Deep Neural Network & Recommendation Engine on TensorFlow

CloudMile

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Outline

- Recommedation Engine in Matrix Factorization
- Variant of Matrix Factorization

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Movielens Data

User Movie Rating

	userId	movieId	rating	timestamp
0	0	30	2.5	1260759144
1	0	833	3.0	1260759179
2	0	859	3.0	1260759182
3	0	906	2.0	1260759185
4	0	931	4.0	1260759205

User Movie Tag

	userId	movieId	tag	timestamp
0	14	304	sandra 'boring' bullock	1138537770
1	14	1517	dentist	1193435061
2	14	5166	Cambodia	1170560997
3	14	6118	Russian	1170626366
4	14	6178	forgettable	1141391765

Movie Metadata

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	1	Jumanji (1995)	Adventure|Children|Fantasy
2	2	Grumpier Old Men (1995)	Comedy|Romance
3	3	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	4	Father of the Bride Part II (1995)	Comedy

How to Treat Your Data?

- ❑ Split **train, valid, test** data

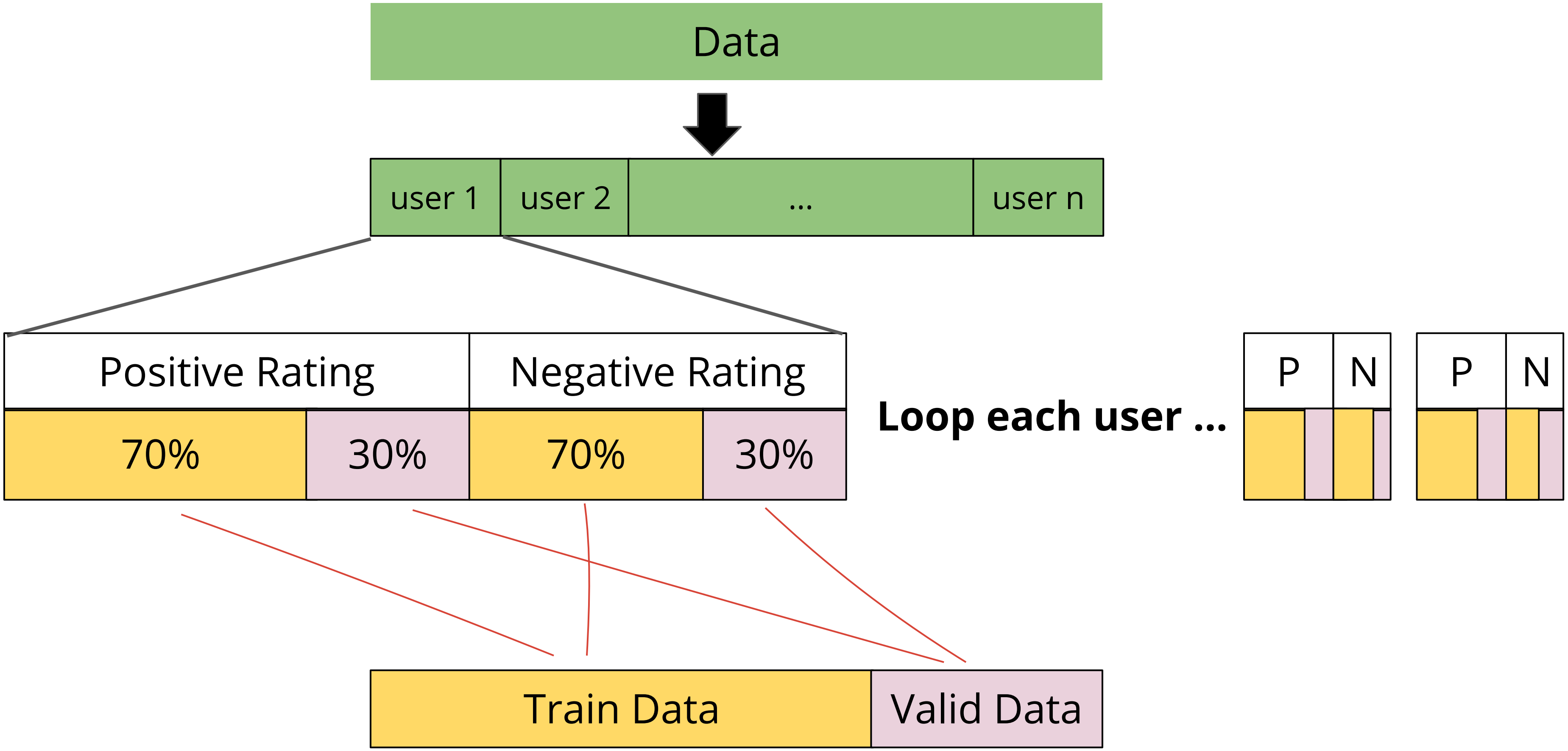
理論上

挑選出最好的模型後，拿
testing 檢驗 generalization

Cross validation:
切出很多組的 (training, validation) 再
拿不同組訓練模型，挑選最好的模型

For Overfitting Check

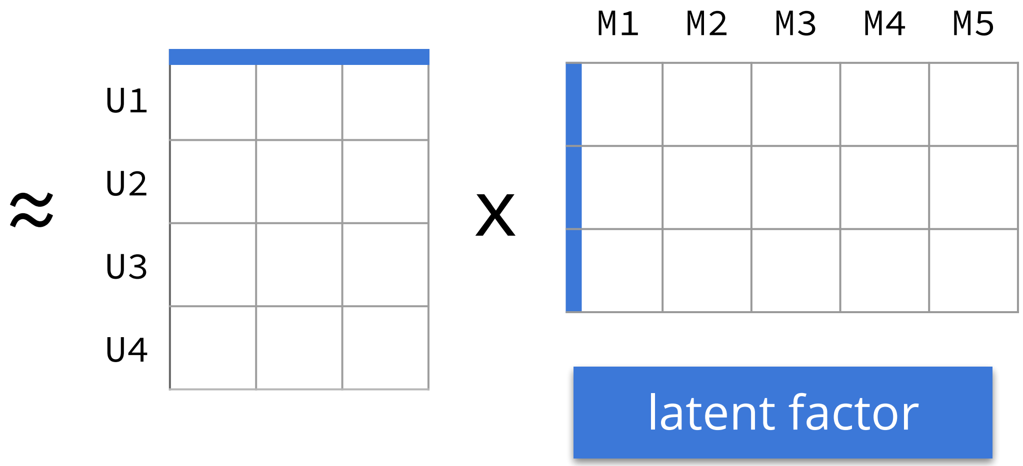
How Did We Split?

