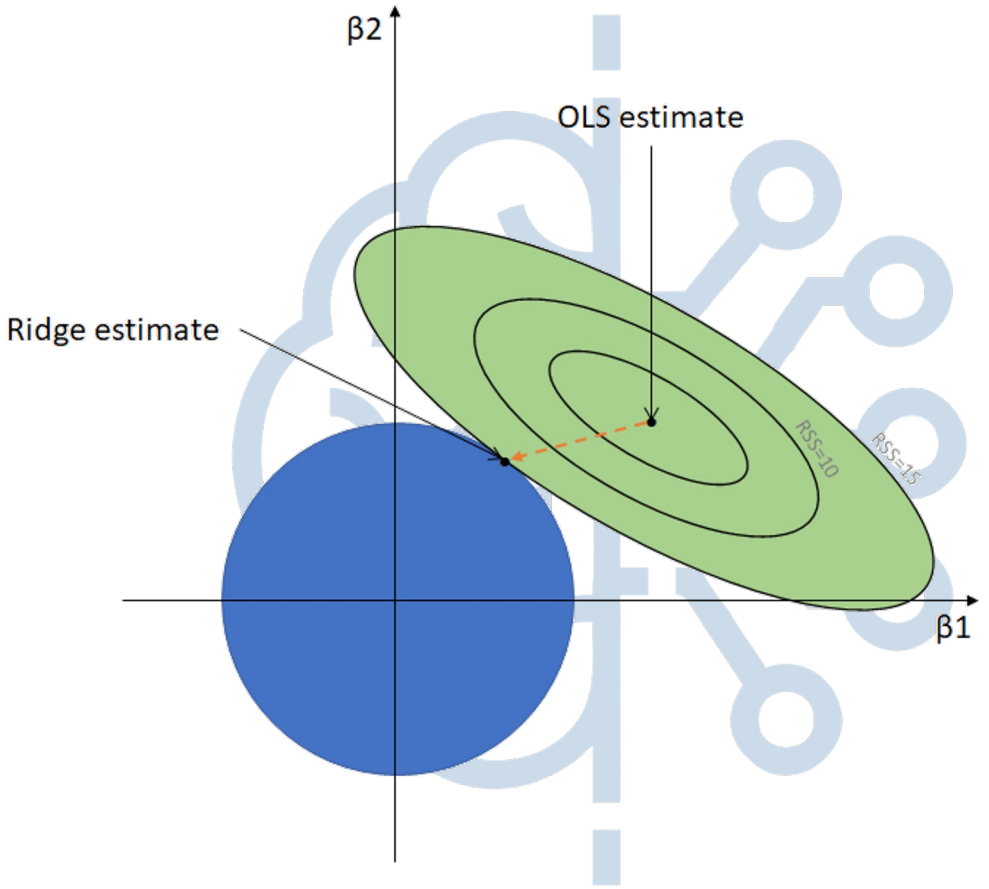
Flowchart of Regression Embedding based recommender system

