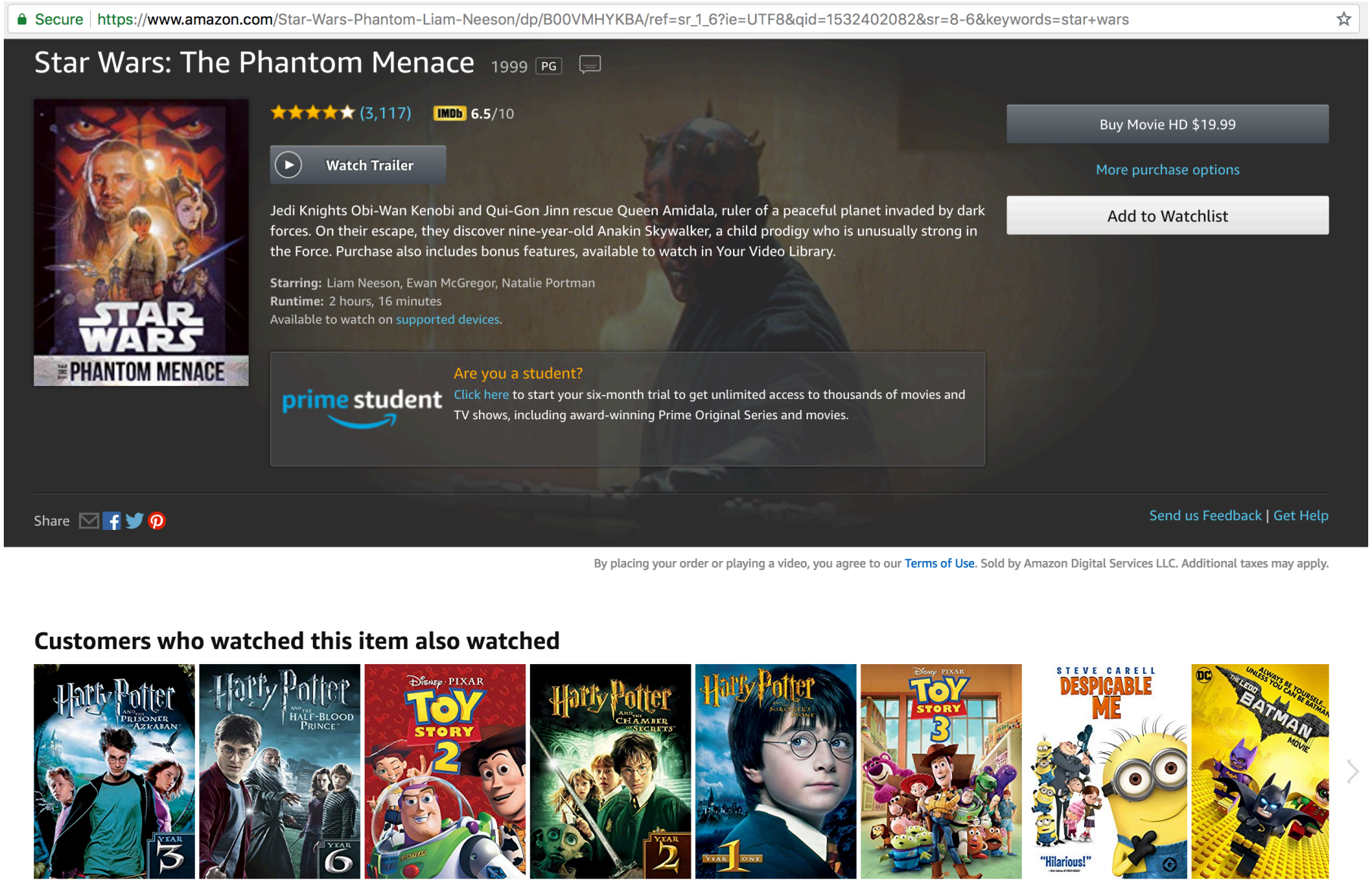
Recommender System

Shusen Wang

Recommender System



Customers who watched this item also watched

Basis of Recommendation

- Users' properties
  - gender, age, income, address, profession, etc.
- Items' properties
  - genre, name, brand, model, price, etc.
- User-item interaction history
  - browse, purchase, rating (score), review (text).

Collaborative Filtering

Basis of Recommendation

- Users' properties
  - gender, age, income, address, profession, etc.
- Items' properties
  - genre, name, brand, model, price, etc.
- User-item interaction history
  - browse, purchase, rating (score), review (text).

Collaborative Filtering

Model assumptions:

- Every user rates one or more items.
- Make recommendation purely based on the ratings.

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- Make recommendation purely based on the ratings.

	Item1	Item2	Item3	Item4	Item5
User1	?	?	4	?	5
User2	3	?	2	?	?
User3	4	?	4	3	5
User4	?	3	?	5	?

Collaborative Filtering

Approach:

- Fill the missing entries based on the observed entries.
- Rank the filled entries to make recommendation.

	Item1	Item2	Item3	Item4	Item5
User1	?	?	4	?	5
User2	3	?	2	?	?
User3	4	?	4	3	5
User4	?	3	?	5	?

Collaborative Filtering

Approach:

- Fill the missing entries based on the observed entries.
- Rank the filled entries to make recommendation.

	Item1	Item2	Item3	Item4	Item5
User1	**4.87**	**2.91**	4	**4.66**	5
User2	3	?	2	?	?
User3	4	?	4	3	5
User4	?	3	?	5	?

Baseline

Beer Review Data (Kaggle)

- Source: https://www.kaggle.com/c/beer-ratings/data

- Number of users: 7442
- Number of beers: 1731
- Number of reviews: 37500

One review

```
'beer/beerId'
'beer/brewerId'
'beer/name'
'beer/style'
'user/ageInSeconds'
'user/birthdayRaw'
'user/birthdayUnix'
'user/gender'
'user/userId'
'review/appearance'
'review/aroma'
'review/overall'
'review/taste'
'review/text'
'review/timeStruct'
'review/timeUnix'
```

Beer Review Data (Kaggle)

- Source: https://www.kaggle.com/c/beer-ratings/data

- Number of users: 7442
- Number of beers: 1731
- Number of reviews: 37500

- 80% for training,
- 10% for validation
- 10% for test.

```
print(x_train)
```

User IDs Beer IDs Ratings

```
[[ 479.    384.      4.5]
 [  97.    159.      4. ]
 [  69.    500.      4. ]
 ...
 [ 220.     27.      4. ]
 [ 198.     36.      4. ]
 [2637.    266.      5. ]]
```

```
print(x_train.shape)
```

```
(30000, 3)
```

A Naïve Baseline Model

- Averaged rating on the training set: 3.889.
- For whatever user and beer, the predicted rating is 3.889.

```
rating_avg = np.mean(x_train[:, 2])
print('averaged rating is ' + str(rating_avg))
```

```
averaged rating is 3.8892333333333333
```

A Naïve Baseline Model

- Averaged rating on the training set: 3.889.
- For whatever user and beer, the predicted rating is 3.889.
- The mean squared error (MSE) on the test set is 0.500.

```
rating_avg = np.mean(x_train[:, 2])
print('averaged rating is ' + str(rating_avg))
```

```
averaged rating is 3.8892333333333333
```

```
test_res = x_test[:, 2] - rating_avg
test_error_baseline = np.mean(np.multiply(test_res, test_res))
print('baseline test MSE: ' + str(test_error_baseline))
```

```
baseline test MSE: 0.49979168111111105
```

A Naïve Baseline Model

- Averaged rating on the training set: 3.889.
- For whatever user and beer, the predicted rating is 3.889.
- The mean squared error (MSE) on the test set is 0.500.