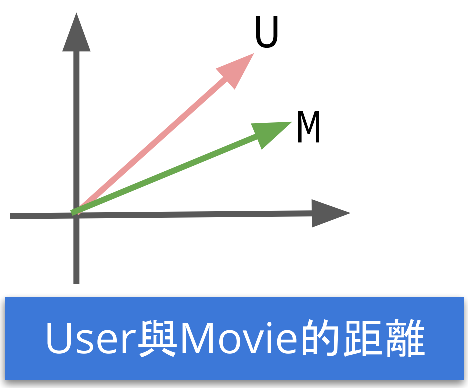


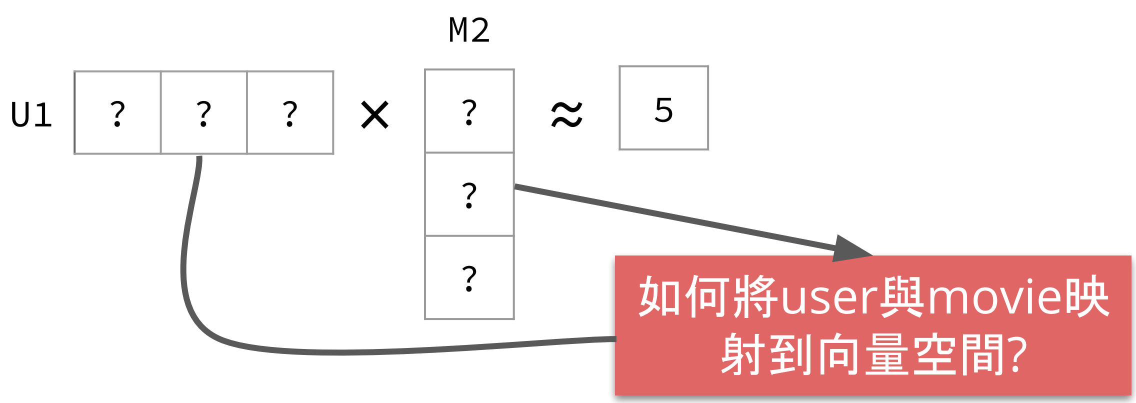
Concept of Latent Factor

U: User, M: Movie, R: Rating(1 ~ 5)

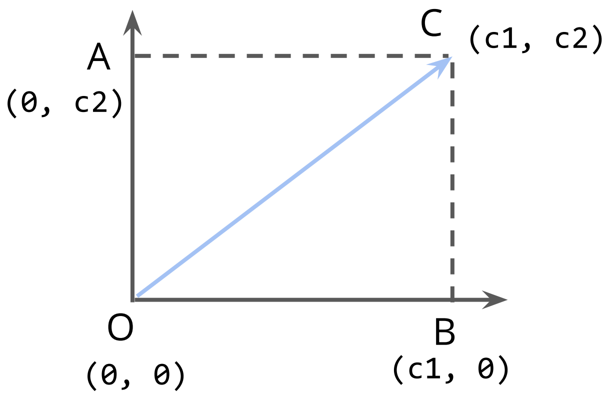
	M1	M2	M3	M4	M5
U1	3	5			1
U2			2	4	
U3	5		1		
U4		3		3	3



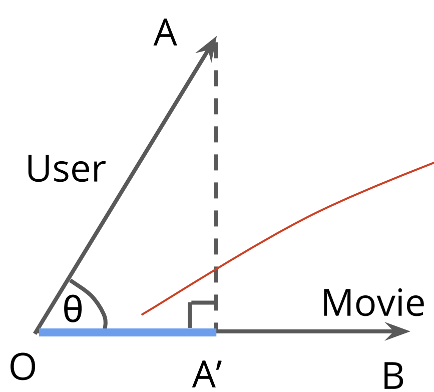




The Vector and Inner Dot



- ➔ 具有**大小(長度)**和**方向**的意義
- ➔ 長度 ⇒ ||C|| = 和原點的距離, 通常使用歐幾里得定義(L2 norm)
- ➔ 可拆成各分量相加 ⇒ OC = OA + OB



A projection on B ⇒ ‖OA’‖
‖OA’‖ = ‖OA‖·cosθ
= ‖OA‖·(OA·OB)/(‖OA‖·‖OB‖)
= (OA·OB) / ‖OB‖

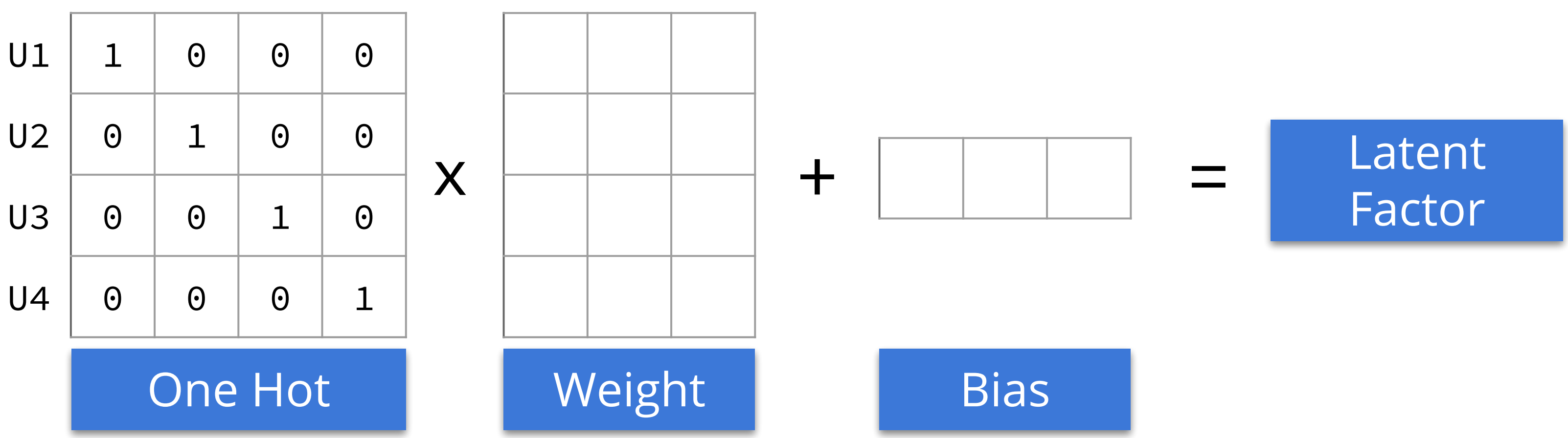
cosθ = (OA·OB)/(‖OA‖·‖OB‖)

|cosθ| <= 1

Reflections(Transformation)

user id ⇒ 1263, 1080, 87...
movie id ⇒ 103, 554, 187...