Data collection
- Get structured data (ratings)
- Get user and course embeddings

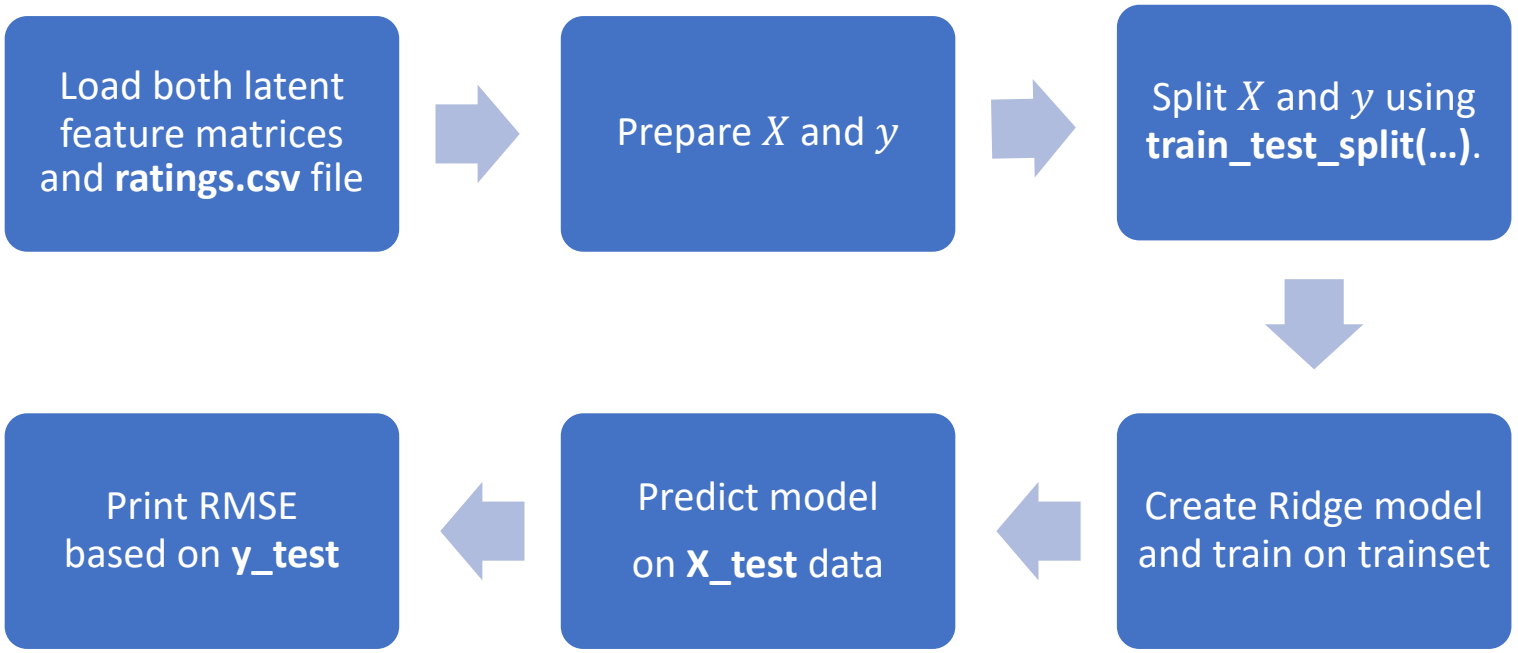
Data exploration & preparation
- Data wrangling & feature engineering
- Aggregate user/course feature vectors

