# Recommendation system
# Build a Personalized Online Course Recommender System with Machine Learning

Anton Nazaruk

**Outline:**

1. Capstone Overview
2. Exploratory Data Analysis and Feature Engineering
3. Unsupervised Learning based Recomendation System
4. Supervised Learning based Recomendation System
5. Conclusion and future work
6. Appendix

# Capstone Overview - Motivation

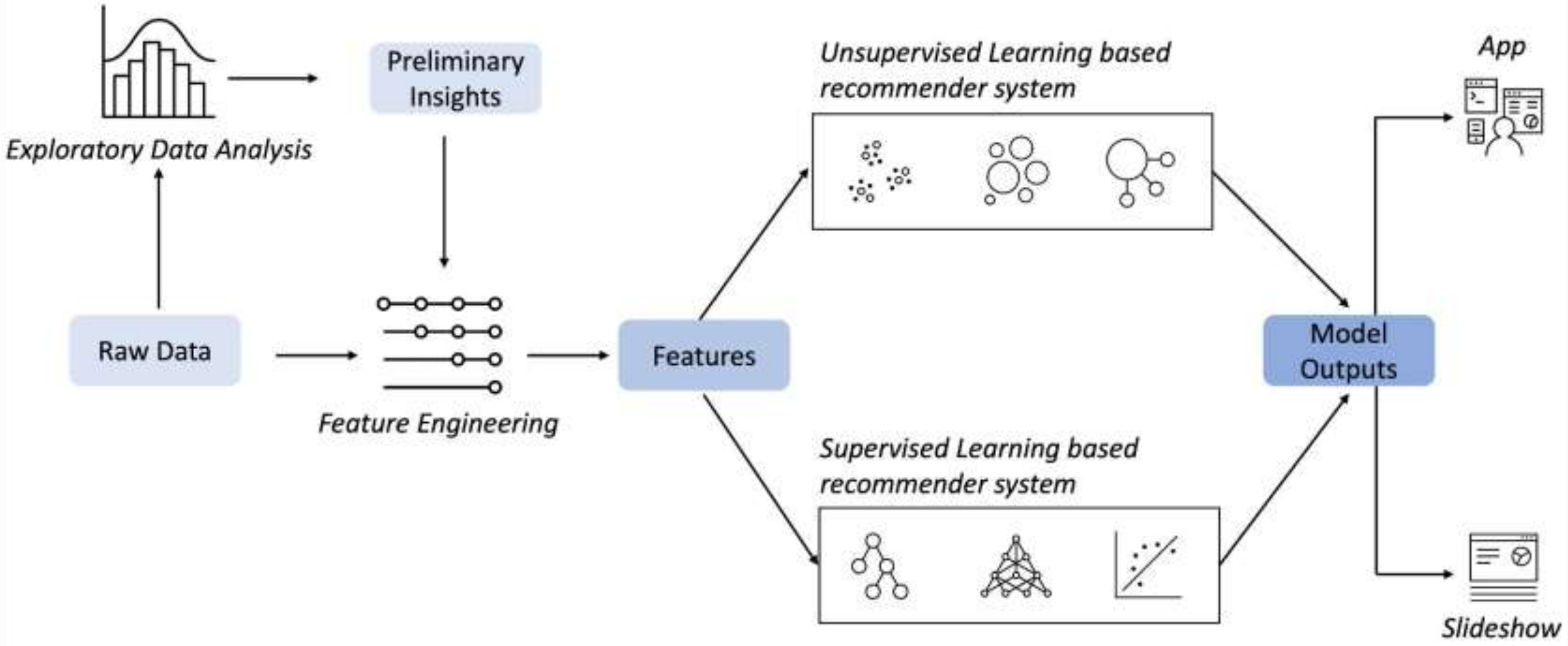
The objective of this project is to create a recommender system that will assist students in discovering new courses that are in line with their interests and academic objectives. The improved user experience will lead to more enrollments, more new users, and more revenue for the business.

- Hypothesis: In order to find new courses that the user would be interested in, we can use information about the user's prior enrollments as well as information about the course's characteristics.

# Capstone Overview - Machine learning pipeline

1. Collecting and understanding data
2. Performing exploratory data analysis on online course enrollments datasets
3. Extracting Bag of Words (BoW) features from course textual content
4. Calculating course similarity using BoW features
5. Building content-based recommender systems using various unsupervised learning algorithms, such as: Distance/Similarity measurements, K-means, Principal Component Analysis (PCA), etc.
6. Building collaborative-filtering recommender systems using various supervised learning algorithms
K Nearest Neighbors, Non-negative Matrix Factorization (NMF), Neural Networks, Linear Regression, Logistic Regression, RandomForest, etc.
7. Presentation.

# Capstone Overview - Machine learning pipeline



# Exploratory Data Analysis and Feature Engineering

# Exploratory Data Analysis

Pipeline:

1. Describe the statistic of data columns
2. Identify keywords in course titles using a WordCloud
3. Determine popular course genres
4. Calculate the summary statistics and create visualizations of the online course enrollment dataset

# Exploratory Data Analysis

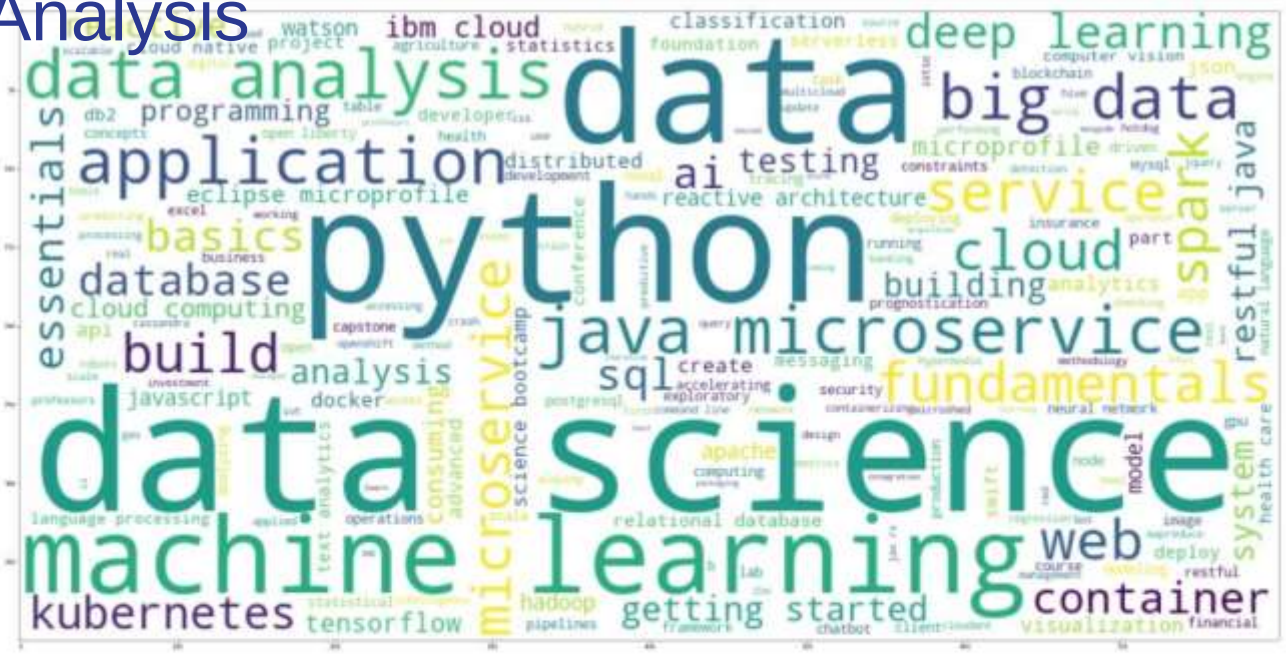
**Describe the statistic of data columns**

- There are 307 courses at total.
- Each course is a vector of genres 1x16.
- 1 means this course is not related to this genre.
- 2 means this course is related to this genre.

```
COURSE_ID          object
TITLE              object
Database            int64
Python              int64
CloudComputing      int64
DataAnalysis        int64
Containers          int64
MachineLearning     int64
ComputerVision      int64
DataScience         int64
BigData             int64
Chatbot             int64
R                   int64
BackendDev          int64
FrontendDev         int64
Blockchain          int64
dtype: object
```

| | COURSE_ID | TITLE | Database | Python | CloudComputing | DataAnalysis | Containers | MachineLearning | ComputerVision | DataScience | BigData | Chatbot | R | BackendDev | FrontendDev | Blockchain |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ML0201EN | robots are coming build iot apps with watson ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| 1 | ML0122EN | accelerating deep learning with gpu | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | GPXX0ZG0EN | consuming restful services using the reactive ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| 3 | RP0105EN | analyzing big data in r using apache spark | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 4 | GPXX0Z2PEN | containerizing packaging and running a sprin... | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |

# Exploratory Data Analysis




**Identify keywords in course titles using a WordCloud**

The omnipresences following by size respectively are:

1. data ->
2. data science ->
3. python ->
4. machine learning ->
5. data analysis ->
6. application ->
7. big data ->
8. java ->
9. microservice
10. web

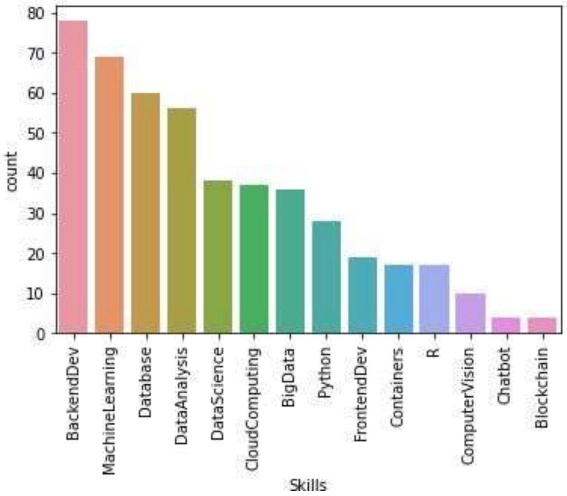
# Exploratory Data Analysis

| | Skills | count |
|---|---|---|
| 11 | BackendDev | 78 |
| 5 | MachineLearning | 69 |
| 0 | Database | 60 |
| 3 | DataAnalysis | 56 |
| 7 | DataScience | 38 |
| 2 | CloudComputing | 37 |
| 8 | BigData | 36 |
| 1 | Python | 28 |
| 12 | FrontendDev | 19 |
| 4 | Containers | 17 |
| 10 | R | 17 |
| 6 | ComputerVision | 10 |
| 9 | Chatbot | 4 |
| 13 | Blockchain | 4 |

**Determine popular course genres**

BackendDev, MachineLearning, Database are the utmost popular genres.