- ❑ 把user和movie看成是categorical variable ⇒ One Hot Encoding
- ❑ **Recap feature transformation(cascading functions)**



User ID to Embedding

U1	1	0	0	0
U2	0	1	0	0
U3	0	0	1	0
U4	0	0	0	1

One Hot

x

1	1	1
2	2	2
3	3	3
4	4	4

Weights

=

1	1	1
2	2	2
3	3	3
4	4	4

第i號user的latent factor等價於取Weight的第i列 ⇒ **Embedding**

U3	3
U4	4
U1	1
U2	2

User inputs

1	1	1
2	2	2
3	3	3
4	4	4

Lookup from weights

U3	3	3	3
U4	4	4	4
U1	1	1	1
U2	2	2	2

User id embedding

- movie id embedding 也是如法炮製
- 實際都會省略 bias

Model Formulation and Loss Function

U, M ⇒ 透過embedding取得的latent factor

	M1	M2	M3	M4	M5
U1	3	5			1
U2			2	4	
U3	5		1		
U4		3		3	3

$r_{12} \Rightarrow u_1 \cdot m_2 \approx 5$
$r_{33} \Rightarrow u_3 \cdot m_3 \approx 1$
$r_{23} \Rightarrow u_2 \cdot m_3 \approx 2$
$\vdots$

Regression

$$L = \sum_{(i,j)} (u_i \cdot m_j - rij)^2$$

model function

- ❑ User rating behavior and movie being rated are highly **biased**
- ❑ Recall linear combination ⇒ **wx + b**

$$\Rightarrow u_i \cdot m_j + b_u + b_m + \boxed{b_{global}}$$

- ❑ 不是U和M的外在影響因素
- ❑ Model bias

Minimizing $$L = \sum_{(i,j)} (\boxed{u_i \cdot m_j + b_u + b_m + b_{global}} - r_{ij})^2$$

model function with bias

Prediction

以向量運算表示 $u_i \cdot m_j + b_u + b_m + b_{global}$

$u_i \cdot m_j$

	M1	M2	M3	M4	M5
U1	3.5	4.7	0.87	1.87	0.8
U2	4.87	5.6	2.1	3.87	4.57
U3	5.87	4.78	1.87	1.2	3.6
U4	1.7	3.2	2.9	2.87	2.6

$Predict =$ $u_i \cdot m_j$ + b_u + b_{global}

Row Wise

b_u

0.1
0.2
0.3
0.4

+

b_{global}: 0.5

Element Wise

+

0.8	0.7	0.6	0.5	0.4

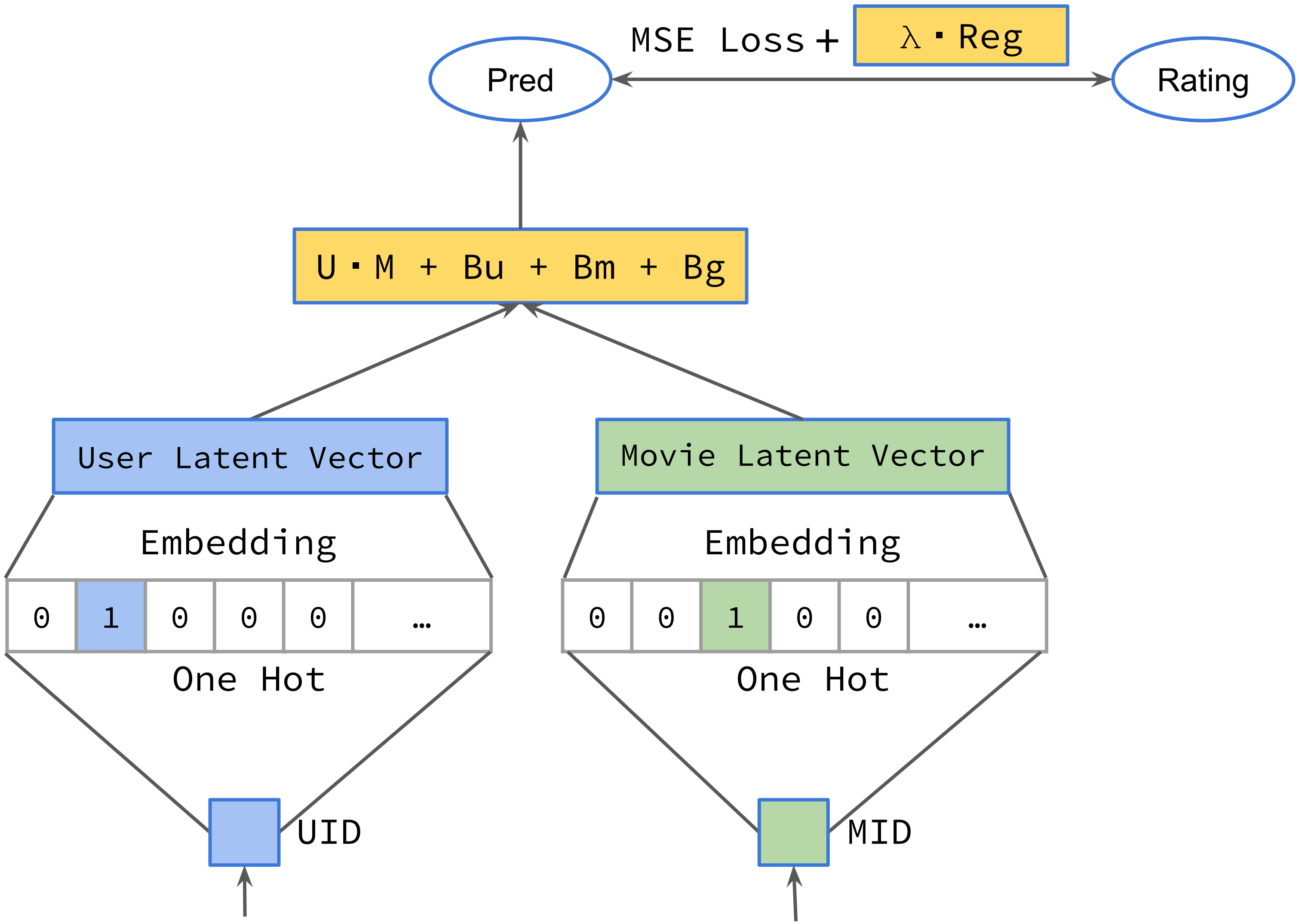
b_m Column Wise

```
[[ 4.9   6.    2.07  2.97  1.8 ]
 [ 6.37  7.    3.4   5.07  5.67]
 [ 7.47  6.28  3.27  2.5   4.8 ]
 [ 3.4   4.8   4.4   4.27  3.9 ]]
```

這個例子實際跑出來的

Recommendation Engine in Matrix Factorization

First Model - Basic MF



First Model - Basic MF

- Function set formulation

$$f_{u,m}(x) = u_i \cdot m_j + b_u + b_m + b_{global}$$

- Loss function

$$L = \sum (f_{u,m}(x) - r_{ij})^2 + \lambda \cdot \frac{1}{2}\left(\sum u^2 + \sum m^2 + \sum b_u^2 + \sum b_m^2\right)$$