- The naïve baseline model itself is not useful.
  - We cannot make recommendation based on the baseline model.
- But the baseline MSE is an important reference.
  - Compare our models with the baseline.
  - Some models may not beat the baseline.

The Sum Model

The Sum Model

- Each item has a score, a_i, indicating its quality.
  - E.g., most people think the movies *Lord of Rings* are better than *Warcraft*.
- Each user has a score, b_u, indicating her rating behavior.
  - E.g., some people are "nice" reviewers on IMDB, Amazon, etc.
  - A "nice" reviewer has a higher b than a "critical" reviewer.

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- Each user has a score, b_u, indicating her rating behavior.
  - E.g., some people are "nice" reviewers on IMDB, Amazon, etc.
  - A "nice" reviewer has a higher b than a "critical" reviewer.
- Predict user-u's rating of item-i by:

$$f_{i,u} = a_i + b_u + c.$$

Common among all the items and users.

Train the Sum Model

- Predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.
- There are m items and n users.
  - In the beer dataset, $m = 1731$ and $n = 7442$.
  - Trainable parameters: $a_1, \cdots, a_m$, $b_1, \cdots, b_n$, and c.

Train the Sum Model

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item-i

embedding → a_i

user-u

embedding → b_u

Train the Sum Model

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- There are m items and n users.
  - In the beer dataset, $m = 1731$ and $n = 7442$.
  - Trainable parameters: $a_1, \cdots, a_m$, $b_1, \cdots, b_n$, and c.
- The set $\Omega = \{(i, u)\}$ indexes all the existing ratings.
  - We know the actual rating $\{r_{i,u}\}$ for all $(i, u) \in \Omega$.
  - In the beer dataset, the cardinality is $|\Omega| = 37{,}500$

If every user has rated every beer, then the number of reviews is mn.

Train the Sum Model

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  - In the beer dataset, the cardinality is $|\Omega| = 37{,}500 = 0.3\%\, mn$.

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- The set $\Omega = \{(i, u)\}$ indexes all the existing ratings.
  - We know the actual rating $\{r_{i,u}\}$ for all $(i, u) \in \Omega$.
  - In the beer dataset, the cardinality is $|\Omega| = 37{,}500 = 0.3\%\, mn$.
- Find $a_1, \cdots, a_m$, $b_1, \cdots, b_n$, and c by minimizing

$$\frac{1}{|\Omega|} \sum_{(i,u)\in\Omega} \left(f_{i,u} - r_{i,u}\right)^2.$$

- $m + n + 1 = 9{,}174$ trainable parameters.
- $|\Omega| = 37{,}500$ samples (80% for training).

Implement the Sum Model Using Keras

- **Embedding of items**: map the index i to a real number a_i.

```
item_id = Input(shape=[1], name='item_id')

embed_dim = 1
item_num = 1731

item_embed = Embedding(item_num, 1, input_length=1, name='item_embed')(item_id)
item_flat = Flatten(name='item_flat')(item_embed)
```

An integer in $\{0, 1, \cdots, 1730\}$

scalar

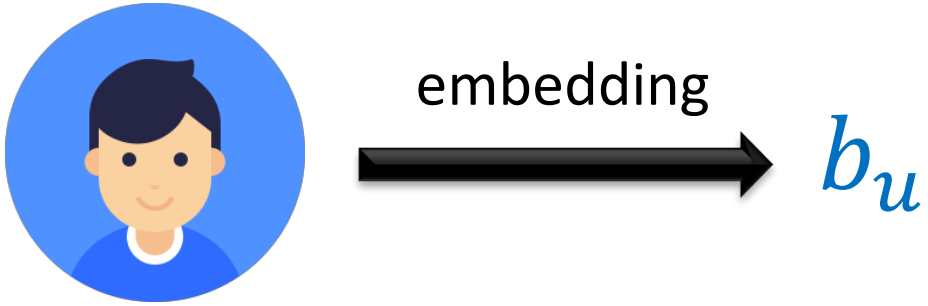
item-i

embedding

a_i

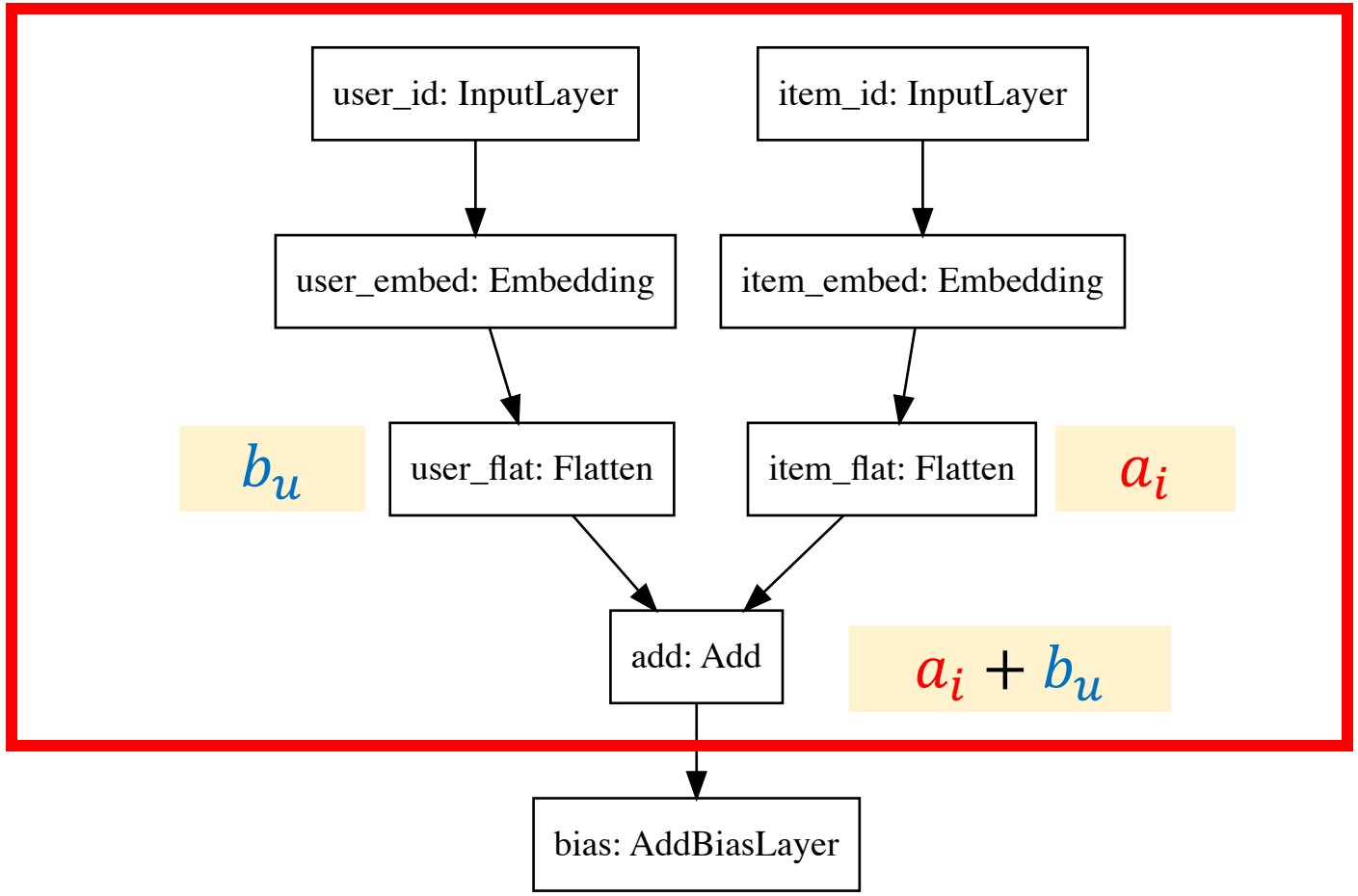
Implement the Sum Model Using Keras

- **Embedding of items**: map the index i to a real number a_i.
- **Embedding of users**: map the index u to a real number b_u.
  - Similarly implemented.