While Blockchain, Chatbot, ComputerVision are the most less common ones.

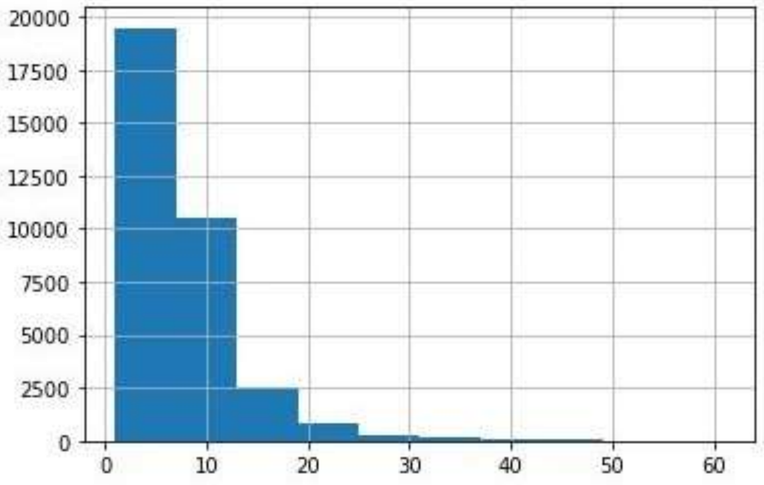


# Exploratory Data Analysis

This given histogram illustrates the amount of user rating counts.

Almost users did not rate any courses or rated rarely.

A few exceptional students rated above 40 courses.




**The histogram of user rating counts**

This below table shows top 20 widespread couses.

9/10 courses of top 10 are belong to data topic.

Only the 4th is the part of software engineer topic.

**Top 20 Most Popular Courses**

| | COURSE_ID | count | TITLE |
|---|---|---|---|
| 0 | DS0301EN | 3624 | data privacy fundamentals |
| 1 | BD0115EN | 3670 | mapreduce and yarn |
| 2 | DB0101EN | 3697 | sql and relational databases 101 |
| 3 | CO0101EN | 4480 | docker essentials a developer introduction |
| 4 | CC0101EN | 4983 | introduction to cloud |
| 5 | ST0101EN | 5015 | statistics 101 |
| 6 | RP0101EN | 5237 | r for data science |
| 7 | CB0103EN | 5512 | build your own chatbot |
| 8 | ML0115EN | 6323 | deep learning 101 |
| 9 | DV0101EN | 6709 | data visualization with python |
| 10 | BC0101EN | 6719 | blockchain essentials |
| 11 | DS0105EN | 7199 | data science hands on with open source tools |
| 12 | BD0211EN | 7551 | spark fundamentals i |
| 13 | ML0101ENv3 | 7644 | machine learning with python |
| 14 | DS0103EN | 7719 | data science methodology |
| 15 | DA0101EN | 8303 | data analysis with python |
| 16 | BD0111EN | 10599 | hadoop 101 |
| 17 | BD0101EN | 13291 | big data 101 |
| 18 | DS0101EN | 14477 | introduction to data science |
| 19 | PY0101EN | 14936 | python for data science |

# Feature Engineering

Pipeline:

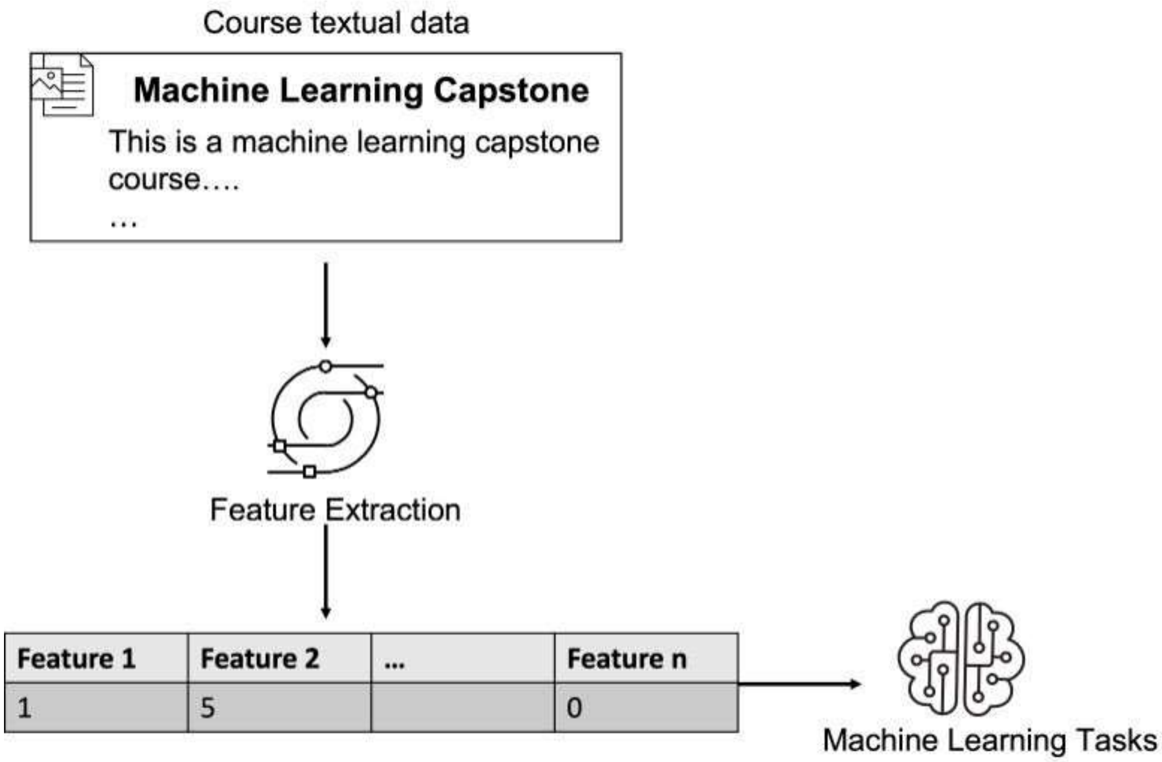
1. Extract Bag of Words (BoW) Features from Course Textual Content
    1. Bag of Words (BoW) features
    2. BoW dimensionality reduction
    3. Extract BoW features for course textual content and build a dataset
2. Calculate Course Similarity using BoW Features
    1. Calculate the consine similarity between two example courses
    2. Find similar courses to the specific course

# Feature Engineering

The main goal of recommender systems is to help users find items they potentially interested in. Depending on the recommendation tasks, an item can be a movie, a restaurant, or, in our case, an online course.

Machine learning algorithms cannot work on an item directly so we first need to extract features and represent the items mathematically, i.e., with a feature vector.

Many items are often described by text so they are associated with textual data, such as the titles and descriptions of a movie or course. Since machine learning algorithms can not process textual data directly, we need to transform the raw text into numeric feature vectors.



# Feature Engineering - BoW

## Bag of Words (BoW) features

BoW features are essentially the counts or frequencies of each word that appears in a text (string). Let's illustrate it with some simple examples.

Suppose we have two course descriptions as follows:

```
course1 = "this is an introduction data science course which introduces data science to beginners"
```

```
course2 = "machine learning for beginners"
```

```
courses = [course1, course2]
courses
```

```
['this is an introduction data science course which introduces data science to beginners',
 'machine learning for beginners']
```

The first step is to split the two strings into words (tokens). A token in the text processing context means the smallest unit of text such as a word, a symbol/punctuation, or a phrase, etc. The process to transform a string into a collection of tokens is called `tokenization`.

One common way to do `tokenization` is to use the Python built-in `split()` method of the `str` class. However, in this lab, we want to leverage the `nltk` (Natural Language Toolkit) package, which is probably the most commonly used package to process text or natural language.

More specifically, we will use the `word_tokenize()` method on the content of course (string):

```
# Tokenize the two courses
tokenized_courses = [word_tokenize(course) for course in courses]
```

# Feature Engineering - BoW

## Bag of Words (BoW) features

```
Bag of words for course 0:
--Token: 'an', Count:1
--Token: 'beginners', Count:1
--Token: 'course', Count:1
--Token: 'data', Count:2
--Token: 'introduces', Count:1
--Token: 'introduction', Count:1
--Token: 'is', Count:1
--Token: 'science', Count:2
--Token: 'this', Count:1
--Token: 'to', Count:1
--Token: 'which', Count:1
Bag of words for course 1:
--Token: 'beginners', Count:1
--Token: 'for', Count:1
--Token: 'learning', Count:1
--Token: 'machine', Count:1
```

If we turn to the long list into a horizontal feature vectors, we can see the two courses become two numerical feature vectors:

| | an | beginners | course | data | science | ... |
|---|---|---|---|---|---|---|
| course1 | 1 | 1 | 1 | 2 | 2 | |
| course2 | 0 | 1 | 0 | 0 | 0 | |

# Feature Engineering - BoW

## BoW dimensionality reduction

- A document may contain tens of thousands of words which makes the dimension of the BoW feature vector huge.
- To reduce the dimensionality, one common way is to filter the relatively meaningless tokens such as stop words or sometimes add position and adjective words.