About The L2 Regularization

Regularization: L2 Norm

L2 regularization:

$$\|\theta\|_2 = (w_1)^2 + (w_2)^2 + \ldots$$

$$\mathrm{L}'(\theta) = L(\theta) + \lambda \frac{1}{2} \|\theta\|_2$$

Gradient: $$\frac{\partial \mathrm{L}'}{\partial w} = \frac{\partial \mathrm{L}}{\partial w} + \lambda w$$

Update: $$w^{t+1} \rightarrow w^t - \eta \frac{\partial \mathrm{L}'}{\partial w} = w^t - \eta \left(\frac{\partial \mathrm{L}}{\partial w} + \lambda w^t \right)$$

$$= \underline{(1 - \eta\lambda)} w^t - \eta \frac{\partial \mathrm{L}}{\partial w}$$

接近0

Weight Decay

Basic MF

filename	lab_reco_model_mf.ipynb
number of users	671
number of movies	9125
rating range	0.5 ~ 5分, ❏ 4分以上算正評 ❏ 未滿4分認為是負評或是不列入推薦名單
neural network	matrix factorization

Model All Metrics

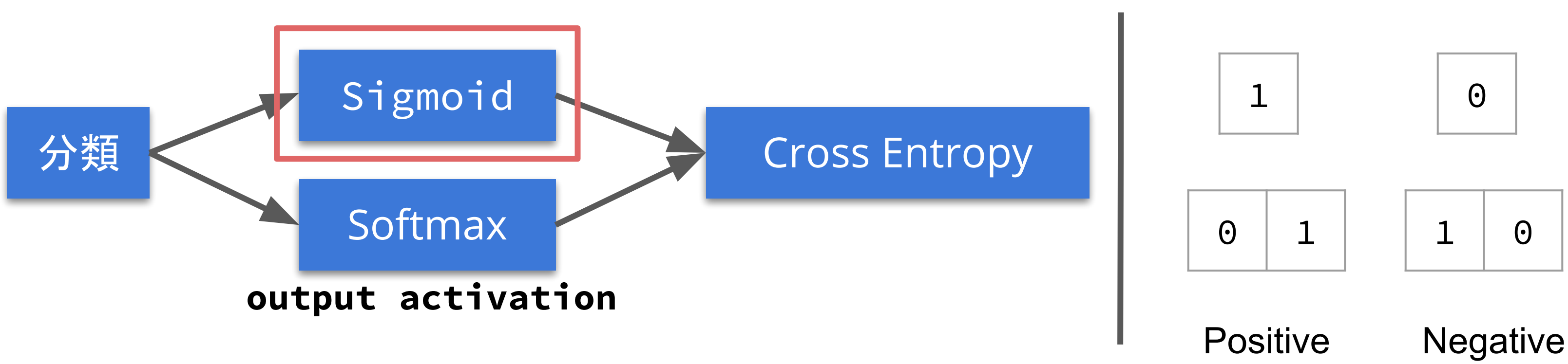
Model	Dummy Model(亂猜)	Basic MF
RMSE Loss	3.23	0.93
ROC AUC	0.50	0.74
NDCG	strict: 0.45 normal: 0.63	strict: 0.63 normal: 0.76
Precision at 10	strict: 0.37 normal: 0.54	strict: 0.50 normal: 0.63

Recommendation Engine in Matrix Factorization

- Movie rating ⇒ explicit feedback
- **通常User不會這麼熱心的對你的商品評價**
  - implicit feedback
    - 商品點閱次數
    - Youtube影片觀看時間
    - …

    ⇒ 通常只能得到1(Positive), 0(Negtive)

- **Label 0.5 ~ 5 ⇒ 1 or 0 (這裡4分以上 = 1 others 0)**
  - Regression ⇒ Binary classification
  - P(使用者A 喜歡 電影B) = ??



Machine Learning Framework

[x₁ ... x₆]

```
[[z11, ...  z61]
 [z12, ...  z62]
        ...
 [z16, ...  z66]]
```

$$z_1 = w_1 \cdot x + b \rightarrow \quad \rightarrow y_1 \quad \hat{y}_1 \quad 1$$
$$z_2 = w_2 \cdot x + b \rightarrow \quad \rightarrow y_2 \quad \hat{y}_2 \quad 0$$
$$z_3 = w_3 \cdot x + b \rightarrow \quad \rightarrow y_3 \quad \hat{y}_3 \quad 0$$
$$z_4 = w_4 \cdot x + b \rightarrow \quad \rightarrow y_4 \quad \hat{y}_4 \quad 0$$
$$z_5 = w_5 \cdot x + b \rightarrow \quad \rightarrow y_5 \quad \hat{y}_5 \quad 0$$
$$z_6 = w_6 \cdot x + b \rightarrow \quad \rightarrow y_6 \quad \hat{y}_6 \quad 0$$

Probability:

- $1 > y_i > 0$ $\quad y_i = P(C_i \mid x)$
- $\sum_i y_i = 1$

Sigmoid不滿足這個需求!

Recommendation Engine in Matrix Factorization

Activation function: Softmax

$$softmax(z) = \frac{e^{z_i}}{\sum_{k=1}^{n} e^{z_k}}$$

類別1

$$x \rightarrow
\begin{cases}
z_1 = w_1 \cdot x + b & 5 \\
z_2 = w_2 \cdot x + b & 1 \\
z_3 = w_3 \cdot x + b & 3 \\
z_4 = w_4 \cdot x + b & -3 \\
z_5 = w_5 \cdot x + b & -3 \\
z_6 = w_6 \cdot x + b & 0
\end{cases}$$

0.8	y_1	$\hat{y}_1$	1
0.01	y_2	$\hat{y}_2$	0
0.11	y_3	$\hat{y}_3$	0
0	y_4	$\hat{y}_4$	0
0	y_5	$\hat{y}_5$	0
0	y_6	$\hat{y}_6$	0

Cross Entropy

$$-\sum_{i=1} \hat{y}_i ln y_i$$

Probability:

