Music Recommendation Service

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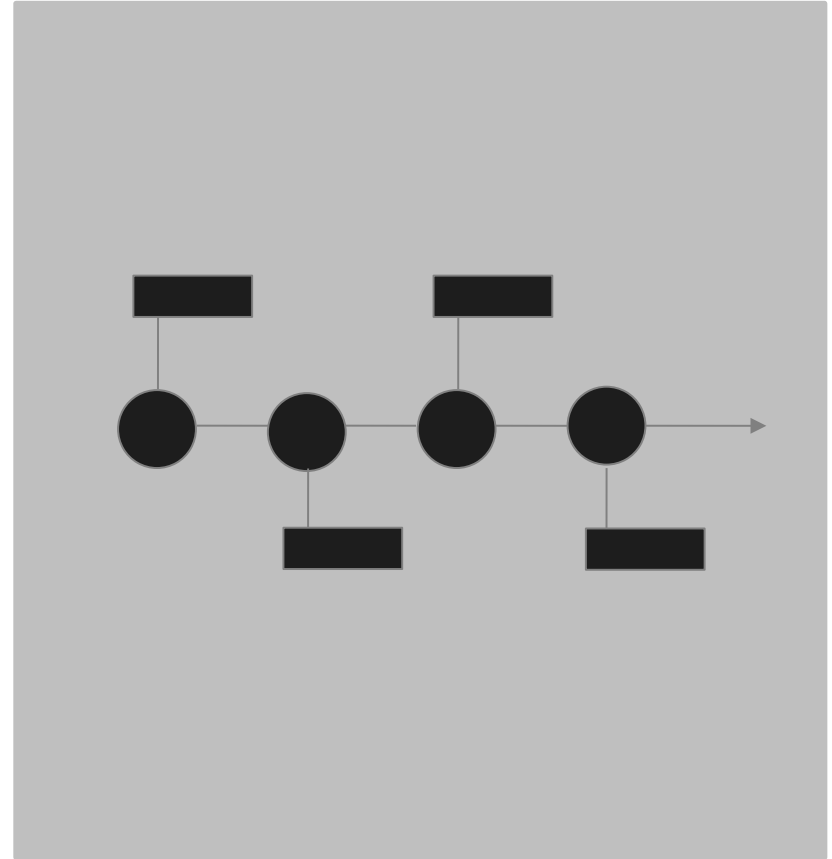
Data
Overview

Data Overview

User and Music Data contained in several 'Parquet' files

- Required an external library - Arrow

- Turned into CSV

Dataset Visualization

	user_id	artist_name	release_name	recording_name	date	time
1	16493	Greg MacPherson Band	Good Times Coming Back Again	Numbers	2006-11-29	13:19:10
2	8793	Wolfgang Amadeus Mozart	The World of Sacred Music	Ave Verum Corpus	2006-11-29	13:52:16
3	6263	Japan	Tin Drum	Ghosts	2006-11-29	13:59:42
4	5838	Enigma	The Cross of Changes	Age of Loneliness (Carly's Song)	2006-11-29	13:55:42
5	1061	Paul Simon	Graceland	All Around the World or the Myth of Fingerprints (early versi...	2006-11-29	14:04:29
6	5838	Enigma	The Cross of Changes	Age of Loneliness (Carly's Song)	2006-11-29	14:39:42
7	8115	Pixies	Surfer Rosa	I'm Amazed	2006-11-29	14:44:38
8	1061	Paul Simon	Graceland	All Around the World or the Myth of Fingerprints (early versi...	2006-11-29	15:07:16
9	6419	Partizani	Unknown Album	Pociva jezero v tihoti	2006-11-29	15:14:45
10	4685	Red Hot Chili Peppers	Stadium Arcadium	Dani California	2006-11-29	15:26:37