# Feature Engineering - BoW

## BoW dimensionality reduction

Then we can filter those English stop words from the tokens in course1:

```python
# Tokens in course 1
tokenized_courses[0]
```

```
['this',
 'is',
 'an',
 'introduction',
 'data',
 'science',
 'course',
 'which',
 'introduces',
 'data',
 'science',
 'to',
 'beginners']
```

```python
processed_tokens = [w for w in tokenized_courses[0] if not w.lower() in stop_words]
```

```python
processed_tokens
```

```
['introduction',
 'data',
 'science',
 'course',
 'introduces',
 'data',
 'science',
 'beginners']
```

You can see the number of tokens for `course1` has been reduced.

Another common way is to only keep nouns in the text. We can use the `nltk.pos_tag()` method to analyze the part of speech (POS) and annotate each word.

```python
tags = nltk.pos_tag(tokenized_courses[0])
tags
```

```
[('this', 'DT'),
 ('is', 'VBZ'),
 ('an', 'DT'),
 ('introduction', 'NN'),
 ('data', 'NNS'),
 ('science', 'NN'),
 ('course', 'NN'),
 ('which', 'WDT'),
 ('introduces', 'VBZ'),
 ('data', 'NNS'),
 ('science', 'NN'),
 ('to', 'TO'),
 ('beginners', 'NNS')]
```

As we can see [ `introduction`, `data`, `science`, `course`, `beginners` ] are all of the nouns and we may keep them in the BoW feature vector.

# Feature Engineering - BoW

Extract BoW features for course textual content and build a dataset

Then we need to create a token dictionary `tokens_dict`

*TODO: Use gensim.corpora.Dictionary(tokenized_courses) to create a token dictionary.*

```
# WRITE YOUR CODE HERE
tokens_dict = gensim.corpora.Dictionary(tokenized_courses)
print(tokens_dict.token2id)
```

```
{'ai': 0, 'apps': 1, 'build': 2, 'cloud': 3, 'coming': 4, 'create': 5, 'data': 6, 'developer': 7, 'found': 8, 'fun': 9, 'iot': 10, 'irobot': 11, 'learn': 12, 'node': 13, 'objects': 14, 'p
i': 15, 'pictures': 16, 'place': 17, 'program': 18, 'raspberry': 19, 'raspcam': 20, 'read': 21, 'recognize': 22, 'red': 23, 'robot': 24, 'robots': 25, 'services': 26, 'swift': 27, 'take':
28, 'temperature': 29, 'use': 30, 'want': 31, 'watson': 32, 'way': 33, 'accelerate': 34, 'accelerated': 35, 'accelerating': 36, 'analyze': 37, 'based': 38, 'benefit': 39, 'caffe': 40, 'ca
se': 41, 'chips': 42, 'classification': 43, 'comfortable': 44, 'complex': 45, 'computations': 46, 'convolutional': 47, 'course': 48, 'datasets': 49, 'deep': 50, 'dependencies': 51, 'deplo
y': 52, 'designed': 53, 'feel': 54, 'google': 55, 'gpu': 56, 'hardware': 57, 'house': 58, 'ibm': 59, 'images': 60, 'including': 61, 'inference': 62, 'large': 63, 'learning': 64, 'librarie
s': 65, 'machine': 66, 'models': 67, 'need': 68, 'needs': 69, 'network': 70, 'networks': 71, 'neural': 72, 'nvidia': 73, 'one': 74, 'overcome': 75, 'platform': 76, 'popular': 77, 'power':
78, 'preferring': 79, 'premise': 80, 'problem': 81, 'problems': 82, 'processing': 83, 'public': 84, 'reduce': 85, 'scalability': 86, 'scaling': 87, 'sensitiveand': 88, 'several': 89, 'sol
ution': 90, 'support': 91, 'supports': 92, 'system': 93, 'systems': 94, 'takes': 95, 'tensor': 96, 'tensorflow': 97, 'theano': 98, 'time': 99, 'torch': 100, 'tpu': 101, 'trained': 102, 't
raining': 103, 'understand': 104, 'unit': 105, 'uploading': 106, 'videos': 107, 'client': 108, 'consuming': 109, 'http': 110, 'invoke': 111, 'jax': 112, 'microservices': 113, 'reactive':
114, 'restful': 115, 'rs': 116, 'using': 117, 'analysis': 118, 'analyzing': 119, 'apache': 120, 'api': 121, 'big': 122, 'cluster': 123, 'computing': 124, 'distributed': 125, 'enables': 12
6, 'familiar': 127, 'frame': 128, 'framework': 129, 'performing': 130, 'provides': 131, 'r': 132, 'scale': 133, 'spark': 134, 'sparkr': 135, 'structured': 136, 'syntax': 137, 'used': 138,
'users': 139, 'application': 140, 'boot': 141, 'containerize': 142, 'containerizing': 143, 'liberty': 144, 'modification': 145, 'open': 146, 'package': 147, 'packaging': 148, 'run': 149,
'running': 150, 'server': 151, 'spring': 152, 'conference': 153, 'introduction': 154, 'native': 155, 'security': 156, 'bootcamp': 157, 'day': 158, 'intensive': 159, 'multi': 160, 'offere
d': 161, 'person': 162, 'proffesors': 163, 'science': 164, 'university': 165, 'containers': 166, 'development': 167, 'docker': 168, 'iterative': 169, 'scorm': 170, 'scron': 171, 'test': 1
72, 'basic': 173, 'collections': 174, 'creating': 175, 'database': 176, 'document': 177, 'first': 178, 'get': 179, 'guided': 180, 'management': 181, 'mongodb': 182, 'project': 183, 'start
ed': 184, 'working': 185, 'arquillian': 186, 'container': 187, 'develop': 188, 'managed': 189, 'testing': 190, 'tests': 191, 'aiops': 192, 'attending': 193, 'comprehensive': 194, 'demonst
rate': 195, 'digital': 196, 'essentials': 197, 'hands': 198, 'integration': 199, 'pak': 200, 'received': 201, 'short': 202, 'analytics': 203, 'assemble': 204, 'base': 205, 'basics': 206,
```

# Feature Engineering - BoW

Extract BoW features for course textual content and build a dataset

Create a new course_bow dataframe based on the extracted BoW features. he new dataframe needs to include the following columns (you may include other relevant columns as well):

- 'doc_index': the course index starting from 0
- 'doc_id': the actual course id such as ML0201EN
- 'token': the tokens for each course
- 'bow': the bow value for each token

| | doc_index | doc_id | token | bow |
|---|---|---|---|---|
| **0** | 0 | ML0201EN | ai | 2 |
| **1** | 0 | ML0201EN | apps | 2 |
| **2** | 0 | ML0201EN | build | 2 |
| **3** | 0 | ML0201EN | cloud | 1 |
| **4** | 0 | ML0201EN | coming | 1 |
| **...** | ... | ... | ... | ... |
| **10358** | 306 | excourse93 | modifying | 1 |
| **10359** | 306 | excourse93 | objectives | 1 |
| **10360** | 306 | excourse93 | pieces | 1 |
| **10361** | 306 | excourse93 | plugins | 1 |
| **10362** | 306 | excourse93 | populate | 1 |

10363 rows × 4 columns

# Feature Engineering - Course Similarity using BoW Features

Similarity measurement between items is the foundation of many recommendation algorithms, especially for content-based recommendation algorithms. For example, if a new course is similar to user's enrolled courses, we could recommend that new similar course to the user. Or If user A is similar to user B, then we can recommend some of user B's courses to user A (the unseen courses) because user A and user B may have similar interests.

We can use many similarity measurements such as consine, jaccard index, or euclidean distance, and these methods need to work on either two vectors or two sets (sometimes even matrices or tensors).

In previous section, we extracted the BoW features from course textual content. Given the course BoW feature vectors, we can easily apply similarity measurement to calculate the course similarity as shown in the next figure.

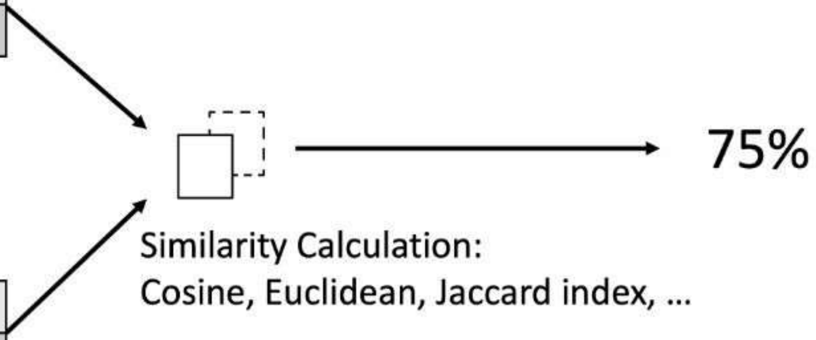
# Feature Engineering - Course Similarity using BoW Features

Course 1: “Machine Learning for Everyone”

| | machine | learning | for | everyone | beginners |
|---|---|---|---|---|---|
| course1 | 1 | 1 | 1 | 1 | 0 |

Course 2: “Machine Learning for Beginners”

| | machine | learning | for | everyone | beginners |
|---|---|---|---|---|---|
| course2 | 1 | 1 | 1 | 0 | 1 |




Similarity Calculation:
Cosine, Euclidean, Jaccard index, …

# Unsupervised Learning based Recomendation System

# Unsupervised Learning based Recomendation System

Outline:

1. Content-based Course Recommender System using User Profile and Course  Genres
2. Content-based Course Recommender System using Course Similarities
3. Clustering based Course Recommender System

# 1. Content-based Course Recommender System using User Profile and Course Genres

The most common type of content-based recommendation system is to recommend items to users based on their profiles.