Modeling
- Using scikit-learn API

Evaluation
- Calculate the root mean square error



Details



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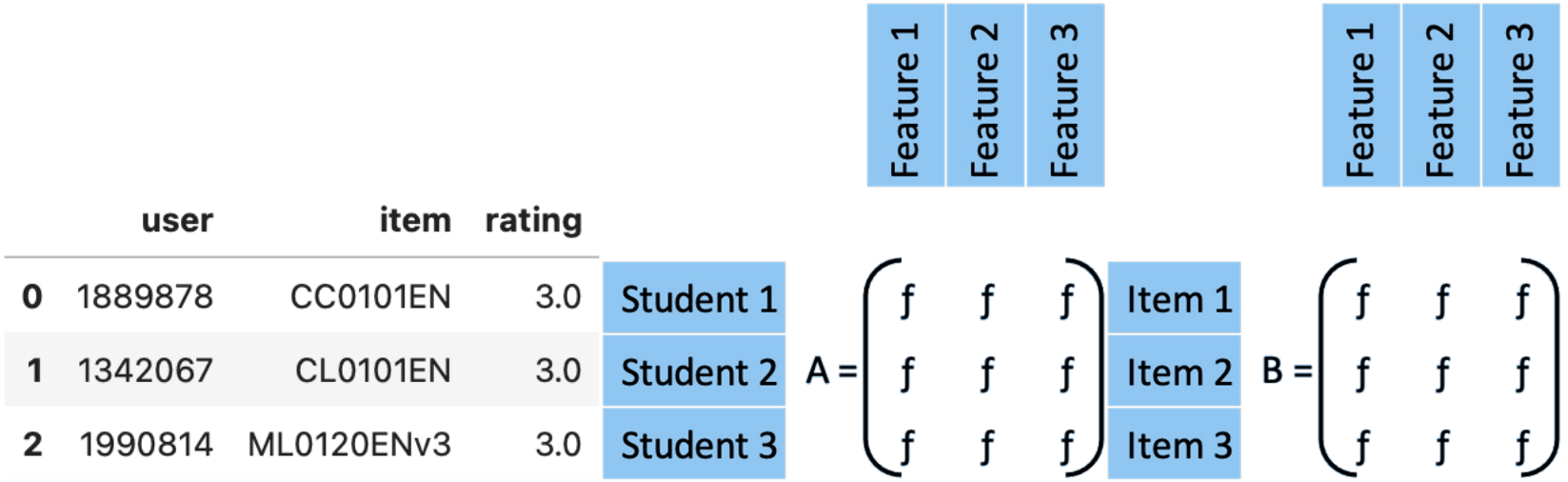
1	1342067	CL0101EN	3.0
2	1990814	ML0120ENv3	3.0
3	380098	BD0211EN	3.0
4	779563	DS0101EN	3.0

Prepare X and y

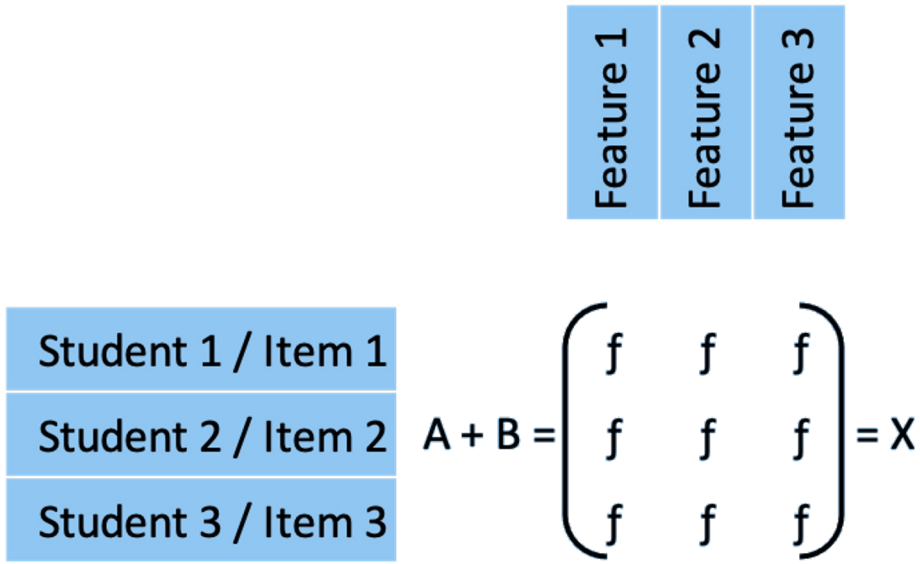
We use the `ratings.csv` table and
merge with both latent feature matrices, A and B.

	user	item	rating
0	1889878	CC0101EN	3.0
1	1342067	CL0101EN	3.0
2	1990814	ML0120ENv3	3.0

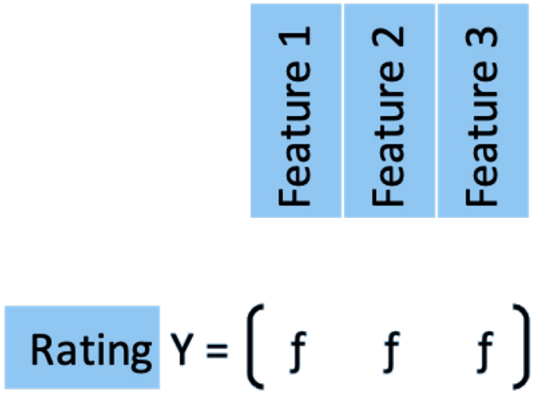


Extract user & item embedding vectors

Next, we assign the sum of both latent feature matrices, joined in the merged dataset, to X.