First 10 entries from file

Data Preparation

Encoded each categorical column:


```python
1   #encode the categorical variables:
2   #artist_name, release_name, recording_name
3
4   df['artist_name'] = df['artist_name'].astype('category').cat.codes
5   df['release_name'] = df['release_name'].astype('category').cat.codes
6   df['recording_name'] = df['recording_name'].astype('category').cat.codes
7
8   #print new head and shape of df
9   print(df.head(), "\n", df.shape)
10
11  #print the translation from code to artists, so we can see it worked
12
13  print(dict(zip(df['artist_name'].astype('category').cat.categories, df['artist_na
                                                                              Python
```

```
   user_id  artist_name  release_name  recording_name        date      time
0    16493         3665          4240            9463  2006-11-29  13:19:10
1     8793         9899         10764            1240  2006-11-29  13:52:16
2     6263         4286         10945            5040  2006-11-29  13:59:42
3     5838         2913          9918             676  2006-11-29  13:55:42
4     1061         6645          4260             759  2006-11-29  14:04:29
  (66936, 6)
{0: 3665, 1: 9899, 2: 4286, 3: 2913, 4: 6645, 5: 2913, 6: 6797, 7: 6645, 8: 6593, 9: 712
```
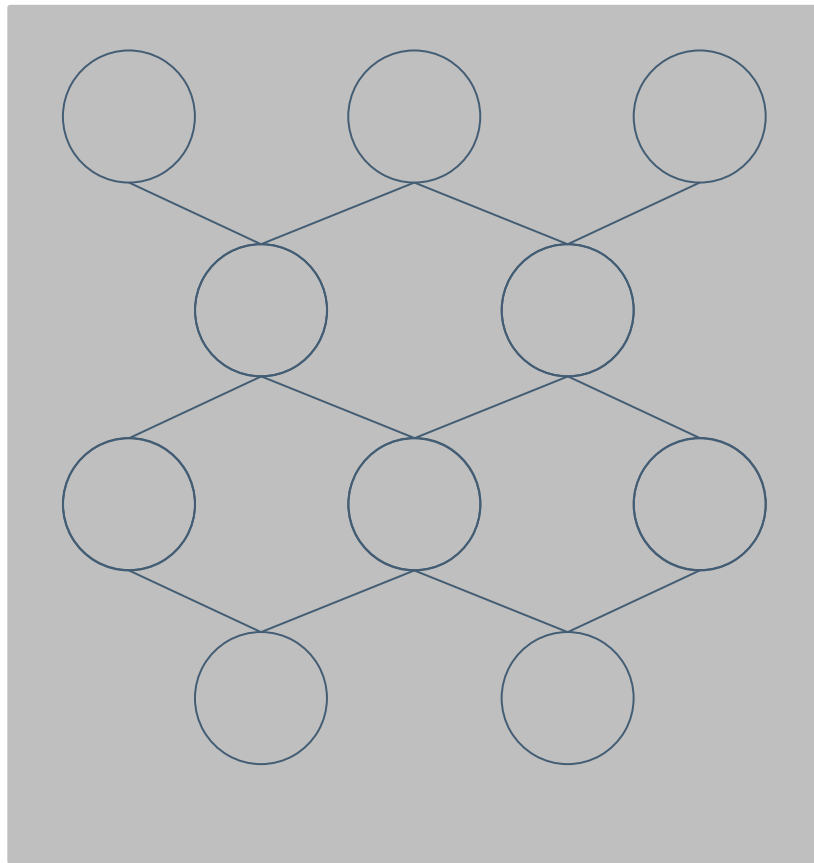
User Interaction Matrix

USERS \ ARTISTS	Artist 1	Artist 2	Artist 3
User 1	1	0	1
User 2	0	1	0
User 3	0	1	1

02

Models & Algorithms

Collaborative Filtering

| ■ | .9 | -.8 | 1 | 1 | -.9 |
| ▲ | -.2 | -.8 | -1 | .9 | 1 |

●	◆
1	.1
-1	0
.2	-1
.1	1

	Harry Potter	Les Triplettes de Belleville	Shrek	The Dark Knight Rises	
	✔		✔	✔	
		✔			✔
	✔	✔	✔		
				✔	✔

?

■ ▲ ● ◆

CF (ALS) - Overview

Step 1

Step 2

Step 3

Analyze smaller k-sized matrices

Optimize User & Item matrices independently

Iterate until convergence

CF (ALS) – Code Explanation

Training

(User_ID, Artist)

```
(5, 3617)     1
(5, 4580)     1
(5, 8272)     1
(5, 10094)    1
(6, 344)      1
(6, 1396)     1
(6, 2571)     1
(6, 2685)     1
(6, 3431)     1
(6, 4560)     1
(6, 5746)     1
(6, 6133)     1
(6, 6346)     1
```

Feeds into →

```python
1  import implicit
2
3  #model fitting
4  model = implicit.als.AlternatingLeastSquares(factors = 150, regularization = 0.001, iterations = 100)
5  model.fit(user_artist_train_matrix)
```

```
0%|          | 0/100 [00:00<?, ?it/s]
100%|████████| 100/100 [00:44<00:00,  2.26it/s]
```

Hyper-parameters:
- Factors (k)
- Regularization (λ)
- Iterations
- Alpha (not seen in the above image)

CF (ALS) – Code Explanation

Testing

```
1  #model predictions
2  import implicit.evaluation
3
4  implicit.evaluation.AUC_at_k(model, train_user_items = user_artist_train_matrix, test_user_items = user_artist_test_matrix, K = 10,
5
6  #AUC score of 0.5210884671362229 ~ random === guessing

100%|          | 1330/1330 [00:00<00:00, 10472.59it/s]
0.5202834576915786
```

Using AUC for performance

How to improve performance?