The user's profile revolves around that user's preferences and tastes. It is shaped based on user ratings, including the number of times a user has clicked on different items or liked those items.

The recommendation process is based on the similarity between those items. The similarity or closeness of items is measured based on the similarity in the content of those items.

When we say content, we're talking about things like the item's category, tag, genre, and so on. Essentially the features about an item.

# 1. Content-based Course Recommender System using User Profile and Course Genres

For online course recommender systems, we already know how to extract features from courses (such as genres or BoW features). Next, based on the course genres and users' ratings, we want to further build user profiles (if unknown).

A user profile can be seen as the user feature vector that mathematically represents a user's learning interests.

With the user profile feature vectors and course genre feature vectors constructed, we can use several computational methods, such as a simple dot product, to compute or predict an interest score for each course and recommend those courses with high interest scores.

# 1. Content-based Course Recommender System using User Profile and Course Genres - Pipeline

Raw data → Feature engineering → Get recommend score → Recomendation

**Raw data**

Course genres dataframe: `course_id, title, [genre_x, genre_y,...]`

User dataframe: `user_id, [genre_interest_x, genre_interest_y,...]`

**Feature engineering**

Analysis data

Drop the exceptions

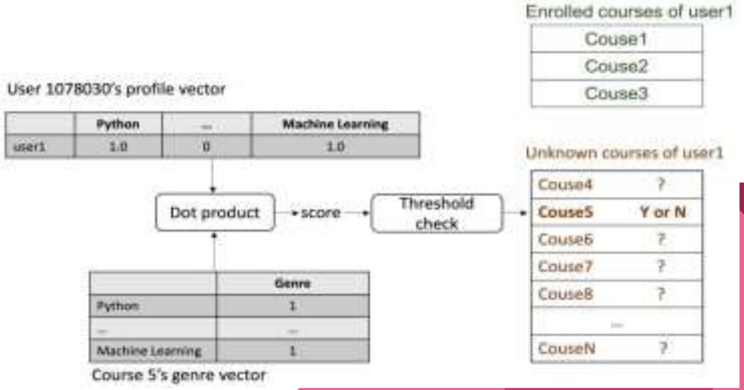
Normalise data

**Get recommend score**

Use dot product between single user vector and specific course to get recommend score

**Recomendation**

Make prediction by comparing score with determine threshold



# 1. Content-based Course Recommender System using User Profile and Course Genres - Result

| | COURSE_ID | TITLE | Database | Python | CloudComputing | DataAnalysis | Containers | MachineLearning |
|---|---|---|---|---|---|---|---|---|
| 0 | ML0201EN | robots are coming build iot apps with watson ... | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | ML0122EN | accelerating deep learning with gpu | 0 | 1 | 0 | 0 | 0 | 1 |
| 2 | GPXX0ZG0EN | consuming restful services using the reactive ... | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | RP0105EN | analyzing big data in r using apache spark | 1 | 0 | 0 | 1 | 0 | 0 |
| 4 | GPXX0Z2PEN | containerizing packaging and running a sprin... | 0 | 0 | 0 | 0 | 1 | 0 |

⊗

| | user | Database | Python | CloudComputing | DataAnalysis | Containers | MachineLearning |
|---|---|---|---|---|---|---|---|
| 0 | 2 | 52.0 | 14.0 | 6.0 | 43.0 | 3.0 | 33.0 |
| 1 | 4 | 40.0 | 2.0 | 4.0 | 28.0 | 0.0 | 14.0 |
| 2 | 5 | 24.0 | 8.0 | 18.0 | 24.0 | 0.0 | 30.0 |
| 3 | 7 | 2.0 | 0.0 | 0.0 | 2.0 | 0.0 | 0.0 |
| 4 | 8 | 6.0 | 0.0 | 0.0 | 4.0 | 0.0 | 0.0 |

=

| | 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 |

# 2. Content-based Course Recommender System using Course Similarities

As we mentioned before, the content-based recommender system is highly based on the similarity calculation among items. The similarity or closeness of items is measured based on the similarity in the content or features of those items. The course genres are important features, and in addition to that, the BoW value is another important type of feature to represent course textual content.

# 2. Content-based Course Recommender System using Course Similarities - Pipeline

Raw data → Features → Score → Prediction

**Raw data**

1.Course similarity matrix

2. Course dataframe: `course_id, title, description`

**Features**

Visualise the similarly metric

Handle data text in title and description

- Remove stop words
- word2vec

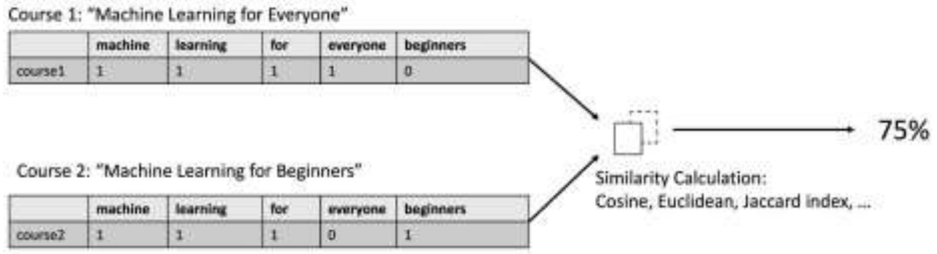
**Score**

Turn a course description to a vector

Check similarity by compare 2 vector

**Prediction**

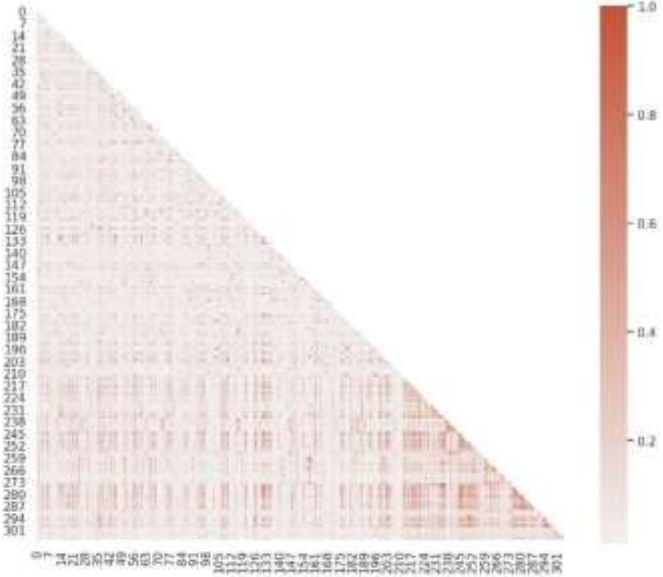
Determine rely on similar score



# 2. Content-based Course Recommender System using Course Similarities

Course similarity matrix:

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **0** | 1.000000 | 0.088889 | 0.088475 | 0.065556 | 0.048810 |
| **1** | 0.088889 | 1.000000 | 0.055202 | 0.057264 | 0.012182 |
| **2** | 0.088475 | 0.055202 | 1.000000 | 0.026463 | 0.039406 |
| **3** | 0.065556 | 0.057264 | 0.026463 | 1.000000 | 0.000000 |
| **4** | 0.048810 | 0.012182 | 0.039406 | 0.000000 | 1.000000 |
| **...** | ... | ... | ... | ... | ... |



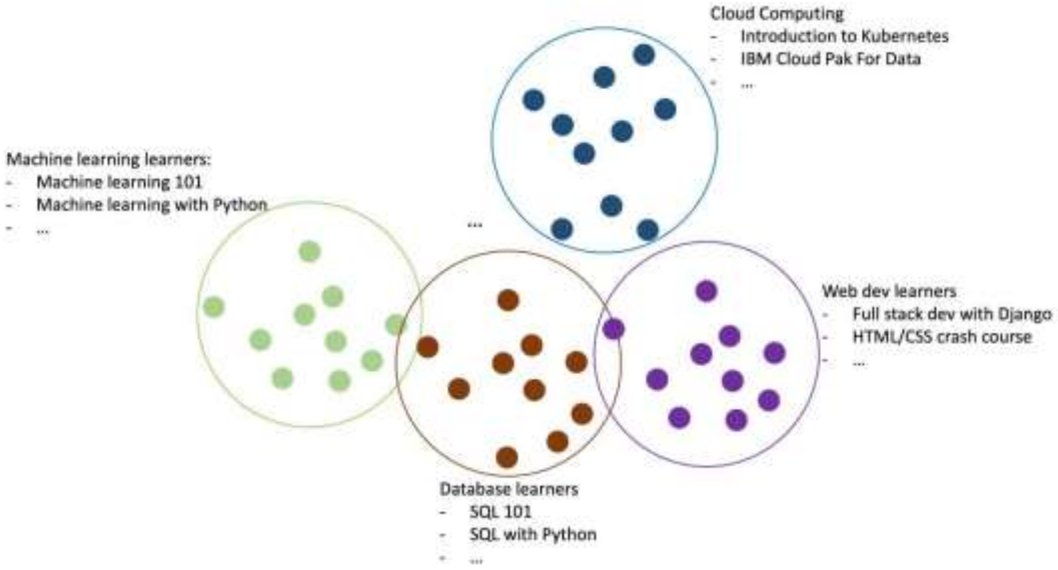
# 2. Content-based Course Recommender System using Course Similarities - Result

Generate course recommendations based on course similarities for all test users

| | USER | COURSE_ID | SCORE |
|---|---|---|---|
| **0** | 37465 | excourse67 | 0.708214 |
| **1** | 37465 | excourse72 | 0.652535 |
| **2** | 37465 | excourse74 | 0.650071 |
| **3** | 37465 | BD0145EN | 0.623544 |
| **4** | 37465 | excourse68 | 0.616759 |

# 3. Clustering based Course Recommender System

We could perform clustering algorithms such as K-means or DBSCAN to group users with similar learning interests. For example, in the below user clusters, we have user clusters whom have learned courses related to machine learning, cloud computing, databases, and web development, etc.