Finally, we assign the rating column from merged dataset to y.



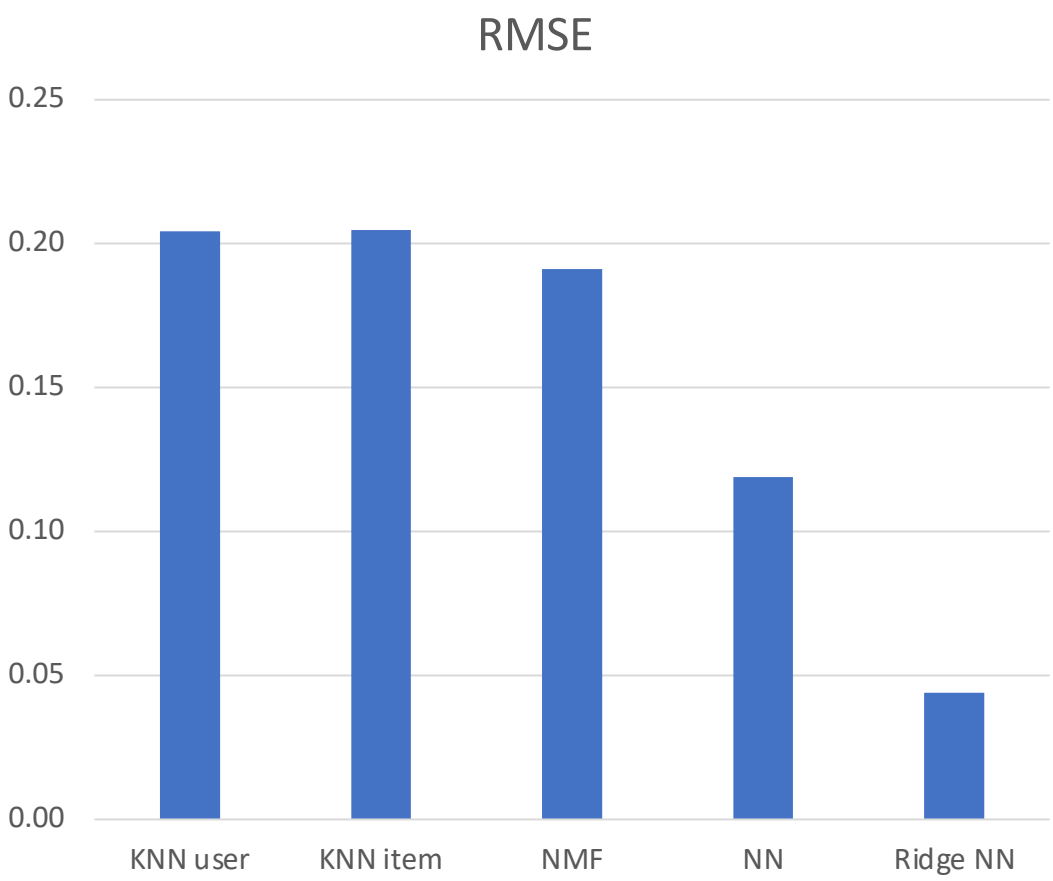
The X and y matrices can now be splitted to a trainset and a testset.

Evaluation results of Regression Embedding based recommender system

After train and prediction,
we found that our regression model based on Ridge regression,
using latent feature matrices trained by neural network,
has a root mean square error (RMSE) of 0.0440.