Grid Search

CF (ALS) – Code Explanation

Grid Search

```
param_grid = {
    'factors' : [8, 10, 15],
    'regularization' : [0.15, 0.18, 0.2, 0.23, 0.27, 0.3],
    'iterations' : [60, 65, 75, 80, 85],
    'alphas' : [10]
}
```

Adjust all parameters to
improve performance

```
#perform Grid Search
for factor in param_grid['factors']:
    for reg in param_grid['regularization']:
        for iter in param_grid['iterations']:
            for alp in param_grid['alphas']:
                #define model with given params
                #utilizing 4 cores on my CPU to speed up process
                model = implicit.als.AlternatingLeastSquares(factors = factor, regularization = reg, iterations = iter, alpha = alp, num_threads = 4)

                #model training
                model.fit(user_artist_train_matrix)

                #obtain AUC (eval)
                #k = 10 => model bases performance on recommendation for top 10 artists
                auc = implicit.evaluation.AUC_at_k(model, train_user_items = user_artist_train_matrix, test_user_items = user_artist_test_matrix, K = 10

                #compare AUC score and if auc is better, we update current stored bests
                if auc > best_AUC:
                    best_AUC = auc
                    best_params = {'factor' : factor, 'reg' : reg, 'iter' : iter, 'alpha' : alp}

print(f"Best hyperparams via grid search: {best_params}\nBest AUC: {best_AUC}")
#order for best_params is: factor, reg, iter, alpha
```

CF (ALS) – Performance Evaluation

```
Best hyperparams via grid search: {'factor': 8, 'reg': 0.2, 'iter': 75, 'alpha': 10}
Best AUC: 0.5472981589956554
```

~0.55 AUC score… Not good

Slightly better than randomly guessing

Take Aways from CF (ALS)

Fast

Avg run time on smaller dataset was < 5 mins per train and test

Easy Tuning

Grid Search allowed for highly varied values to be tried in sequence

Poor Prediction

Such a low AUC means it is not learning well. This would require many more iterations of Grid Search to find optimal solutions

Neural Collaborative Filtering

NCF – Overview

Step 1

User Matrix and Item Matrix are fed. Then performs Dot product to create input matrix

Step 2

Run through Hidden Layers

Step 3

Output Binary Classifier (0;1) for interactions

NCF – Code Explanation

Setup

```
import tensorflow as tf

if tf.config.list_physical_devices('GPU'):
    print("GPU is available")
else:
    print("GPU is not available")

# List the available GPUs and their memory information
gpus = tf.config.get_visible_devices('GPU')
for gpu in gpus:
    memory_info = tf.config.experimental.get_memory_info('GPU:0')
    print(f"GPU: {gpu.name}")
    print(f"Current memory usage: {memory_info['current']} bytes")
    print(f"Peak memory usage: {memory_info['peak']} bytes")

#ensure we're able to use the GPU for processing the stuff
#I'm utilizing my home PC which has an NVIDIA RTX 3070
```

```
GPU is available
GPU: /physical_device:GPU:0
Current memory usage: 0 bytes
Peak memory usage: 0 bytes
```

Use GPU for faster processing

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, Dot, Dense, Flatten, Dropout

#create NCF model structure

#input layers for user and item
user_input = Input(shape=(1,), name='user_input')
item_input = Input(shape=(1,), name='item_input')

#embedding layers to flatten the information from user-item interaction matrix
user_embedding = Embedding(input_dim=len(user_ids_flat), output_dim=5, name='user_embedding')(user_input)
item_embedding = Embedding(input_dim=len(item_ids_flat), output_dim=5, name='item_embedding')(item_input)

#flatten embedding layers for dot product
user_vec = Flatten()(user_embedding)
item_vec = Flatten()(item_embedding)