# 3. Clustering based Course Recommender System - Pipeline

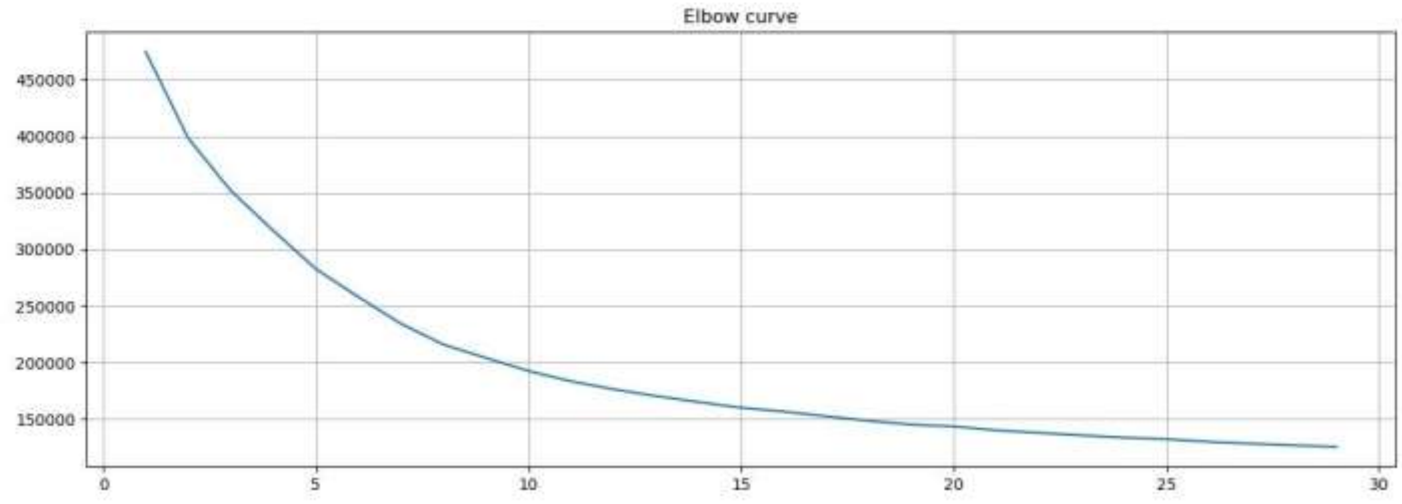
Raw data → Features → Clusters → Prediction

1. Raw data:
    - User profile dataframe: user_id, [genre_x, genre_y,...]
2. Features:
    - Normalise user profile features
    - Apply PCA to keep only important features
3. Apply Clustering algorithms to group similar courses
4. Make recommendation by taking courses in user’s interest group

# 3. Clustering based Course Recommender System

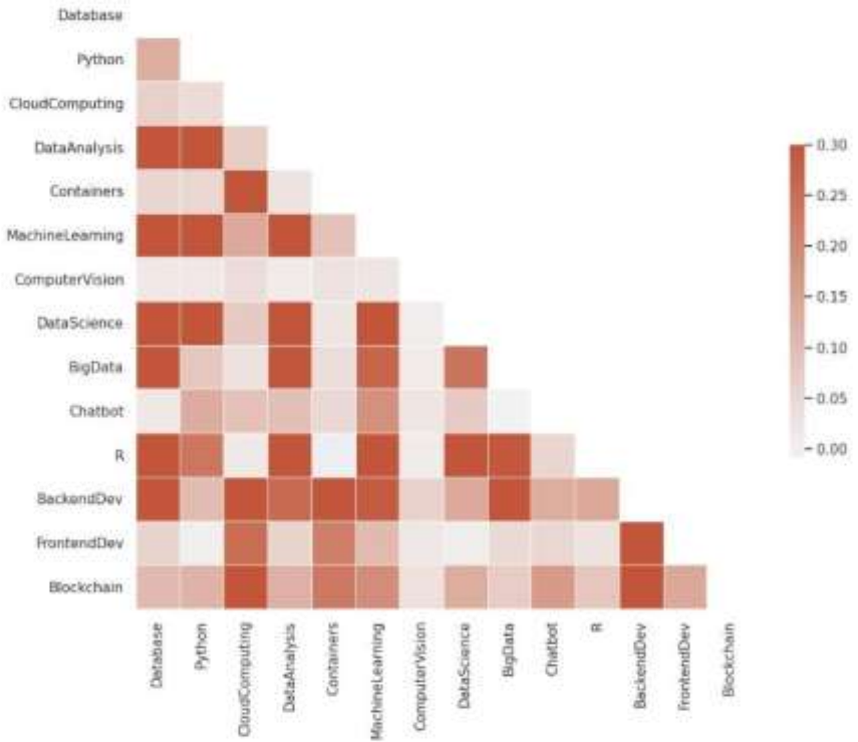
For KMeans algorithm, one important hyperparameter is the number of clusters *n_cluster*, and a good way to find the optimized *n_cluster* is using to grid search a list of candidates and find the one with the best or optimized clustering evaluation metrics such as minimal sum of squared distance.

**Grid search the optimized n_cluster for KMeans() model**



# 3. Clustering based Course Recommender System

Plot a covariance matrix of the user profile feature vectors with 14 features, we can observe that some features are actually correlated

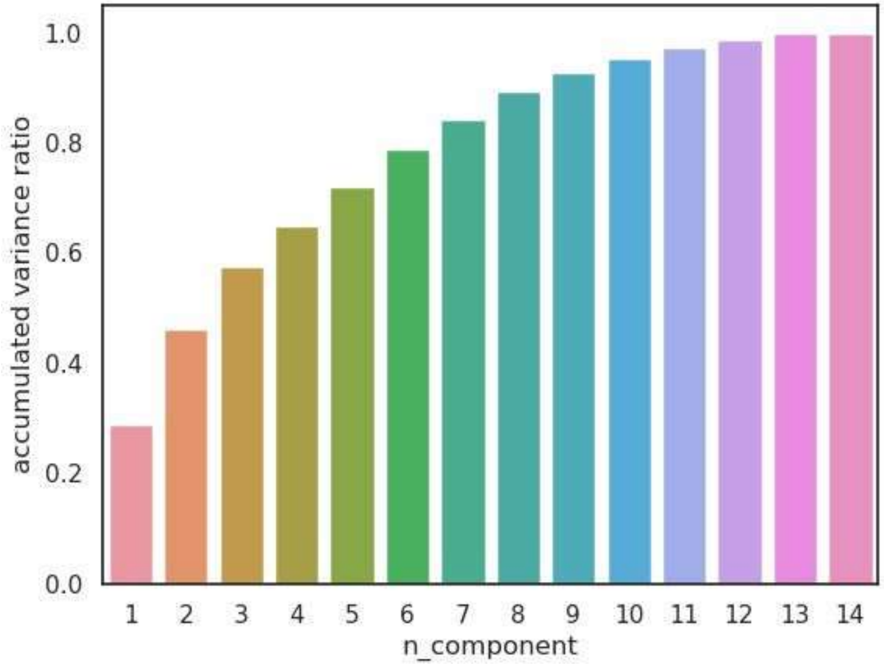


# 3. Clustering based Course Recommender System

Apply the PCA() provided by scikit-learn to find the main components in user profile feature vectors and see if we can reduce its dimensions by only keeping the main components.

If the accumulated variances ratio of a candidate n_components is larger than a threshold, e.g., 90%, then we can say the transformed n_components could explain about 90% of variances of the original data variance and can be considered as an optimized components size.

We select n_component = 8, due to the minimal ratio > 0.9



# 3. Clustering based Course Recommender System

Apply KMean on transformed features:

| | user | cluster |
|---|---|---|
| **0** | 2 | 9 |
| **1** | 4 | 23 |
| **2** | 5 | 9 |
| **3** | 7 | 15 |
| **4** | 8 | 8 |
| **...** | ... | ... |
| **33896** | 2102054 | 21 |
| **33897** | 2102356 | 15 |
| **33898** | 2102680 | 17 |
| **33899** | 2102983 | 15 |
| **33900** | 2103039 | 15 |

33901 rows × 2 columns

Apply PCA to features:

| | user | PC0 | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 17.772494 | 0.200681 | 1.730609 | 2.567359 | -3.825814 | 2.707154 | 0.681042 | 2.312613 | 0.868272 |
| **1** | 4 | 7.145199 | -2.847481 | 2.358636 | -0.576654 | 0.398803 | -0.134533 | 0.549769 | 0.469033 | 0.033405 |
| **2** | 5 | 11.363270 | 1.873619 | -1.522077 | 1.076144 | -1.711688 | 0.883212 | 1.677582 | 2.937669 | 2.097639 |
| **3** | 7 | -1.834033 | -0.277462 | 0.564905 | 0.053470 | -0.064440 | 0.165757 | 0.030956 | 0.039519 | 0.210887 |
| **4** | 8 | -1.049125 | -0.684767 | 1.072765 | 0.006371 | -0.005695 | 0.118686 | 0.118559 | 0.559292 | 0.186379 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **33896** | 2102054 | 0.633824 | 0.108815 | -0.388871 | -0.122665 | -0.098364 | 0.358333 | 1.752049 | 1.486542 | -0.523600 |
| **33897** | 2102356 | -2.095339 | 0.135058 | 0.244727 | -0.088185 | 0.025081 | 0.183641 | 0.046413 | 0.191709 | 0.260437 |
| **33898** | 2102680 | 0.625943 | -0.547167 | -1.692824 | -0.630589 | 0.166632 | 0.676244 | -0.055100 | 0.582091 | 1.703193 |
| **33899** | 2102983 | -2.036832 | -0.153534 | 0.162852 | 0.082651 | -0.126419 | 0.255109 | 0.072496 | 0.113750 | 0.622900 |
| **33900** | 2103039 | -2.036832 | -0.153534 | 0.162852 | 0.082651 | -0.126419 | 0.255109 | 0.072496 | 0.113750 | 0.622900 |