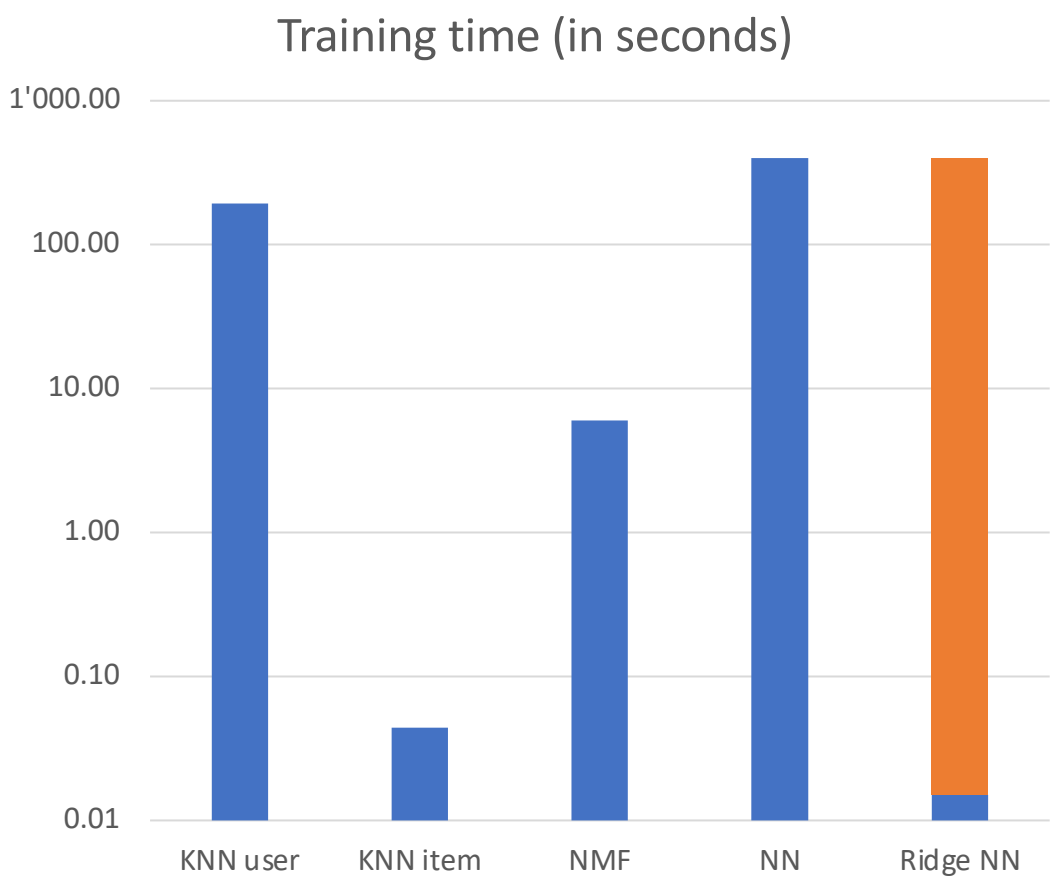
Compare the performance of collaborative-filtering models

Model	RMSE
KNN user-based	0.2042
KNN item-based	0.2048
Non-negative Matrix Factorization (NMF)	0.1912
Neuronal network (NN)	0.1190
Ridge using embedding features	**0.0440**