#dot product between user and item vectors (matrices)
dot_product = Dot(axes=1)([user_vec, item_vec])
```

Input → Embedding → Dot product

NCF – Code Explanation

Model Structure

```python
#hidden layer with 2048 neurons
h1 = Dense(2048, activation = 'relu') (dot_product)

#add 20% dropout to reduce overfitting
h1 = Dropout(0.2)(h1)


#hidden layer with 1024 neurons
h2 = Dense(1024, activation = 'relu')(h1)

#add 20% dropout to reduce overfitting
h2 = Dropout(0.2)(h2)
```

```python
#hidden layer with 512 neurons
h3 = Dense(512, activation = 'relu')(h2)

#add 20% dropout to reduce overfitting
h3 = Dropout(0.2)(h3)

#output with sigmoid activation function for binary classification (user likes artist)
output = Dense(1, activation='sigmoid')(h3)

#defining the model
ncf_model = Model(inputs=[user_input, item_input], outputs=output)
```

Dot Product → Hidden layers 1 → 2 → 3 → output

NCF – Code Explanation

Compile then Train model

```
1  from tensorflow.keras import metrics
2
3  #model compilation
4  ncf_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', metrics.Precision(), metrics.Recall()])
5
6  #print summary of model too
7  ncf_model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
user_input (InputLayer)	[(None, 1)]	0	[]
item_input (InputLayer)	[(None, 1)]	0	[]
user_embedding (Embedding)	(None, 1, 5)	77220560	['user_input[0][0]']
item_embedding (Embedding)	(None, 1, 5)	77220560	['item_input[0][0]']
flatten (Flatten)	(None, 5)	0	['user_embedding[0][0]']
flatten_1 (Flatten)	(None, 5)	0	['item_embedding[0][0]']
dot (Dot)	(None, 1)	0	['flatten[0][0]', 'flatten_1[0][0]']
dense (Dense)	(None, 2048)	4096	['dot[0][0]']
dropout (Dropout)	(None, 2048)	0	['dense[0][0]']
dense_1 (Dense)	(None, 1024)	2098176	['dropout[0][0]']
dropout_1 (Dropout)	(None, 1024)	0	['dense_1[0][0]']
dense_2 (Dense)	(None, 512)	524800	['dropout_1[0][0]']
dropout_2 (Dropout)	(None, 512)	0	['dense_2[0][0]']
dense_3 (Dense)	(None, 1)	513	['dropout_2[0][0]']

Model summary

```
1  #insert data as a single table into the model
2  user_item_data = [user_ids_flat, item_ids_flat]
3
4  #train the model on the combined data
5  ncf_model.fit(user_item_data, labels, epochs=5, batch_size=32768) # 65536 32768
```

```
Epoch 1/5
472/472 [==============================] - 59s 121ms/step - loss: 0.0228 - accuracy: 0.9972 - precision: 0.0016 - recall: 0.0010
Epoch 2/5
472/472 [==============================] - 58s 124ms/step - loss: 0.0122 - accuracy: 0.9983 - precision: 0.0000e+00 - recall: 0.0000e+00
Epoch 3/5
472/472 [==============================] - 58s 123ms/step - loss: 0.0105 - accuracy: 0.9983 - precision: 0.0000e+00 - recall: 0.0000e+00
Epoch 4/5
472/472 [==============================] - 58s 124ms/step - loss: 0.0098 - accuracy: 0.9983 - precision: 0.0000e+00 - recall: 0.0000e+00
Epoch 5/5
472/472 [==============================] - 58s 123ms/step - loss: 0.0095 - accuracy: 0.9983 - precision: 0.0000e+00 - recall: 0.0000e+00
```

Model Training

<u>Note</u>: I printed Precision and Recall to get a better idea of performance

NCF – Performance Evaluation

```
1  #reshape the prediction so we can see the results
2  pred = pred.reshape(len(user_artist_test.index.to_numpy()),len(user_artist_test.columns.to_numpy()))
3  print(pred.shape)
4  print(pred)
5
6  #save to csv for viewing on machine
7  np.savetxt("test.csv", pred, delimiter=',')
```

```
(1422, 4595)
[[6.41770894e-05 1.50387571e-03 1.14942246e-04 ... 3.81117308e-04
  6.41770894e-05 6.85204053e-03]
 [3.93285554e-05 4.01007431e-03 6.11971179e-03 ... 3.90591379e-03
  2.04896159e-03 2.10656915e-02]
 [3.27590038e-03 1.05575717e-03 2.87834046e-05 ... 7.01974437e-04
  1.40420525e-04 1.94723054e-03]
 ...
 [1.51610207e-02 3.65556101e-03 9.83655264e-05 ... 3.49230453e-04
  5.85206086e-04 4.67651896e-03]
 [4.98800888e-04 1.44600589e-02 9.85409133e-04 ... 1.17245328e-03
  2.76998297e-04 9.75499395e-03]
 [1.29936016e-04 8.16146086e-04 8.52018013e-04 ... 2.89623014e-04
  2.62918533e-04 8.34032334e-03]]
```