Implement the Sum Model Using Keras

The sum model: predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.



Implement the Sum Model Using Keras

The sum model: predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.

```
from keras.models import Model
from keras.layers import Input, Embedding, Flatten, Add

embed_dim = 1

user_id = Input(shape=[1], name='user_id')
item_id = Input(shape=[1], name='item_id')

user_num = 7442
user_embed = Embedding(user_num, embed_dim, input_length=1, name='user_embed')(user_id)
user_flat = Flatten(name='user_flat')(user_embed)

item_num = 1731
item_embed = Embedding(item_num, embed_dim, input_length=1, name='item_embed')(item_id)
item_flat = Flatten(name='item_flat')(item_embed)

added = Add(name='add')([user_flat, item_flat])
```

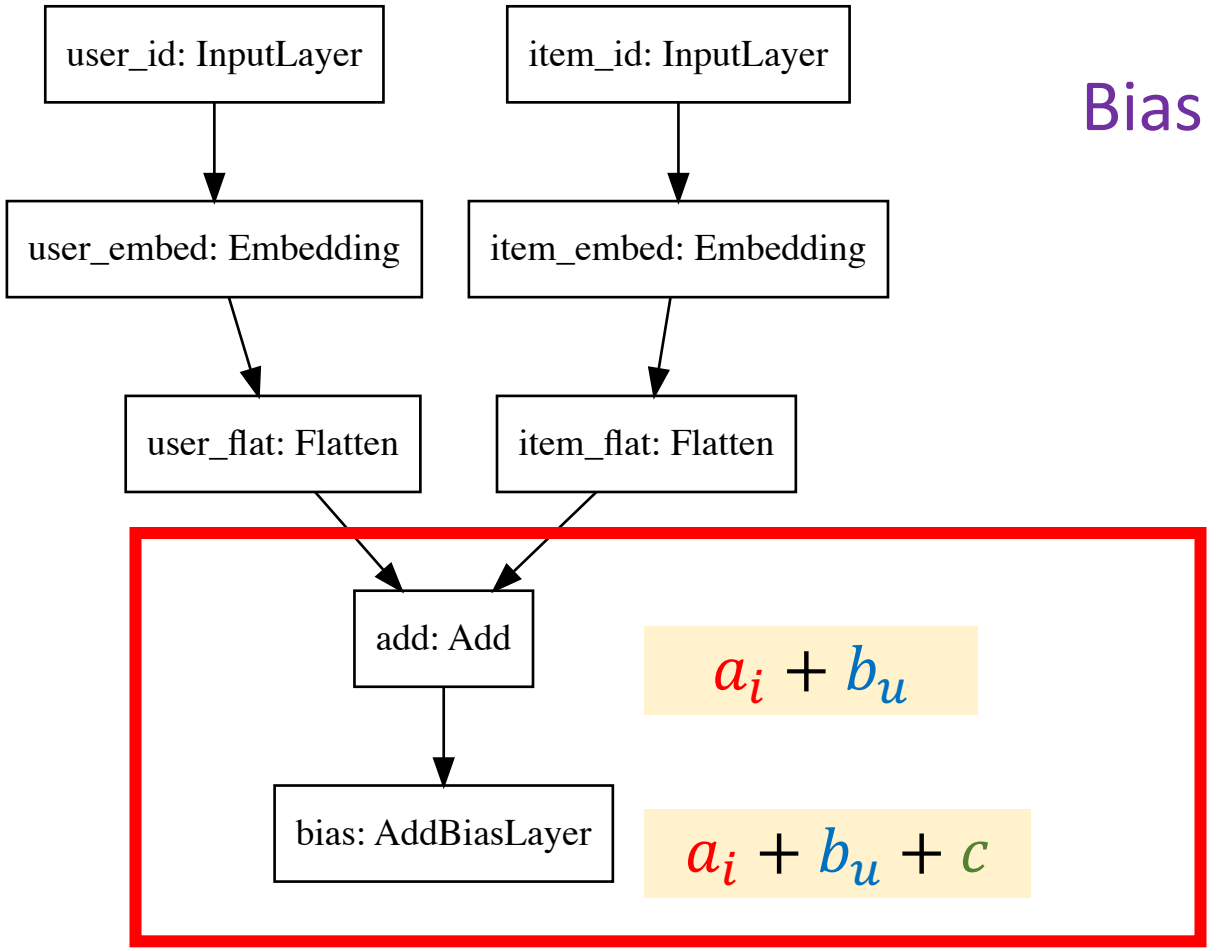
$= b_u$

$= a_i$

$= a_i + b_u$

Implement the Sum Model Using Keras

The sum model: predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.



Bias (aka intercept)

Implement the Sum Model Using Keras

The sum model: predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.

```
from keras import backend as K
from keras.engine.topology import Layer

class AddBiasLayer(Layer):
    def __init__(self, output_dim, **kwargs):
        self.output_dim = output_dim
        super(AddBiasLayer, self).__init__(**kwargs)

    def build(self, input_shape):
        self.bias = self.add_weight(name='bias', shape=(self.output_dim,),
                                    initializer='uniform', trainable=True)
        super(AddBiasLayer, self).build(input_shape)

    def call(self, inputs):
        c = K.bias_add(inputs, self.bias)
        return c

    def compute_output_shape(self, input_shape):
        return (input_shape[0], self.output_dim)
```

Implement the Sum Model Using Keras

The sum model: predict user-u's rating of item-i by: $f_{i,u} = a_i + b_u + c$.

```
added = Add(name='add')([user_flat, item_flat])
```
$= a_i + b_u$

```
pred = AddBiasLayer(output_dim=1, name='bias')(added)
```
$= a_i + b_u + c$

```
sum_model = Model(inputs=[user_id, item_id], outputs=pred, name='sum_model')
```

Implement the Sum Model Using Keras

```
sum_model.compile(loss='mse', optimizer='RMSprop')

history = sum_model.fit([x_train[:, 0], x_train[:, 1]],
                        x_train[:, 2], batch_size=64,
                        epochs=30, shuffle=True,
                        validation_data=([x_val[:, 0], x_val[:, 1]], x_val[:, 2]))
```

```
Train on 30000 samples, validate on 3750 samples
Epoch 1/30
30000/30000 [==============================] - 1s 22us/step - loss: 12.7309 - val_loss: 10.276
Epoch 2/30
30000/30000 [==============================] - 1s 17us/step - loss: 8.1294 - val_loss: 6.2546
Epoch 3/30
30000/30000 [==============================] - 1s 17us/step - loss: 4.6506 - val_loss: 3.3405
            :
Epoch 29/30
30000/30000 [==============================] - 1s 18us/step - loss: 0.3283 - val_loss: 0.3754
Epoch 30/30
30000/30000 [==============================] - 0s 16us/step - loss: 0.3266 - val_loss: 0.3753
```

Sum Model

- The baseline model
  - Validation error: 0.496
  - Test error: 0.4998

- The sum model
  - Validation error: 0.375
  - Test error: 0.393

- The sum model beats the baseline.
- The sum model is simple but hard to beat!