- $1 > y_i > 0$ $\quad y_i = P(C_i \mid x)$
- $\sum_i y_i = 1$

計算argmax，最大的數字都在
index 0 ⇒ 命中！

Recommendation Engine in Matrix Factorization

Activation function: Sigmoid

$$\sigma(z) = \frac{1}{1+exp(-z)}$$

類別1

$z_1 = w_1 \cdot x + b$	5	0.99	y_1	$\hat{y}_1$	1
$z_2 = w_2 \cdot x + b$	1	0.73	y_2	$\hat{y}_2$	0
$z_3 = w_3 \cdot x + b$	3	0.95	y_3	$\hat{y}_3$	0
$z_4 = w_4 \cdot x + b$	-3	0.04	y_4	$\hat{y}_4$	0
$z_5 = w_5 \cdot x + b$	-3	0.04	y_5	$\hat{y}_5$	0
$z_6 = w_6 \cdot x + b$	0	0.5	y_6	$\hat{y}_6$	0

x

Cross Entropy

$$-\sum_{i=1} \hat{y}_i ln y_i$$

算argmax是沒有意義的! 要考慮的是每個class的分數

Softmax與Sigmoid的差別

$$softmax(z) = \frac{e^{z_i}}{\sum_{k=1}^{n} e^{z_k}}$$

$$\sigma(z) = \frac{1}{1 + exp(-z)}$$

- ❑ 所有類別視為一個母體
- ❑ Single-label for one record

一筆record一個label

- ❑ 不考慮類別間的關係
- ❑ Multi-label for one record

一筆record可有多個label

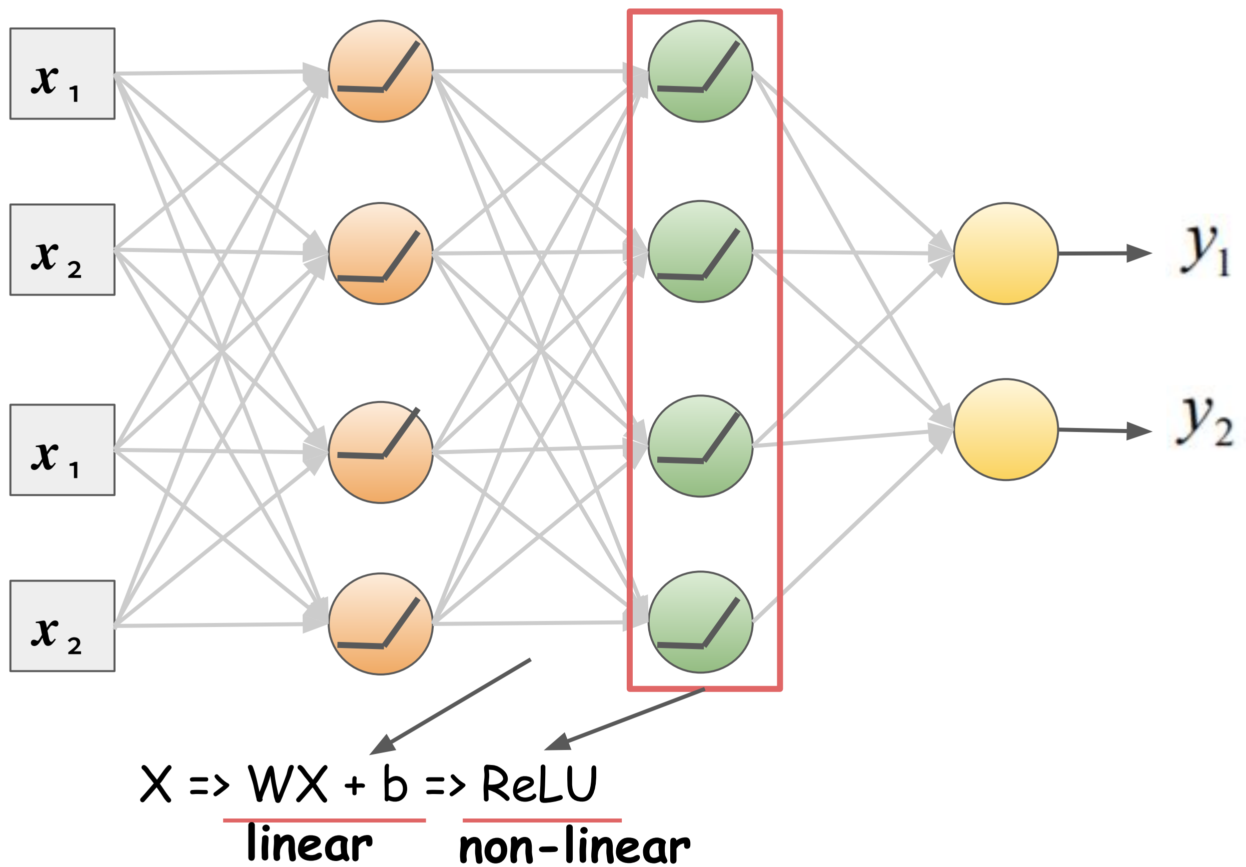
Computes sigmoid cross entropy given `logits`.

Measures the probability error in discrete classification tasks in which each class is independent and not mutually exclusive. For instance, one could perform multilabel classification where a picture can contain both an elephant and a dog at the same time.

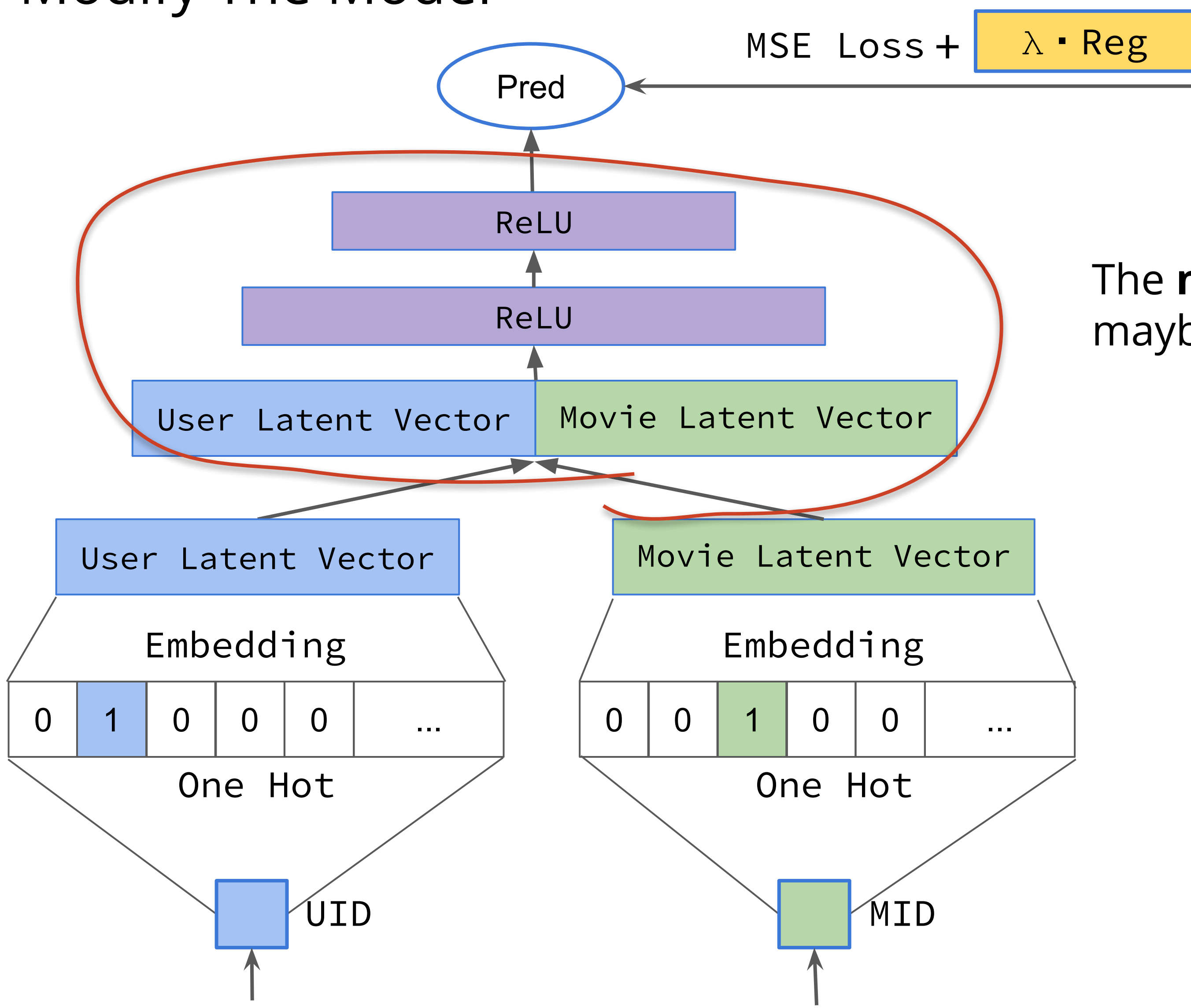
整個Model似乎是線性的...?