33901 rows × 10 columns

# 3. Clustering based Course Recommender System

Find popular courses in clusters and suggest to user in cluster:

Insights:

- On average, how many new/unseen courses have been recommended per user (in the test user dataset)
- What are the most frequently recommended courses? Return the top-10 commonly recommended courses

```
user in cluster 0 will be sugessted 3 courses as ['BC0101EN' 'BD0101EN' 'DS0101EN']
user in cluster 1 will be sugessted 3 courses as ['CO0101EN' 'CC0101EN' 'CO0201EN']
user in cluster 2 will be sugessted 3 courses as ['PY0101EN' 'CB0103EN' 'DA0101EN']
user in cluster 3 will be sugessted 3 courses as ['CB0103EN' 'BC0101EN' 'PY0101EN']
user in cluster 4 will be sugessted 3 courses as []
user in cluster 5 will be sugessted 3 courses as ['PY0101EN' 'DS0101EN' 'DA0101EN']
user in cluster 6 will be sugessted 3 courses as ['CC0101EN' 'PY0101EN' 'CC0103EN']
user in cluster 7 will be sugessted 3 courses as ['BC0101EN' 'BC0201EN' 'PY0101EN']
user in cluster 8 will be sugessted 3 courses as ['BD0101EN' 'BD0111EN' 'DS0101EN']
user in cluster 9 will be sugessted 3 courses as ['BD0101EN' 'BD0111EN' 'SW0101EN']
user in cluster 10 will be sugessted 3 courses as ['DS0101EN' 'RP0101EN' 'PY0101EN']
user in cluster 11 will be sugessted 3 courses as ['CO0101EN' 'LB0101ENv1' 'CO0401EN']
user in cluster 12 will be sugessted 3 courses as ['BD0111EN' 'BD0115EN' 'BD0141EN']
user in cluster 13 will be sugessted 3 courses as ['CO0101EN' 'CO0201EN' 'CO0301EN']
user in cluster 14 will be sugessted 3 courses as ['BC0101EN' 'PY0101EN' 'DA0101EN']
user in cluster 15 will be sugessted 3 courses as ['DS0101EN' 'BD0101EN' 'PY0101EN']
user in cluster 16 will be sugessted 3 courses as ['CB0103EN' 'PY0101EN' 'DA0101EN']
user in cluster 17 will be sugessted 3 courses as ['PY0101EN' 'ML0101ENv3' 'ML0115EN']
user in cluster 18 will be sugessted 3 courses as ['BD0111EN' 'BD0211EN' 'BD0101EN']
user in cluster 19 will be sugessted 3 courses as ['BD0211EN' 'BD0101EN' 'DS0101EN']
user in cluster 20 will be sugessted 3 courses as ['BD0111EN' 'BD0101EN' 'BD0211EN']
user in cluster 21 will be sugessted 3 courses as ['RP0101EN' 'DS0101EN' 'DS0103EN']
user in cluster 22 will be sugessted 3 courses as ['LB0101ENv1' 'LB0103ENv1' 'LB0105ENv1']
user in cluster 23 will be sugessted 3 courses as ['BD0111EN' 'PY0101EN' 'BD0211EN']
user in cluster 24 will be sugessted 3 courses as ['CB0103EN' 'DS0101EN' 'BD0101EN']
```

# Supervised Learning based Recomendation System

# Supervised Learning based Recomendation System

Outline:

1. CF using K Nearest Neighbor
2. CF using Non-negative Matrix Factorization
3. Course Rating Prediction using Neural Networks
4. Regression-Based Rating Score Prediction Using Embedding Features
5. Classification-based Rating Mode Prediction using Embedding Features

# 1. CF using K Nearest Neighbor

Collaborative filtering is probably the most commonly used recommendation algorithm, there are two main types of methods:

- **User-based** collaborative filtering is based on the user similarity or neighborhood
- **Item-based** collaborative filtering is based on similarity among items

# 1. CF using K Nearest Neighbor

User-based collaborative filtering looks for users who are similar. This is very similar to the user clustering method done previously; where we employed explicit user profiles to calculate user similarity. However, the user profiles may not be available, so how can we determine if two users are similar?

For most collaborative filtering-based recommender systems, the main dataset format is a 2-D matrix called the user-item interaction matrix. In the matrix, its row is labeled as the user id/index and column labelled to be the item id/index, and the element (i, j) represents the rating of user i to item j.

Below is a simple example of a user-item interaction matrix:

**User-Item interaction matrix**

Similar users

| | Machine Learning With Python | Machine Learning 101 | Machine Learning Capstone | SQL with Python | Python 101 |
|---|---|---|---|---|---|
| ... | ... | ... | ... | ... | |
| user2 | 3.0 | 3.0 | 3.0 | 3.0 | 3.0 |
| user3 | 2.0 | 3.0 | 3.0 | 2.0 | |
| user4 | 3.0 | 3.0 | 2.0 | 2.0 | 3.0 |
| user5 | 2.0 | 3.0 | 3.0 | | |
| user6 | 3.0 | 3.0 | ? | | 3.0 |
| ... | ... | ... | ... | ... | |

Predict the rating of user *user6* to item *Machine Learning Capstone*

# 1. CF using K Nearest Neighbor

We used the library `surprise` library to handle dataset and fit the data.

Distance metric: Only common users (or items) are taken into account. The cosine similarity is defined as:

For users u, v:

$$\text{cosine\_sim}(u, v) = \frac{\sum\limits_{i \in I_{uv}} r_{ui} \cdot r_{vi}}{\sqrt{\sum\limits_{i \in I_{uv}} r_{ui}^2} \cdot \sqrt{\sum\limits_{i \in I_{uv}} r_{vi}^2}}$$

For items i, j:

$$\text{cosine\_sim}(i, j) = \frac{\sum\limits_{u \in U_{ij}} r_{ui} \cdot r_{uj}}{\sqrt{\sum\limits_{u \in U_{ij}} r_{ui}^2} \cdot \sqrt{\sum\limits_{u \in U_{ij}} r_{uj}^2}}$$

# 1. CF using K Nearest Neighbor - Pipeline & Result

**Raw data** → **Spare data** → **Model** → **Prediction**

**Raw data**

User - item - rating - dataframe: `user_id, item, rating`

**Spare data**

Use *pivot* method in pandas to turn data to features

| | user | AI0111EN | BC0101EN | BC0201EN | BC0202EN | BD0101EN |
|---|---|---|---|---|---|---|
| 0 | 2 | 0.0 | 3.0 | 0.0 | 0.0 | 3.0 |
| 1 | 4 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 |
| 2 | 5 | 2.0 | 2.0 | 2.0 | 0.0 | 2.0 |
| 3 | 7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 4 | 8 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

5 rows × 127 columns

**Model**

Fit data to KNN model based on *surprise* library

Use distance metric listed in previous page

**Prediction**

Make prediction by test data, use RMSE metric to evaluate model performance

```
# Then compute RMSE
accuracy.rmse(predictions)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.1935
```

```
: 0.19350741218895207
```

# 2. CF using Non-negative Matrix Factorization

A dimensionality reduction algorithm called Non-negative matrix factorization (NMF), which decomposes a big sparse matrix into two smaller and dense matrices.

Non-negative matrix factorization can be one solution to big matrix issues. The main idea is to decompose the big and sparse user-interaction into two smaller dense matrices, one represents the transformed user features and another represents the transformed item features

# 2. CF using Non-negative Matrix Factorization

An example is shown below, suppose we have a user-item interaction matrix $A$ with 10000 users and 100 items (10000 x 100), and its element (j, k) represents the rating of item k from user j. Then we could decompose $A$ into two smaller and dense matrices $U$ (10000 x 16) and $I$ (16 x 100). for user matrix $U$ , each row vector is a transformed latent feature vector of a user, and for the item matrix $I$ , each column is a transformed latent feature vector of an item.

Here the dimension 16 is a hyperparameter defines the size of the hidden user and item features, which means now the shape of transposed user feature vector and item feature vector is now 16 x 1.

The magic here is when we multiply the row j of $U$ and column k of matrix $I$ , we can get an estimation to the original rating ˆ_$jk$ .

For example, if we preform the dot product user ones row vector in $U$ and item ones column vector in $I$ , we can get the rating estimation of user one to item one, which is the element (1, 1) in the original interaction matrix $I$ .

# 2. CF using Non-negative Matrix Factorization

User-item interaction matrix: **A** 10000 x 100

| | item1 | ... | item100 |
|---|---|---|---|
| user1 | ... | ... | |
| user2 | 3.0 | 3.0 | 3.0 |
| user3 | 2.0 | 2.0 | - |
| user4 | 3.0 | 2.0 | 3.0 |
| user5 | 2.0 | - | - |
| user6 | 3.0 | - | 3.0 |
| ... | ... | ... | |

≈

User matrix: **U** 10000 x 16

| | feature1 | ... | feature16 |
|---|---|---|---|
| user1 | ... | ... | ... |
| user2 | ... | ... | ... |
| user3 | ... | ... | ... |
| user4 | ... | ... | ... |
| ... | ... | ... | ... |
| ... | ... | ... | ... |
| user6 | ... | ... | ... |

X

Item matrix: **I** 16 x 100

| | item1 | ... | item100 |
|---|---|---|---|
| feature1 | ... | ... | ... |
| feature2 | ... | ... | ... |
| ... | ... | ... | ... |
| feature16 | ... | ... | ... |