Product Model

Product Model

- Each item is represented by a feature vector $\mathbf{a}_i \in \mathbb{R}^k$.
- Each user is represented by a feature vector $\mathbf{b}_u \in \mathbb{R}^k$.

item-i

embedding → $\mathbf{a}_i$

user-u

embedding → $\mathbf{b}_u$

Product Model

- Each item is represented by a feature vector $\mathbf{a}_i \in \mathbb{R}^k$.
- Each user is represented by a feature vector $\mathbf{b}_u \in \mathbb{R}^k$.
- Predict user-u's rating of item-i by: $f_{i,u} = \mathbf{a}_i^T \mathbf{b}_u + c$.

item-i

embedding

$\mathbf{a}_i$

user-u

embedding

$\mathbf{b}_u$

Train the Product Model

- Each item is represented by a feature vector $\mathbf{a}_i \in \mathbb{R}^k$.
- Each user is represented by a feature vector $\mathbf{b}_u \in \mathbb{R}^k$.
- Predict user-u's rating of item-i by: $f_{i,u} = \mathbf{a}_i^T \mathbf{b}_u + c$.

- Find $\mathbf{a}_1, \cdots, \mathbf{a}_m, \mathbf{b}_1, \cdots, \mathbf{b}_n \in \mathbb{R}^k$ and $c \in \mathbb{R}$ by minimizing

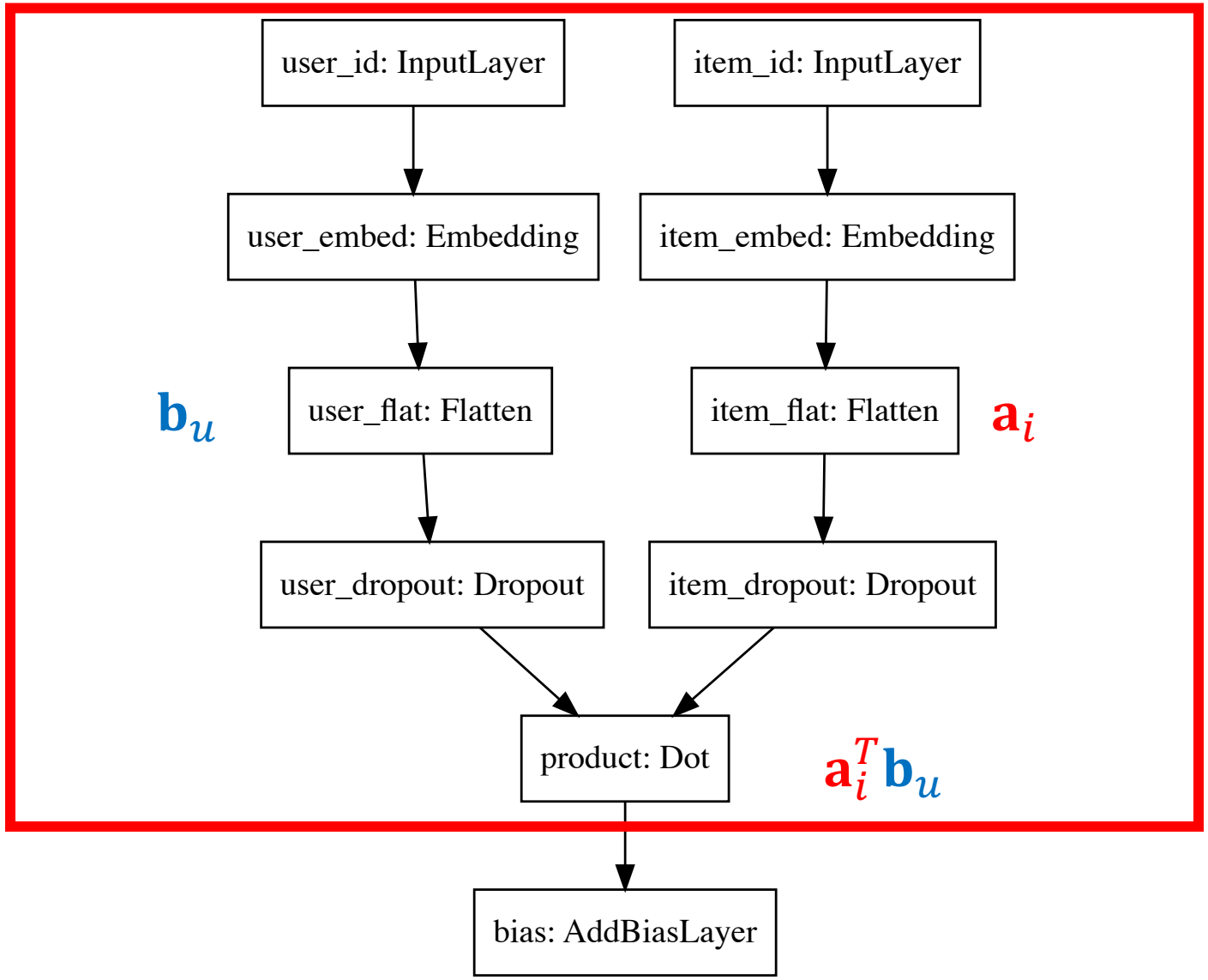
$$\frac{1}{|\Omega|} \sum_{(i,u)\in\Omega} \left(r_{i,u} - f_{i,u}\right)^2.$$

Product Model

Also known as "***Matrix Factorization***".

- Let the full item-user rating matrix be $\mathbf{R} \in \mathbb{R}^{m \times n}$.
- Observe part of $\mathbf{R}$ (entries indexed by Ω) .
- Seek to learn such $\mathbf{A} \in \mathbb{R}^{m \times k}$ and $\mathbf{B} \in \mathbb{R}^{n \times k}$ that $\mathbf{A}\mathbf{B}^T \approx \mathbf{R}$.
- $(m + n)k$ trainable parameters and $|\Omega|$ samples.