$$f_{u,m}(x) = u_i \cdot m_j + b_u + b_m + b_{global}$$

Dense ReLU Layer



Modify The Model



The **non-linear model** maybe got better result ?

Recommendation Engine with DNN

- Recommedation Engine in Matrix Factorization
- Variant of Matrix Factorization

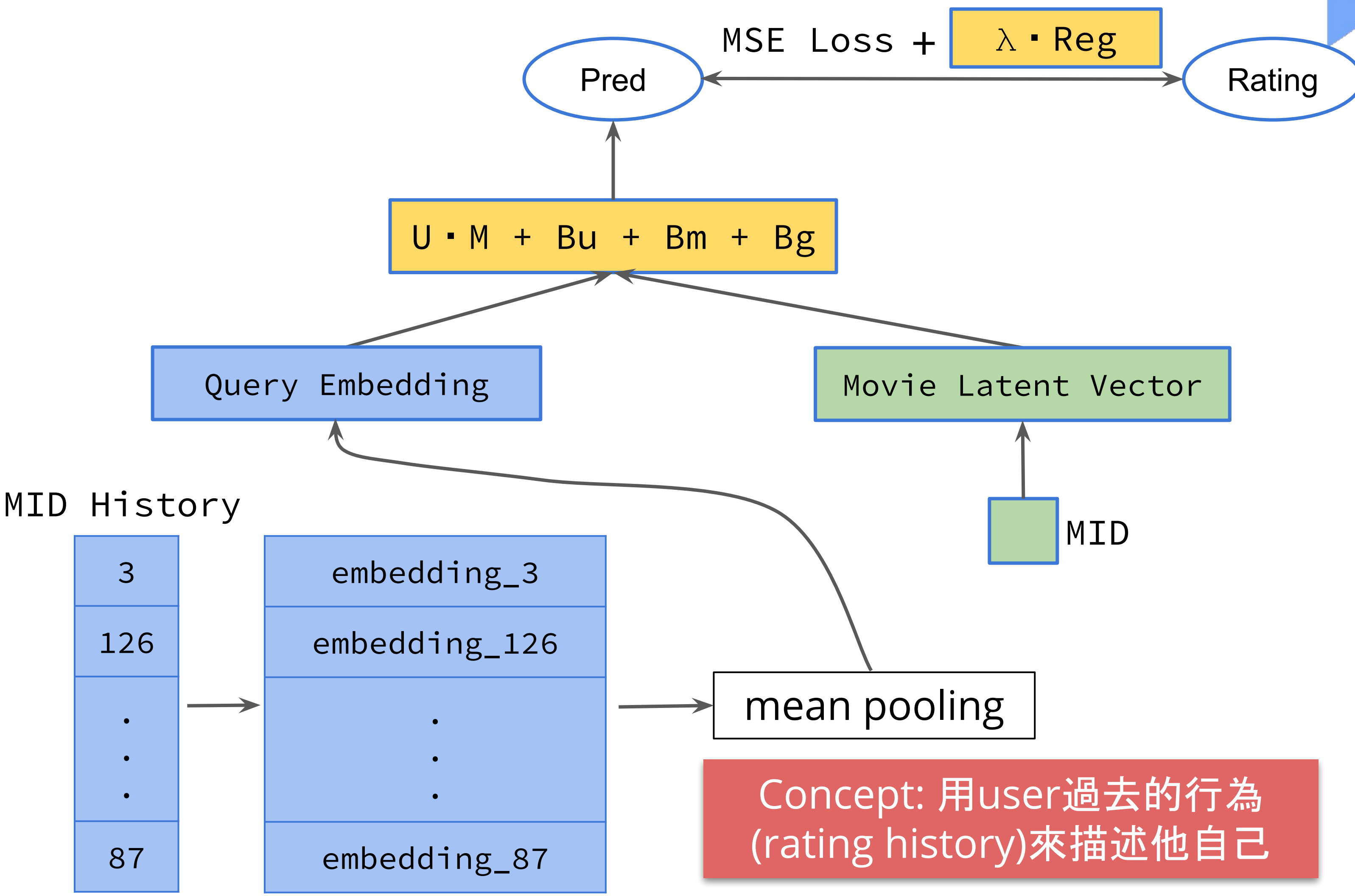
Model - MF with History

- 如果新的User進來…
  - 推薦最受歡迎的電影 (完全沒User rating)
  - 就算累積了Rating history，Model無法使用(不認識新ID)