Very low probability for interactions (< 0.2)

Take Aways from NCF
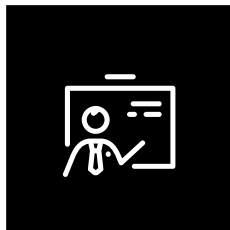
Slower than CF

Despite me running many different models using both my CPU and GPU, NCF would run slower on average for training and testing

High PC Req's

I frequently would run out of Memory (VRAM) when using the GPU. Using the CPU it would take many hours (>6 hours) per training session

Poor Learning

High Accuracy but Extremely low Precision and Recall indicates model is overfitting

K-Nearest Neighbors

Algorithm - Overview

Step 1

...

Step 2

...

Step 3

...

Algorithm - Explanation

Step 1

Algorithm - Explanation

Step 2

Algorithm - Explanation

Step 3

Algorithm – Performance Evaluation

…

Take Aways from Algorithm

Mercury

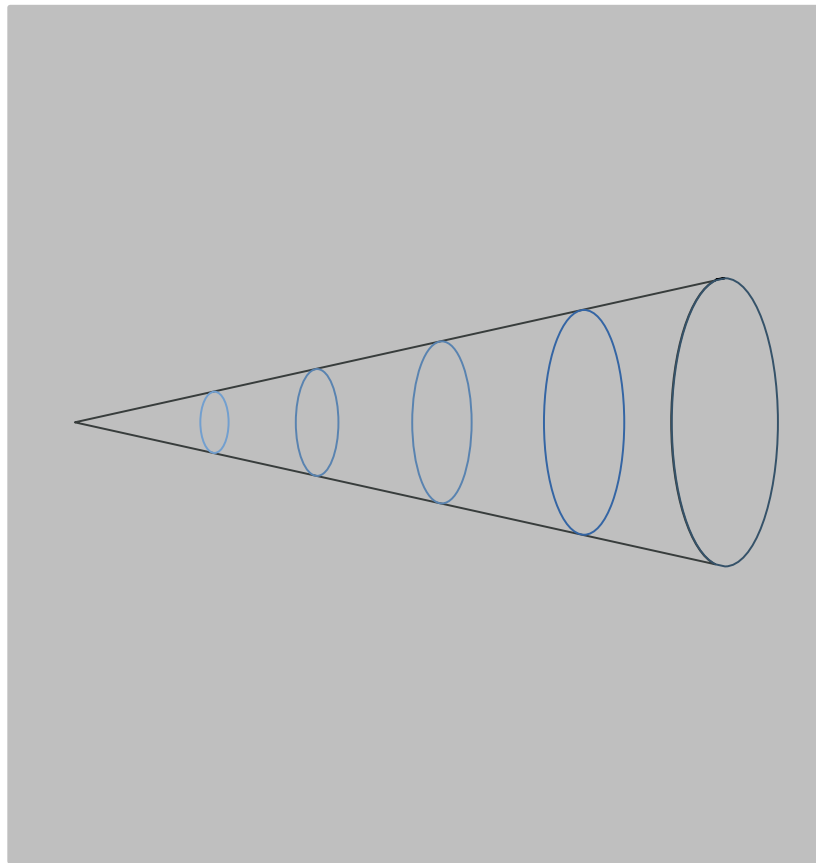Despite being red, Mars is actually a cold place. It is the fourth planet from the Sun, right after Earth