Implement the Product Model using Keras



Implement the Product Model using Keras

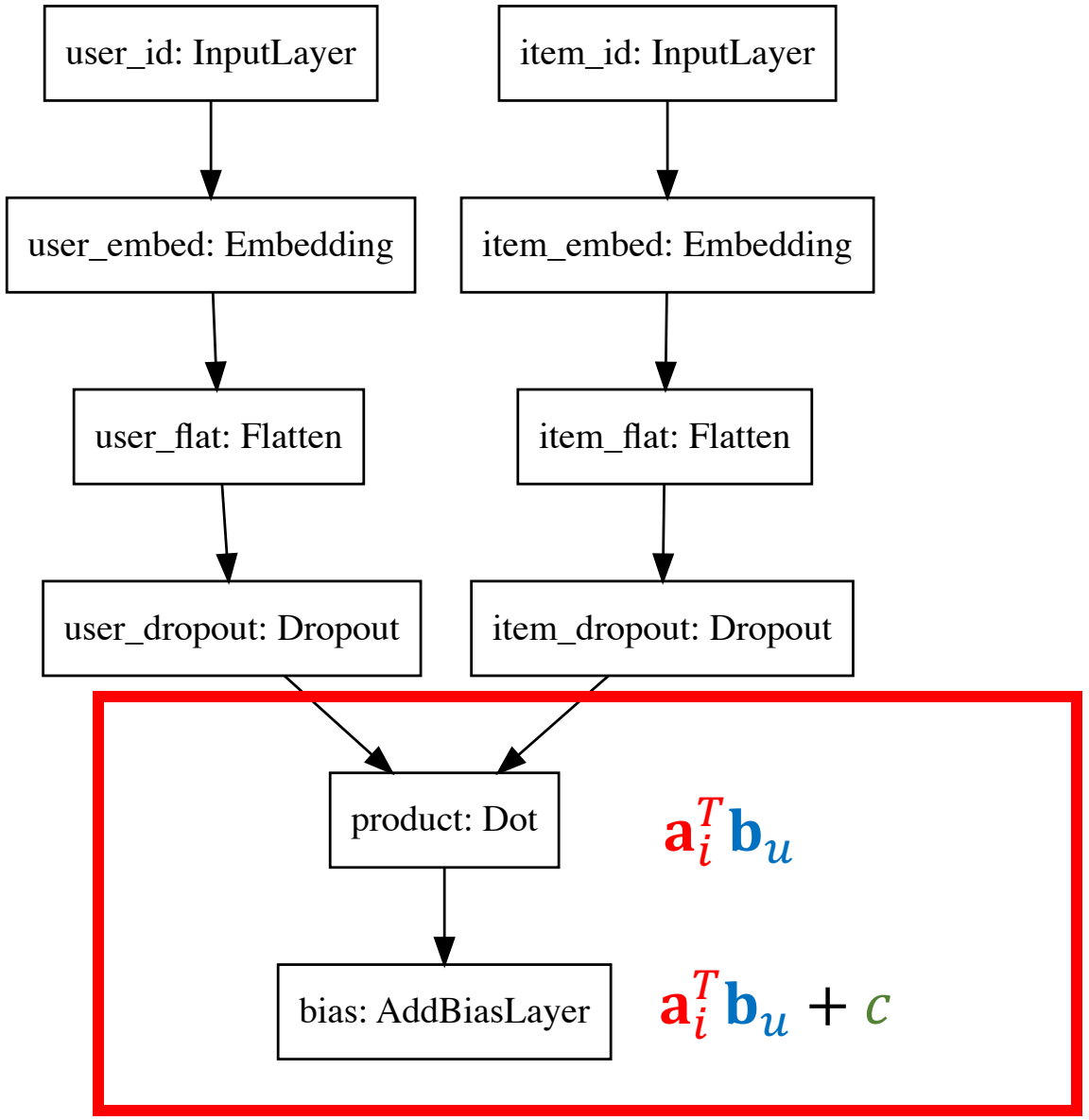
```
from keras.models import Model
from keras.layers import Input, Embedding, Flatten, Dot, Dropout

embed_dim = 10
dropout_rate = 0.5

user_id = Input(shape=[1], name='user_id')
item_id = Input(shape=[1], name='item_id')

user_num = len(user_name_index)
user_embed = Embedding(user_num, embed_dim, input_length=1, name='user_embed')(user_id)
user_flat = Flatten(name='user_flat')(user_embed)
user_dropout = Dropout(rate=dropout_rate, name='user_dropout')(user_flat)

item_num = len(beer_id_index)
item_embed = Embedding(item_num, embed_dim, input_length=1, name='item_embed')(item_id)
item_flat = Flatten(name='item_flat')(item_embed)
item_dropout = Dropout(rate=dropout_rate, name='item_dropout')(item_flat)

product = Dot(1, normalize=False, name='product')([user_dropout, item_dropout])
```

$= \mathbf{b}_u$

$= \mathbf{a}_i$

$= \mathbf{a}_i^T \mathbf{b}_u$

Implement the Product Model using Keras



Implement the Product Model using Keras

The product model: predict user-u's rating of item-i by: $f_{i,u} = \mathbf{a}_i^T \mathbf{b}_u + c$.

```
product = Dot(1, normalize=False, name='product')([user_dropout, item_dropout])
```
$= \mathbf{a}_i^T \mathbf{b}_u$

```
pred = AddBiasLayer(output_dim=1, name='bias')(product)
```
$= \mathbf{a}_i^T \mathbf{b}_u + c$

```
prod_model = Model(inputs=[user_id, item_id], outputs=pred, name='product_model')
```

Implement the Product Model using Keras

```
prod_model.compile(loss='mse', optimizer='RMSprop')

history = prod_model.fit([x_train[:, 0], x_train[:, 1]],
                         x_train[:, 2], batch_size=64,
                         epochs=50, shuffle=True,
                         validation_data=([x_val[:, 0], x_val[:, 1]], x_val[:, 2]))
```

```
Train on 30000 samples, validate on 3750 samples
Epoch 1/50
30000/30000 [==============================] - 1s 35us/step - loss: 13.8177 - val_loss: 12.106
Epoch 2/50
30000/30000 [==============================] - 1s 23us/step - loss: 10.6212 - val_loss: 9.1376
Epoch 3/50
30000/30000 [==============================] - 1s 24us/step - loss: 7.8628 - val_loss: 6.6029
```



```
Epoch 49/50
30000/30000 [==============================] - 1s 21us/step - loss: 0.3943 - val_loss: 0.4338
Epoch 50/50
30000/30000 [==============================] - 1s 22us/step - loss: 0.3942 - val_loss: 0.4338
```

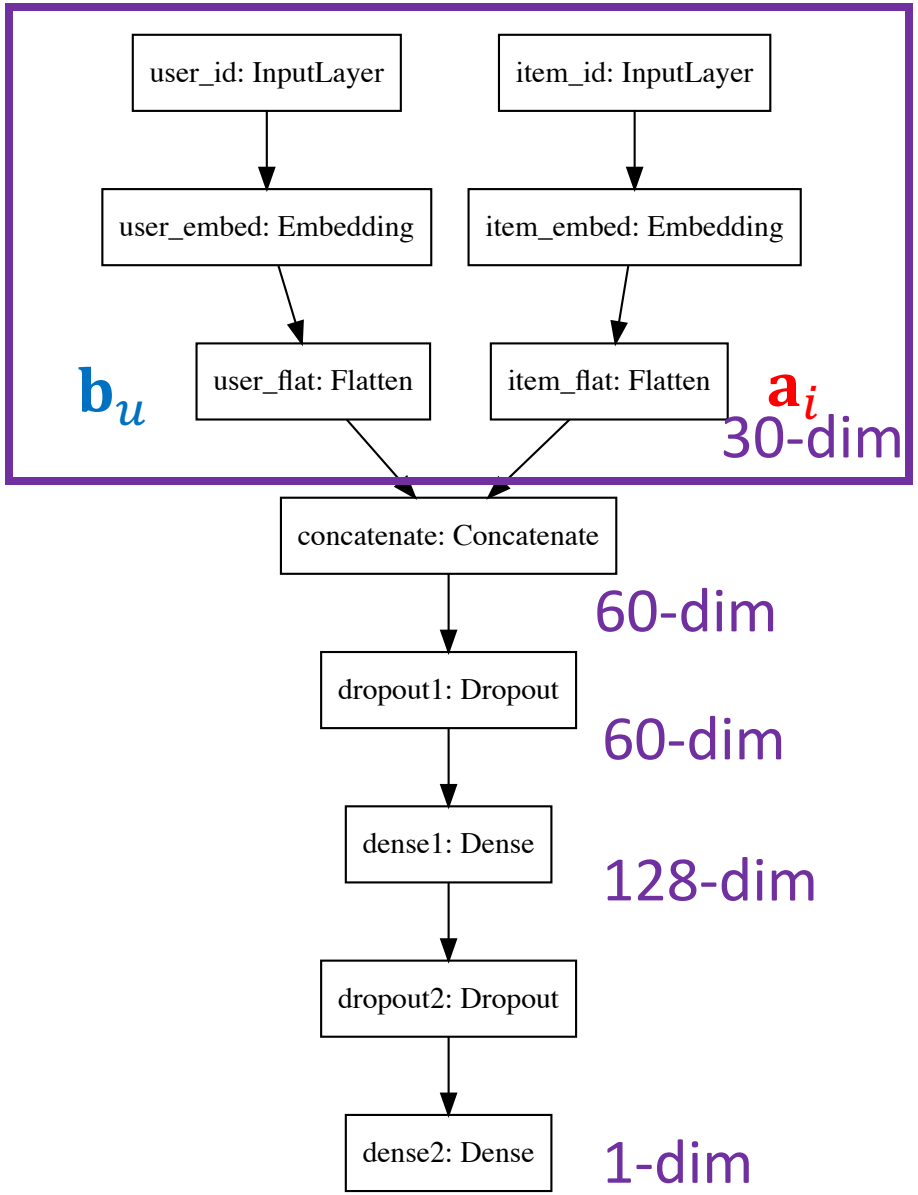
Product Model

- The baseline model
  - Validation error: 0.496
  - Test error: 0.50
- The sum model
  - Validation error: 0.3753
  - Test error: 0.3928
- The product model
  - Validation error: 0.4338
  - Test error: 0.4468