➡ 在不重train model的狀況下，希望能夠對新來的user(有rating history)做推薦

Variant of Matrix Factorization

Model - MF with History

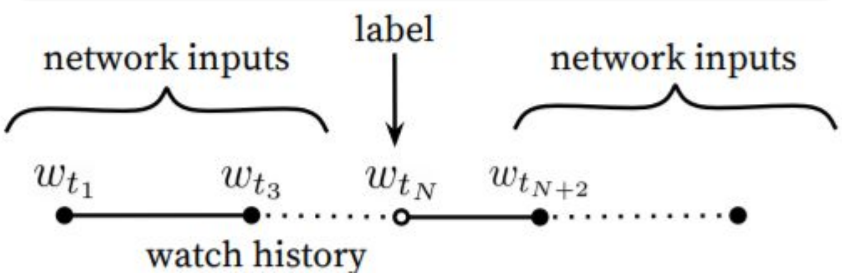


Model - MF with History

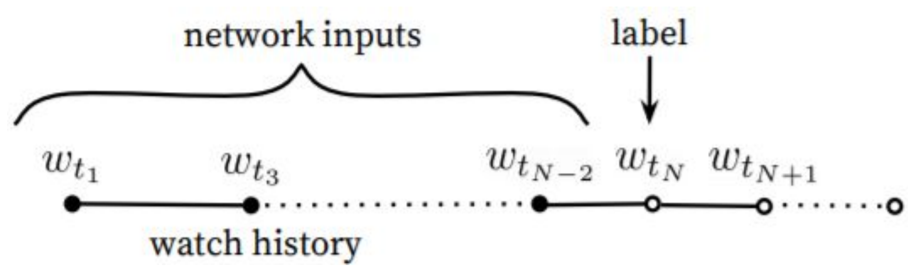
	user_id	query_movie_ids	query_movie_ids_len	candidate_movie_id	rating
0	47	[263, 2860, 3856, 6034, 2409, 2374, 7128, 5339...	357	1393	4.5
1	175	[966, 5026, 4395, 6042, 3871, 6521, 5020, 953,...	177	4002	3.0
2	261	[45, 1104, 154, 4514, 4171, 3801, 3727, 3644, ...	471	3089	2.0

- 觀察47號user
  - query_movie_ids: train data中47號的有rating的movie id，排除1393號 ⇒ leave one out (這裡的設計也可以只用47號喜歡的電影)

leave one out for predict



leave one out(考慮時間)



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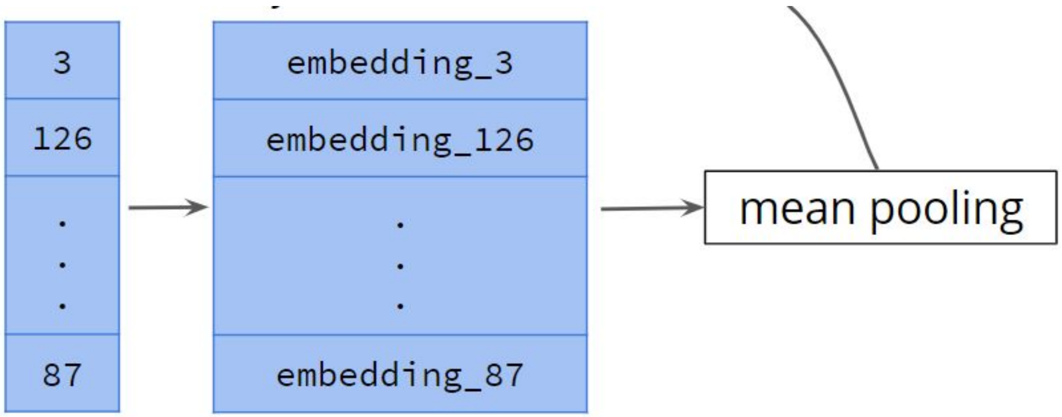
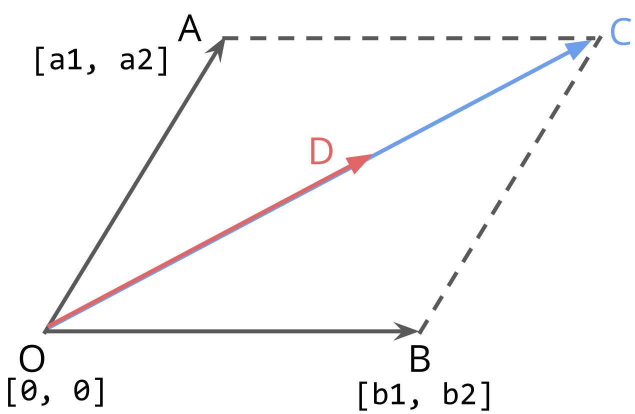
- 觀察47號user
  - query_movie_ids: train data中47號的有rating的movie id，排除1393號 ⇒ leave one out (這裡的設計也可以只用47號喜歡的電影)
  - query_movie_ids_len: 描述query_movie_ids movie id的個數(tensorflow限制，mini batch裡面的變數長度必須要一致)

所以47號User在train data裡只有一筆資料了?

Variant of Matrix Factorization

Vector Computation



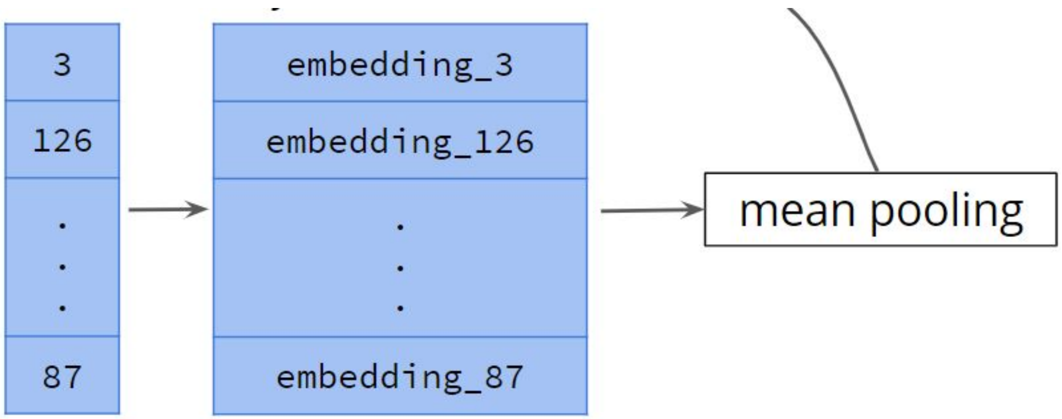


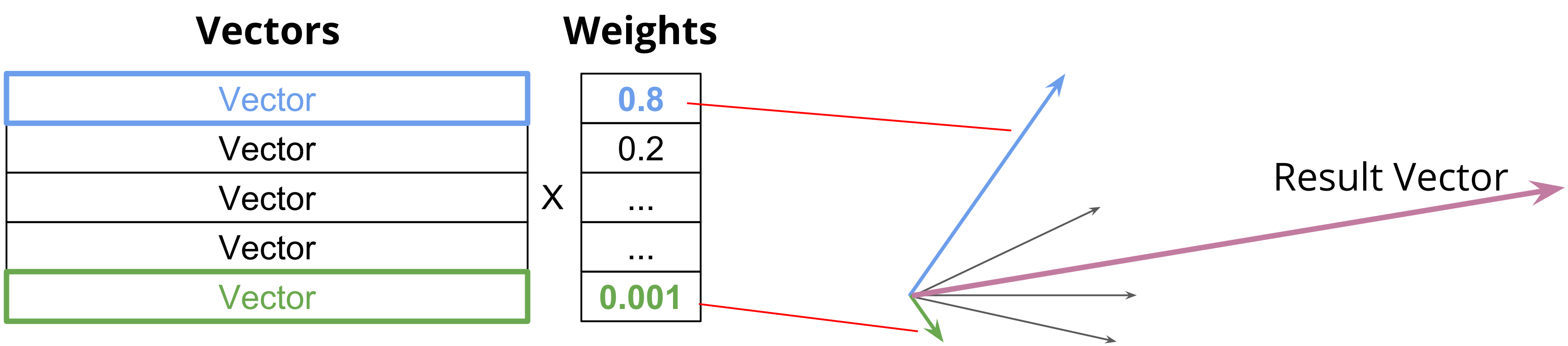

```
OC = OA + OB
OA = [a1, a2]
OB = [b1, b2]
```