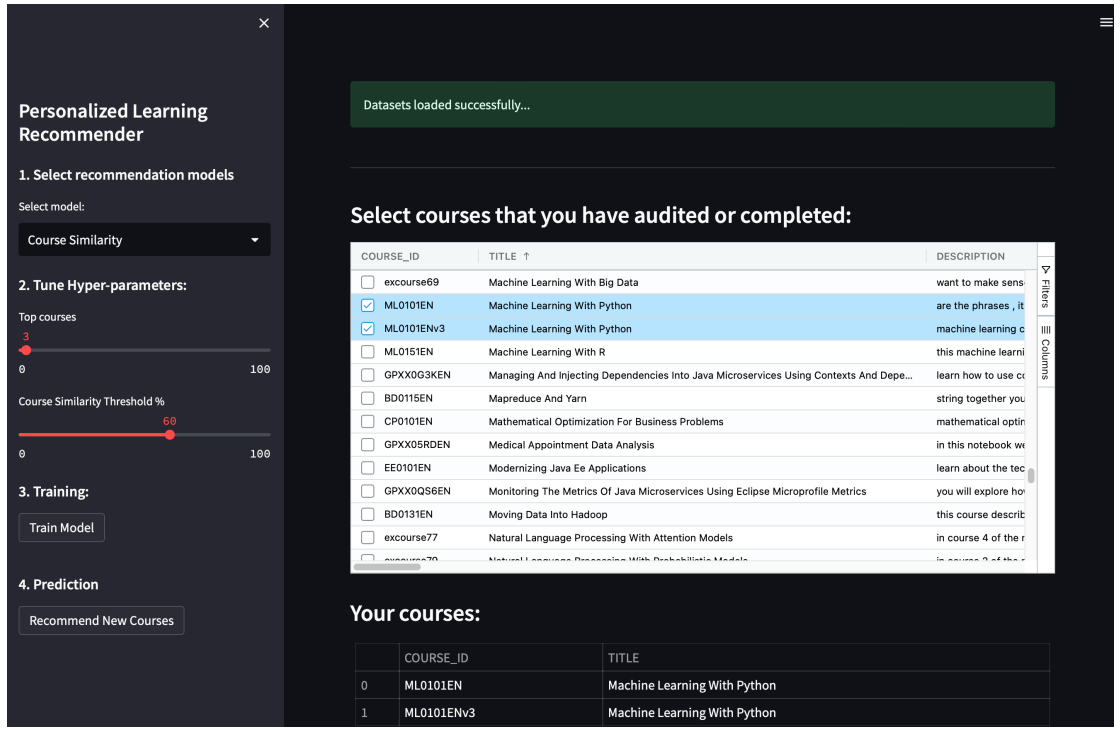


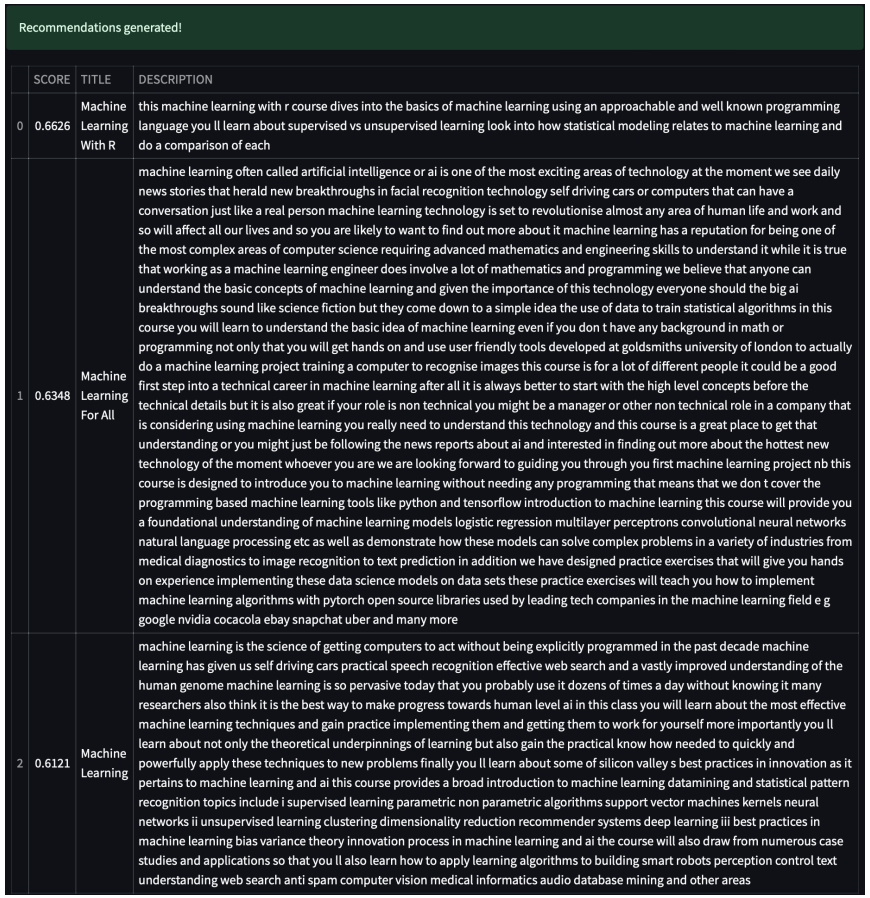
Compare the performance of collaborative-filtering models