Neural Networks

Neural Networks

The same as the product model



Neural Networks

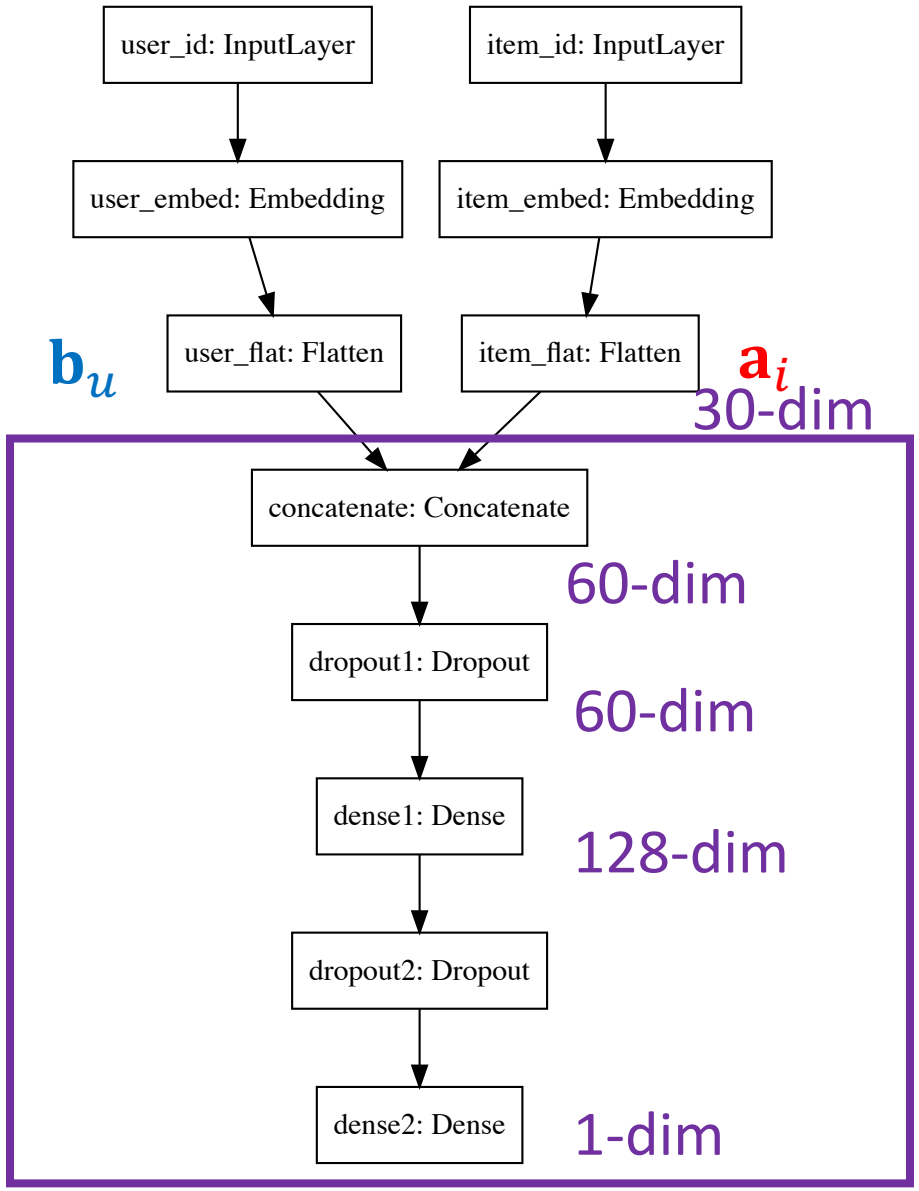
```
from keras.models import Model
from keras.layers import Input, Embedding, Flatten, Dense, Dropout, Concatenate

embed_dim = 30
dropout_rate = 0.5

user_id = Input(shape=[1], name='user_id')
item_id = Input(shape=[1], name='item_id')

user_num = len(user_name_index)
user_embed = Embedding(user_num, embed_dim, input_length=1, name='user_embed')(user_id)
user_flat = Flatten(name='user_flat')(user_embed)

item_num = len(beer_id_index)
item_embed = Embedding(item_num, embed_dim, input_length=1, name='item_embed')(item_id)
item_flat = Flatten(name='item_flat')(item_embed)
```

$= \mathbf{b}_u$

$= \mathbf{a}_i$

Neural Networks

A standard fully-connected neural network



Neural Networks

```
concatenate = Concatenate(name='concatenate')([user_flat, item_flat])
dropout1 = Dropout(rate=dropout_rate, name='dropout1')(concatenate)
dense1 = Dense(128, activation='relu', name='dense1')(dropout1)
dropout2 = Dropout(rate=dropout_rate, name='dropout2')(dense1)
pred = Dense(1, activation='relu', name='dense2')(dropout2)

neuralnet = Model(inputs=[user_id, item_id], outputs=pred, name='neural_net')
```

Neural Networks

```
neuralnet.compile(loss='mse', optimizer='RMSprop')

history = neuralnet.fit([x_train[:, 0], x_train[:, 1]],
                        x_train[:, 2], batch_size=16,
                        epochs=10, shuffle=True,
                        validation_data=([x_val[:, 0], x_val[:, 1]], x_val[:, 2]))
```

```
Train on 30000 samples, validate on 3750 samples
Epoch 1/10
30000/30000 [==============================] - 4s 149us/step - loss: 1.1534 - val_loss: 0.3959
Epoch 2/10
30000/30000 [==============================] - 4s 142us/step - loss: 0.5304 - val_loss: 0.3833
Epoch 3/10
30000/30000 [==============================] - 4s 134us/step - loss: 0.4830 - val_loss: 0.3657
```