Venus

Venus has a beautiful name but it's terribly hot. It is the second planet from the Sun
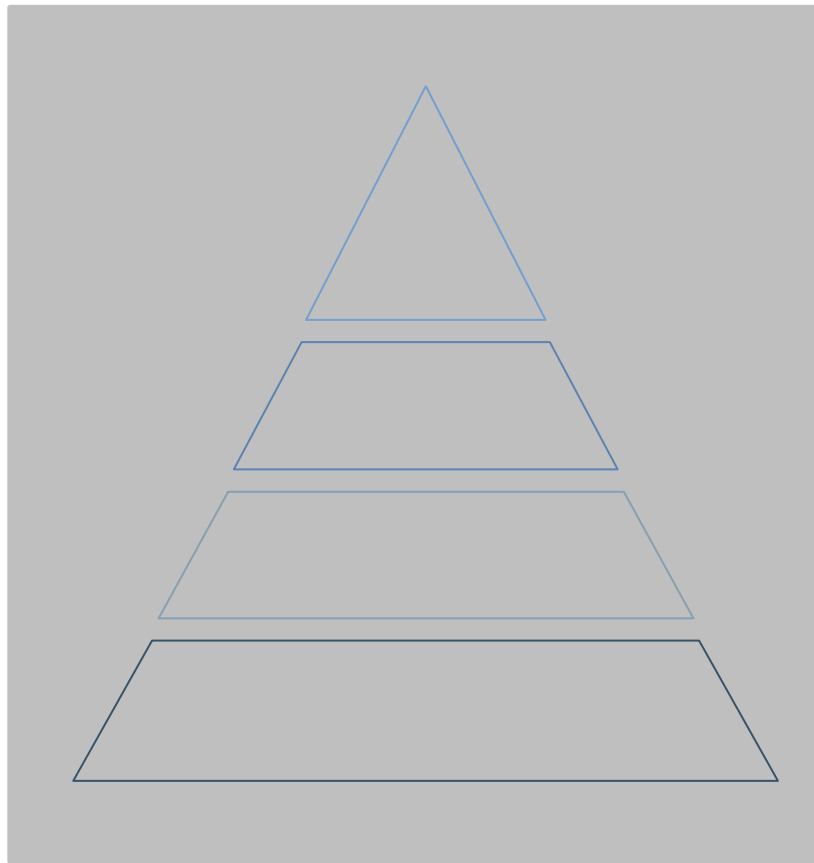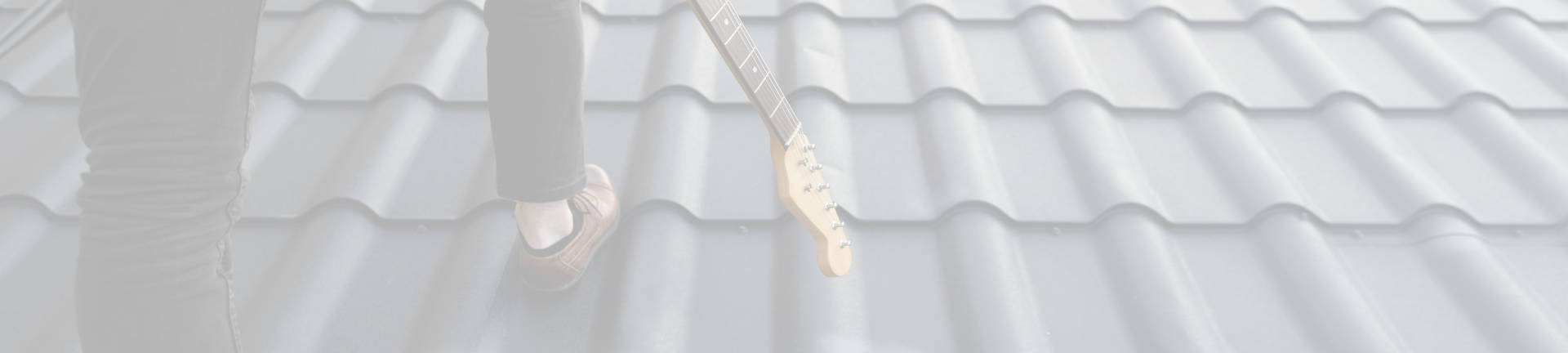
03
Future Work

Future Work

- Utilize Cloud Services for DL models

- Obtain dataset with user ratings

- Pick alternative algorithms

- Utilize Hybrid Methods

04

Conclusion

Conclusion

This was a fun yet challenging project. Our models' performance wasn't great, but demonstrates the difficulty with building an implicit recommender system.

References

- Neural Collaborative Filtering (2017) He, Liao, Zhang, et. al.
- https://developers.google.com/machine-learning/recommendation/collaborative/basics

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

- https://towardsdatascience.com/alternating-least-square-for-implicit-dataset-with-code-8e7999277f4b

- https://towardsdatascience.com/recommendation-system-matrix-factorization-d61978660b4b

- AUTHOR (YEAR). Title of publication. Publisher

Questions?

Thank you for your time and attention