# 2. CF using Non-negative Matrix Factorization
# - Pipeline & Result

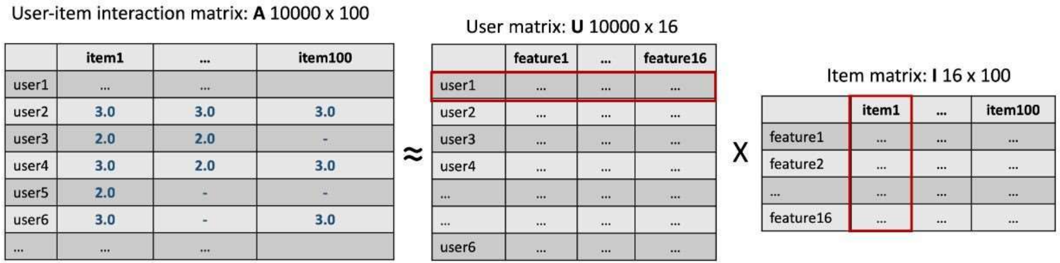
**Raw data** → **Decomposed matrix** → **Model** → **Prediction**

**Raw data:** User - item - rating - dataframe: `user_id, item, rating`

**Decomposed matrix:** Use *surprise* library to decompose full matrix to two smaller and denser ones: user matrix and item matrix

**Model:** Dot product each row in user matrix with each column in item matrix

**Prediction:** Make prediction by test data, use RMSE metric to evaluate model performance



User-item interaction matrix: **A** 10000 x 100

| | item1 | ... | item100 |
|---|---|---|---|
| user1 | ... | ... | |
| user2 | 3.0 | 3.0 | 3.0 |
| user3 | 2.0 | 2.0 | - |
| user4 | 3.0 | 2.0 | 3.0 |
| user5 | 2.0 | - | - |
| user6 | 3.0 | - | 3.0 |
| ... | ... | ... | |

≈

User matrix: **U** 10000 x 16

| | feature1 | ... | feature16 |
|---|---|---|---|
| user1 | ... | ... | ... |
| user2 | ... | ... | ... |
| user3 | ... | ... | ... |
| user4 | ... | ... | ... |
| ... | ... | ... | ... |
| ... | ... | ... | ... |
| user6 | ... | ... | ... |

X

Item matrix: **I** 16 x 100

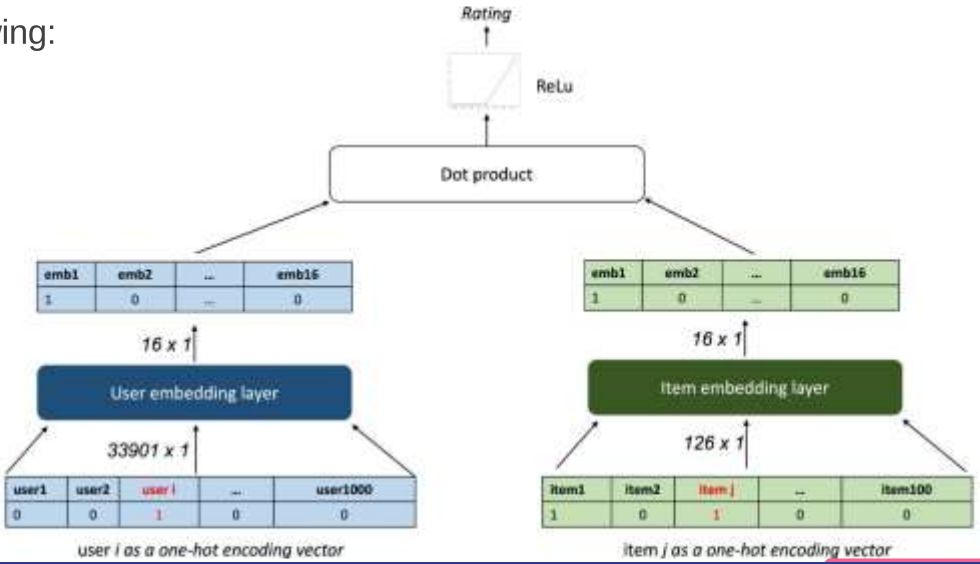
| | item1 | ... | item100 |
|---|---|---|---|
| feature1 | ... | ... | ... |
| feature2 | ... | ... | ... |
| ... | ... | ... | ... |
| feature16 | ... | ... | ... |

```
Processing epoch 39
Processing epoch 40
Processing epoch 41
Processing epoch 42
Processing epoch 43
Processing epoch 44
Processing epoch 45
Processing epoch 46
Processing epoch 47
Processing epoch 48
Processing epoch 49
RMSE: 0.2078
: 0.20782347708297272
```

# 3. Course Rating Prediction using Neural Networks

The goal is to create a neural network structure that can take the user and item one-hot vectors as inputs and outputs a rating  estimation or the probability of interaction (such as the probability of completing a course).

While training and updating the weights in the neural network, its hidden layers should be able to capture the pattern or features  for each user and item. Based on this idea, we can design a simple neural network architecture like the following:



# 3. Course Rating Prediction using Neural Networks

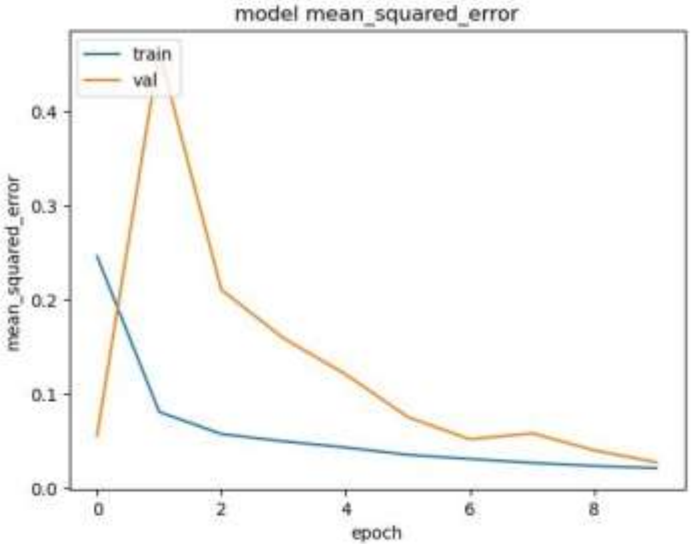
Model:

- Optimizer: Adam
- Loss: Mean Square Error
- Metric: Mean Square Error
- Epoch 12
- Batch size: 512

```
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
```

# 3. Course Rating Prediction using Neural Networks - Result

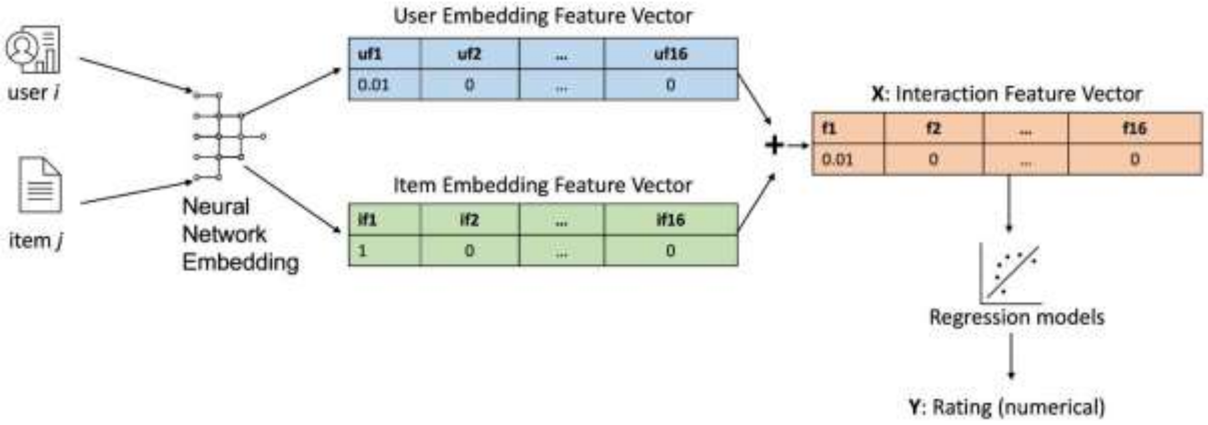
Train and Validate:




Result on test data:

Mean squared error: 0.258
Root mean squared error: 0.508

# 4. Regression-Based Rating Score Prediction Using Embedding Features




Another way to make rating predictions is to use the embedding as an input to a neural network by aggregating them into a single feature vector as input data X.

With the interaction label Y such as a rating score or an enrollment mode, we can build our other standalone predictive models to approximate the mapping from X to Y, as shown in the above flowchart.

# 4. Regression-Based Rating Score Prediction Using Embedding Features - Result

```
# Evaluation metrics
mae_lm = metrics.mean_absolute_error(y_test, lm_prediction)
mse_lm =  metrics.mean_squared_error(y_test, lm_prediction)
rmse_lm =  np.sqrt(mse_lm)

print('MAE:', mae_lm)
print('MSE:', mse_lm)
print('RMSE:', rmse_lm)
```

```
MAE: 0.41428838083033687
MSE: 0.9932500760760065
RMSE: 0.9966193235513781
```