⋮

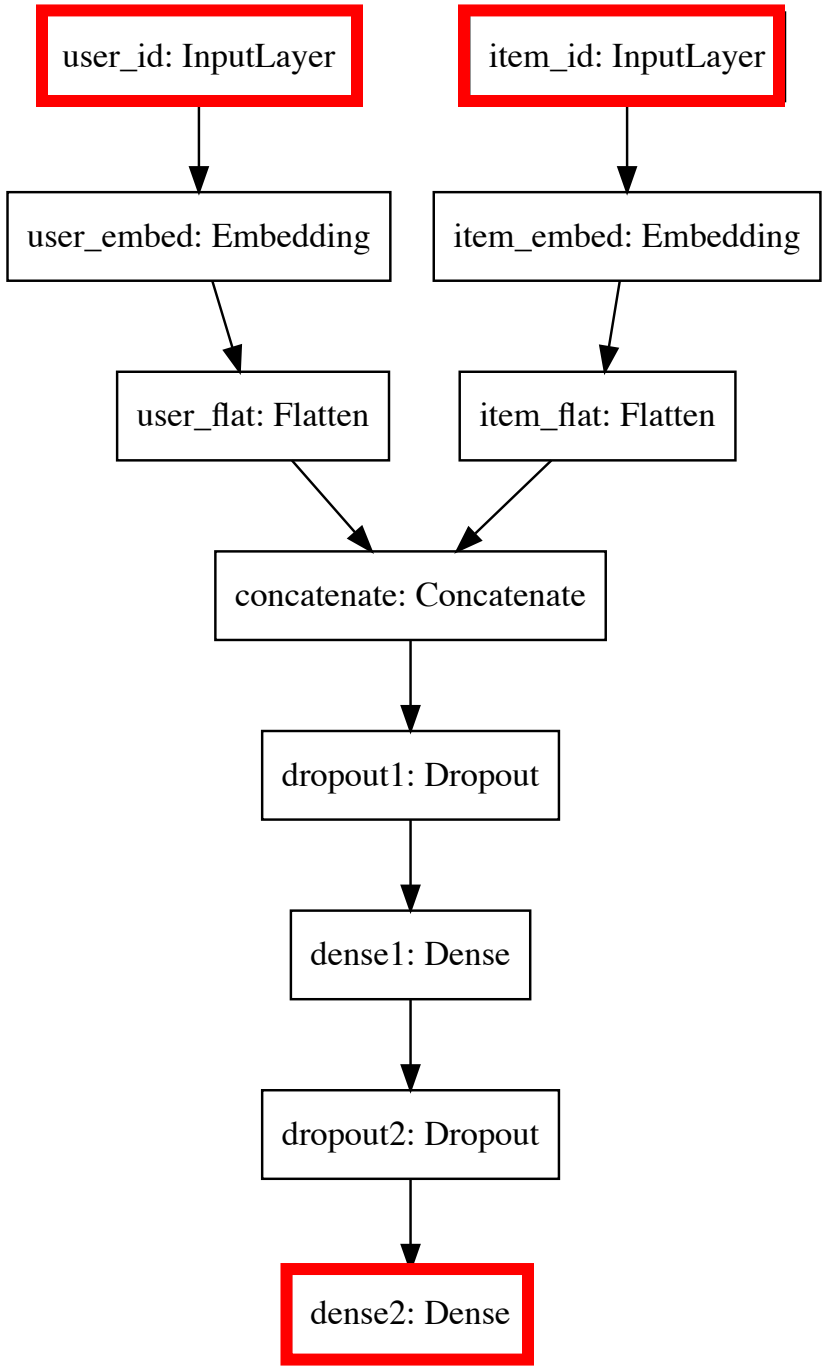
```
Epoch 9/10
30000/30000 [==============================] - 4s 122us/step - loss: 0.3522 - val_loss: 0.3637
Epoch 10/10
30000/30000 [==============================] - 4s 120us/step - loss: 0.3441 - val_loss: 0.3697
```

Comparisons on the Beer Dataset

- The baseline model
  - Validation error: 0.496
  - Test error: 0.50
- The product model
  - Validation error: 0.4338
  - Test error: 0.4468
- The sum model
  - Validation error: 0.3753
  - Test error: 0.3928
- Neural network
  - Validation error: 0.3697
  - Test error: 0.3891

Discussions

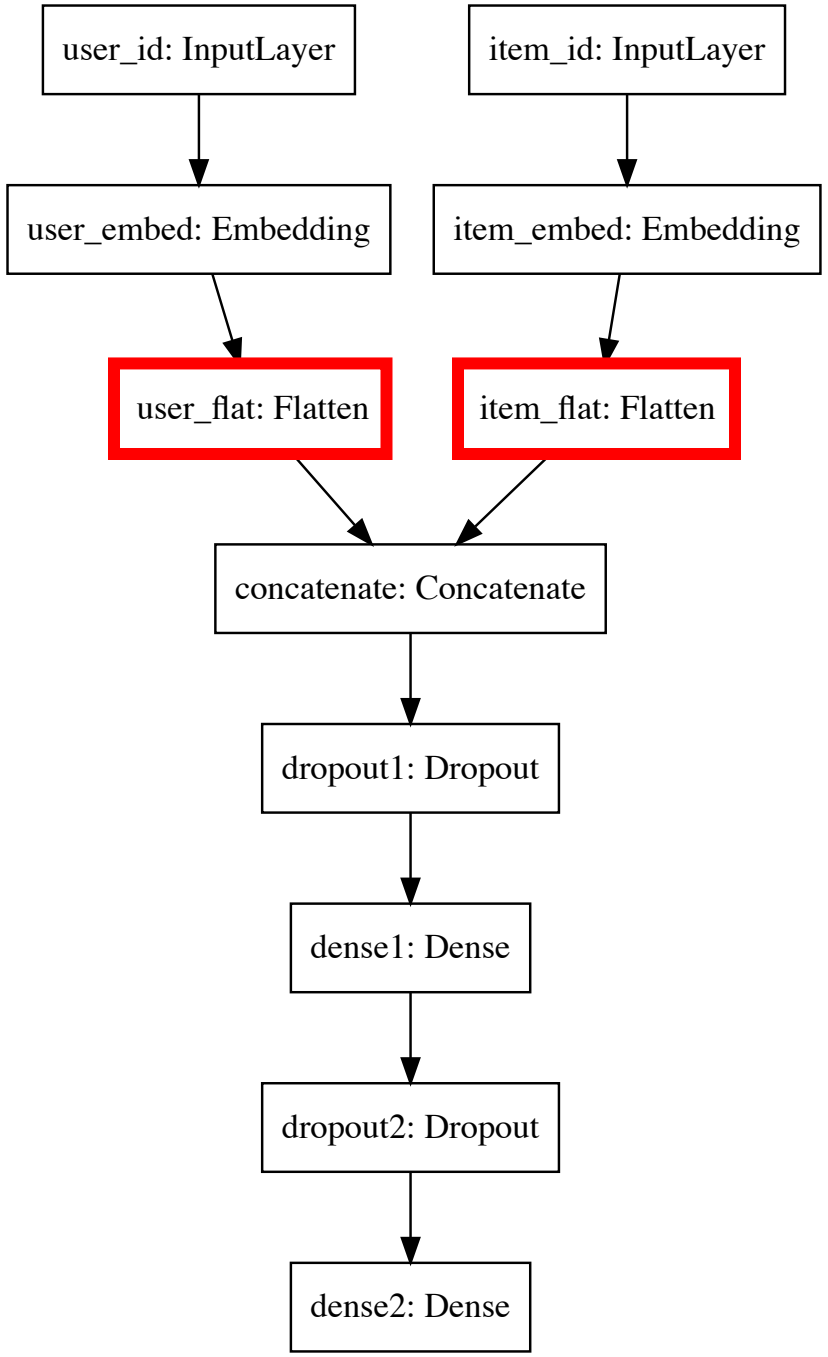
Collaborative Filtering



- Trained a model for predicting user-item rating.
- Did not using items and users' features.

```
'beer/beerId'
'beer/brewerId'
'beer/name'
'beer/style'
'user/ageInSeconds'
'user/birthdayRaw'
'user/birthdayUnix'
'user/gender'
'user/userId'
'review/appearance'
'review/aroma'
'review/overall'
'review/taste'
'review/text'
'review/timeStruct'
'review/timeUnix'
```