Model	Seconds
KNN user-based	192.926
KNN item-based	0.044
Non-negative Matrix Factorization (NMF)	5.986
Neuronal network (NN)	399.978
Ridge using embedding features	0.015 +399.978



Build a course recommender system app with Streamlit






```
$ python -m venv $APP_PATH
$ streamlit run recommender_app.py
```

Conclusions

- There is not much significant RMSE differences between KNN and NMF models.
- Time measurement between the non-neuronal networks revealed that the KNN item-based training is the fastest and KNN user-based the slowest.
- Ridge regression using the embedding features, trained by a neuronal network, has the best predictability
- RMSE is 2.7 times lower than the second best (NN) and 4.6 times lower than the worst model (KNN user-based).
- Drawback is the higher computing costs to get the best model. In addition, the workload is higher, especially for neuronal networks.
- A pre-trained neuronal network reduces the computing costs insofar as the Ridge regression becomes the fastest trained model overall with the best predictability.

Appendix

- Python snippets
- Github repository: https://github.com/starfile/machine-learning-capstone

Python snippets

Calculate the top-10 commonly recommended courses across all test users for **profile-based** recommender system:

```
most_freq_recommendations = res_df.groupby('COURSE_ID').sum() \
  .sort_values('SCORE', ascending = False) \
  .head(10) \
  .reset_index()

filtered_courses = course_genres_df.iloc[
  pd.Index(course_genres_df['COURSE_ID']) \
  .get_indexer(most_freq_recommendations['COURSE_ID'])] \
  .reset_index()

most_freq_recommendations = filtered_courses.join(
  most_freq_recommendations['SCORE'])[['TITLE', 'COURSE_ID', 'SCORE']]

most_freq_recommendations
```

Calculate the top-10 commonly recommended courses across all test users for **similarity based** recommender system:

```
most_freq_recommendations = res_df.groupby('COURSE_ID').sum() \
  .sort_values('SCORE', ascending = False) \
  .head(10) \
  .reset_index()

filtered_courses = course_df.iloc[
  pd.Index(course_df['COURSE_ID']) \
  .get_indexer(most_freq_recommendations['COURSE_ID'])] \
  .reset_index()

most_freq_recommendations = filtered_courses.join(
  most_freq_recommendations['SCORE'])[['TITLE', 'COURSE_ID', 'SCORE']]

most_freq_recommendations
```

Python snippets

Calculate the top-10 commonly recommended courses across all test users for **clustering-based** recommender system:

```
course_url = "https://cf-courses-data.s3.us.cloud-object-storage" + \
  ".appdomain.cloud/IBM-ML321EN-SkillsNetwork/labs/datasets/" + \
  "course_processed.csv"

course_df = pd.read_csv(course_url)

most_freq_recommendations = res_df.groupby('COURSE_ID').count() \
  .sort_values('USER', ascending = False) \
  .head(10) \
  .reset_index()

filtered_courses = course_df.iloc[
  pd.Index(course_df['COURSE_ID']) \
  .get_indexer(most_freq_recommendations['COURSE_ID'])] \
  .reset_index()

most_freq_recommendations = filtered_courses.join(
  most_freq_recommendations['USER'])[['TITLE', 'COURSE_ID', 'USER']]

most_freq_recommendations
```

Thank you!