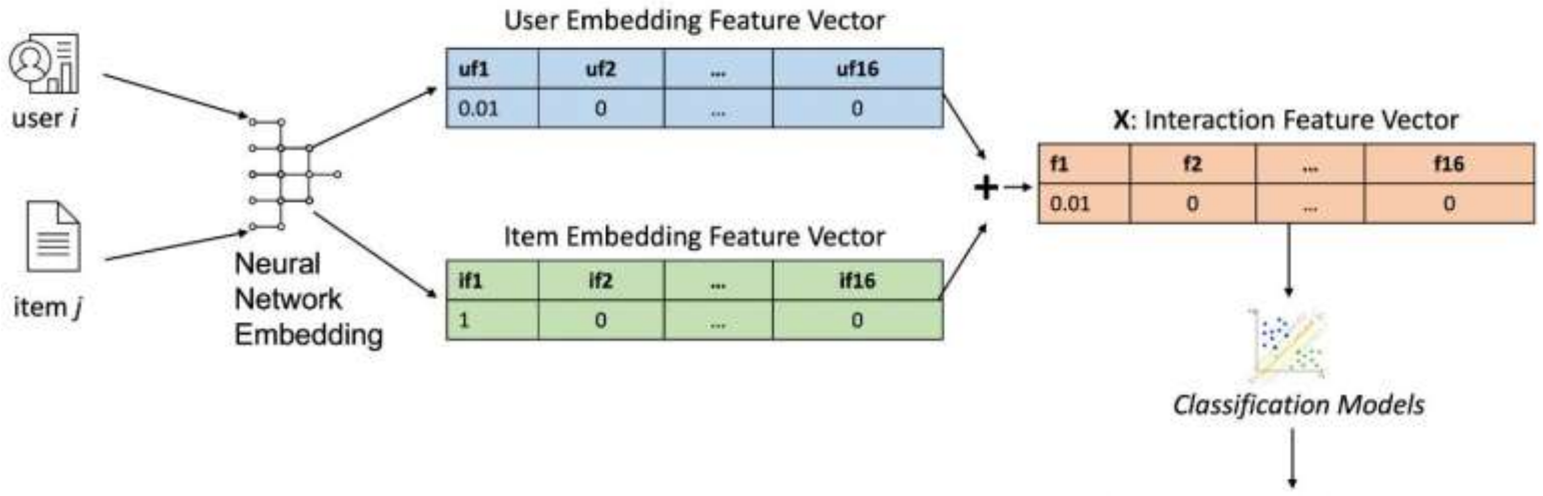
*TODO: Try different regression models such as Ridge, Lasso, Elastic*

```
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
```

```
### WRITE YOUR CODE HERE
rd = ElasticNet()
rd.fit(X_train,y_train)
rd_prediction = rd.predict(X_test)

mae_rd = metrics.mean_absolute_error(y_test, rd_prediction)
mse_rd =  metrics.mean_squared_error(y_test, rd_prediction)
rmse_rd =  np.sqrt(mse_rd)

print('MAE:', mae_rd)
print('MSE:', mse_rd)
print('RMSE:', rmse_rd)
```

```
MAE: 0.4167848022681181
MSE: 1.0000000000000002
RMSE: 1.0
```

# Classification-based Rating Mode Prediction using Embedding Features

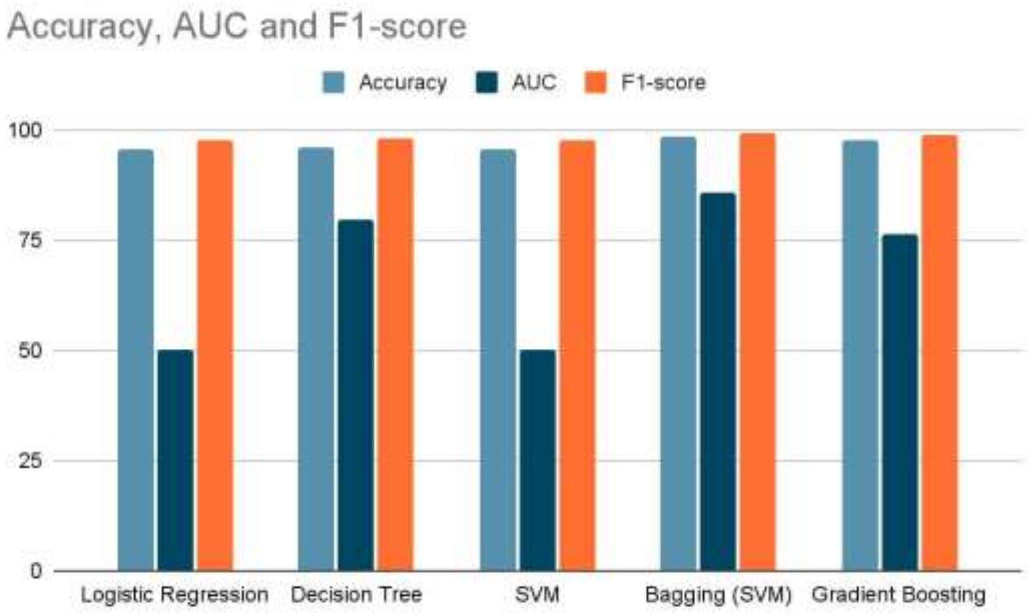



We first extract two embedding matrices out of the neural network, and aggregate them to be a single interaction feature vector as input data X.

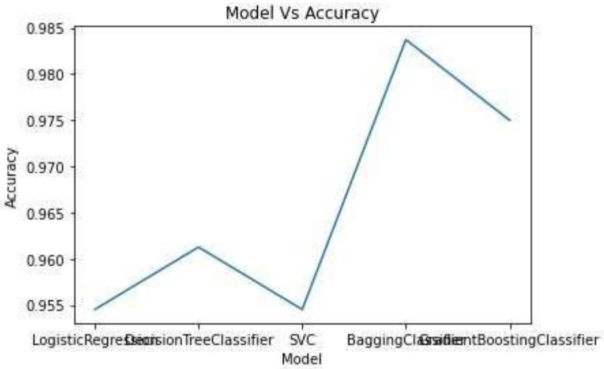
This time, with the interaction label Y as categorical rating mode, we can build classification models to approximate the mapping from X to Y, as shown in the above flowchart.

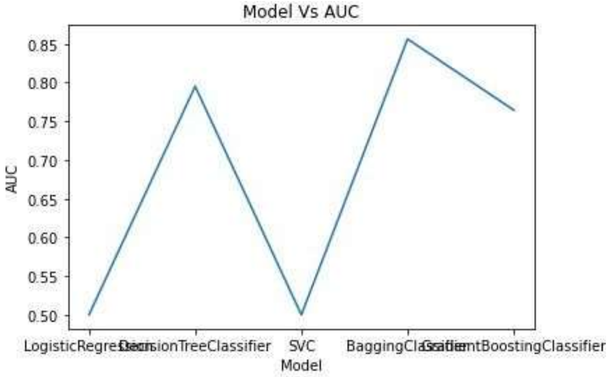
# 5. Classification-based Rating Mode Prediction using Embedding Features

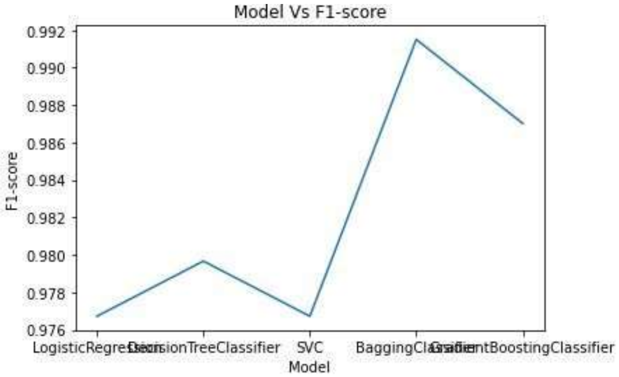
| | Accuracy | AUC | F1-score |
|---|---|---|---|
| Logistic Regression | 95.45 | 0.5 | 97.67 |
| Decision Tree | 96.12 | 79.51 | 97.97 |
| SVM | 95.45 | 0.5 | 97.67 |
| Bagging (SVM) | 98.37 | 85.62 | 99.15 |
| Gradient Boosting | 97.5 | 76.44 | 98.7 |



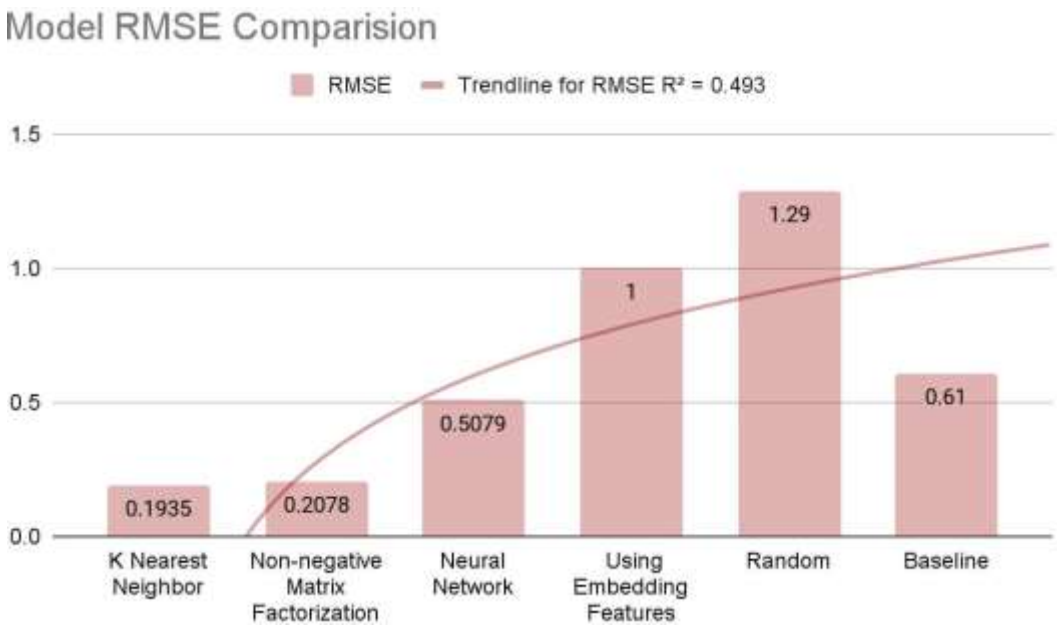
# 5. Classification-based Rating Mode Prediction using Embedding Features



# Compare the performance of collaborative-filtering models




Insights:

- Random prediction is obviously worst
- KNN method have

# Future work

This project shows how a end-to-end machine learning pipeline work. Although we pass all requirement of course's creator, there are several enhancements can be applied for better accuracy and complete the perfection:

- Experience with bigger amount of customer data
- Apply more pre-processing techniques
- Deal with spare data which can cause full of memory

Thanks for your reading!