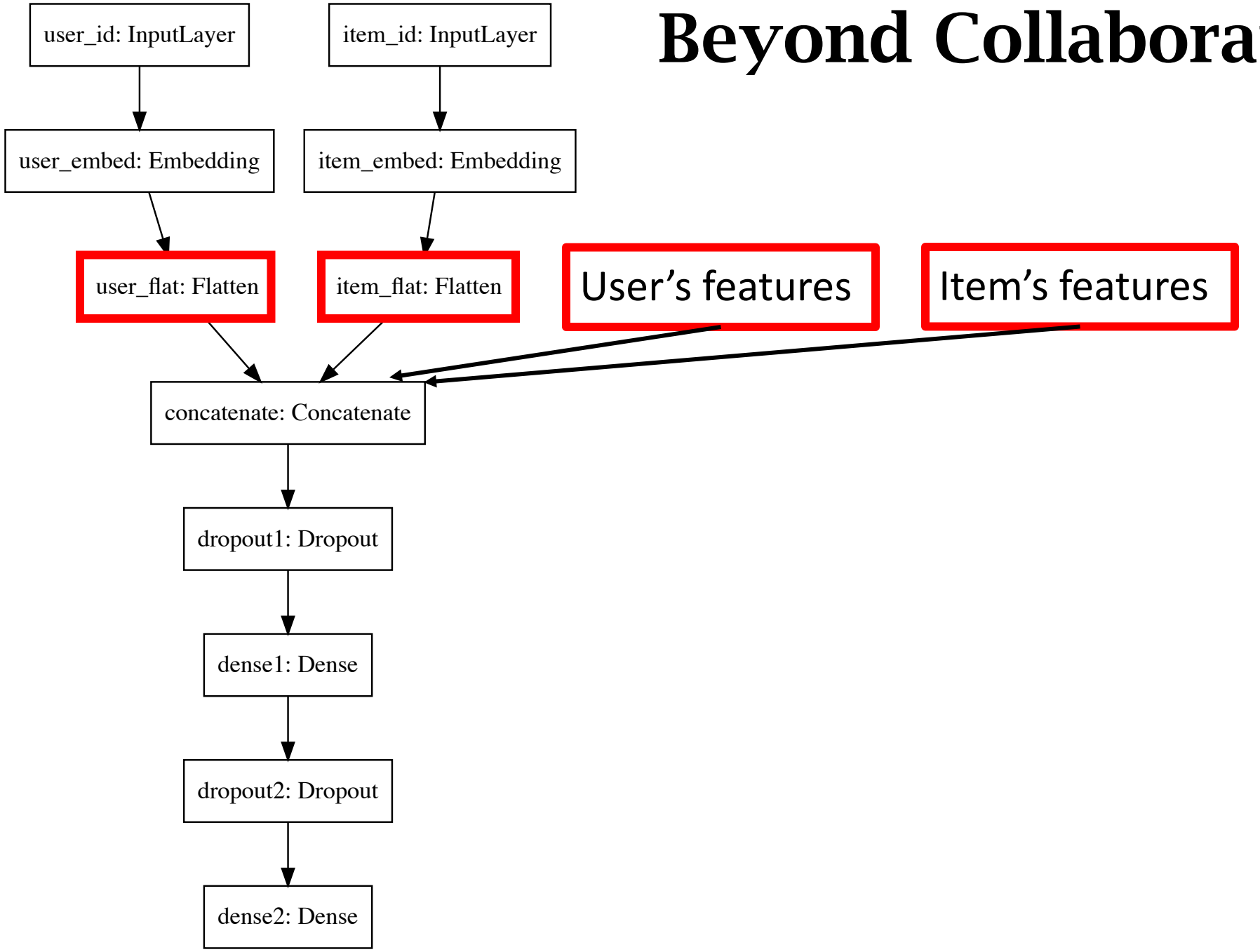
Collaborative Filtering



- Trained a model for predicting user-item rating.
- Did not using items and users' features.
- The learned features are effective. (Beat the baselines.)

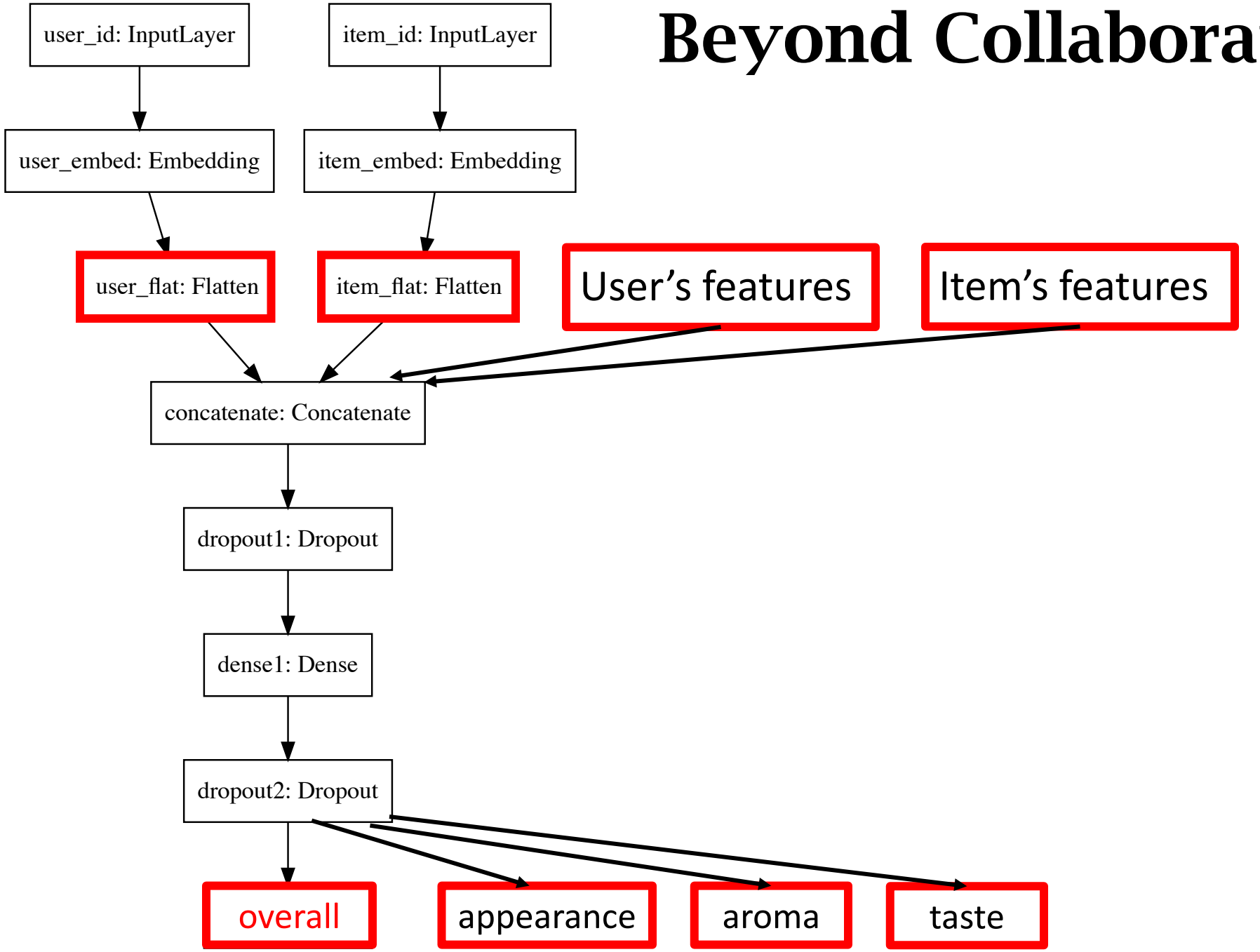
```
'beer/beerId'
'beer/brewerId'
'beer/name'
'beer/style'
'user/ageInSeconds'
'user/birthdayRaw'
'user/birthdayUnix'
'user/gender'
'user/userId'
'review/appearance'
'review/aroma'
'review/overall'
'review/taste'
'review/text'
'review/timeStruct'
'review/timeUnix'
```

Beyond Collaborative Filtering




```
'beer/beerId'
'beer/brewerId'
'beer/name'
'beer/style'
'user/ageInSeconds'
'user/birthdayRaw'
'user/birthdayUnix'
'user/gender'
'user/userId'
'review/appearance'
'review/aroma'
'review/overall'
'review/taste'
'review/text'
'review/timeStruct'
'review/timeUnix'
```

Beyond Collaborative Filtering




```
'beer/beerId'
'beer/brewerId'
'beer/name'
'beer/style'
'user/ageInSeconds'
'user/birthdayRaw'
'user/birthdayUnix'
'user/gender'
'user/userId'
'review/appearance'
'review/aroma'
'review/overall'
'review/taste'
'review/text'
'review/timeStruct'
'review/timeUnix'
```