SUM	OC = [a1 + b1, a2 + b2]
MEAN	OD = [(a1 + b1) / 2, (a2 + b2) / 2]

Variant of Matrix Factorization

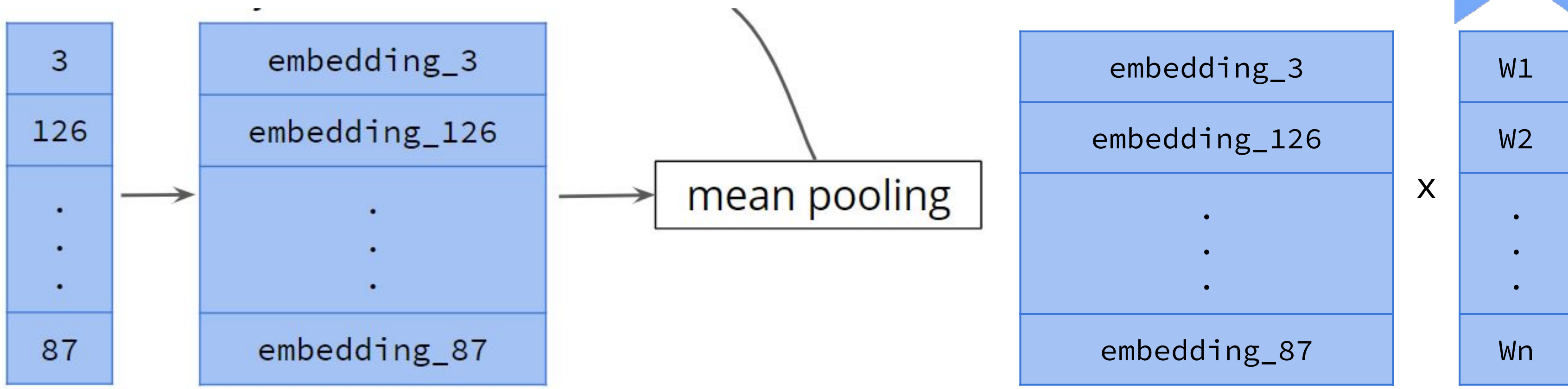
向量的加權和 (Weighted Sum)





Variant of Matrix Factorization

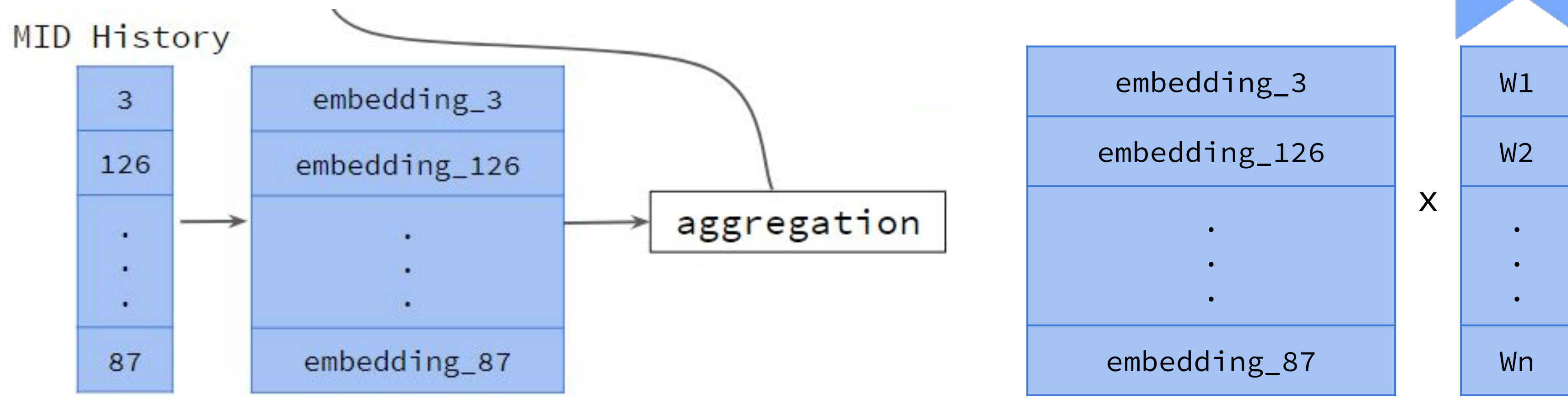
Movie ID Aggregation(Pooling)?



Tensorflow documentation上找到處理multivalent embedding的方式	
Sum	embedding向量相加
Mean	embedding向量相加後平均
SqrtN	將weights normalize之後再對embeddings做weighted sum

通常效果較好

Movie ID Aggregation(Pooling)?



$X = [X_1, X_2, \dots, Xn]$, $W = [W_1, W_2, \dots, Wn]$

$$sqrtn = \frac{x_1 \cdot w_1 + x_2 \cdot w_2 + \ldots + x_n \cdot w_n}{\sqrt{w_1^2 + w_2^2 + \ldots + w_n^2}} = [x_1, x_2, \ldots, x_n] \cdot \frac{[w_1, w_2, \ldots, w_n]}{\sqrt{w_1^2 + w_2^2 + \ldots + w_n^2}}$$

$$= X \cdot l2\_nomalize(W)$$

Variant of Matrix Factorization

Function **sqrtn**

```
def sqrtn(x):
    qry, lens = x
    lens = tf.reshape(lens, [-1])
    weights = tf.nn.l2_normalize(tf.sequence_mask(lens, dtype=tf.float32), 1)
    weights = tf.expand_dims(weights, -1)
    return tf.reduce_sum(qry * weights, 1)
emb_query = Lambda(sqrtn, name='emb_query')([emb_query, inp_query_len])
```

```
[2]     [1, 1, 0, 0]     [0.7, 0.7,   0, 0]     [array, array,     0, 0]     [array]
[3]  ➜  [1, 1, 1, 0]  ➜  [0.6, 0.6, 0.6, 0]  X  [array, array, array, 0]  =  [array]
[1]     [1, 0, 0, 0]     [  1,   0,   0, 0]     [array,     0,     0, 0]     [array]
```

lens   *tf.sequence_mask*   *normalize*   *query_emb*   *mean pooling*

Weighted Sum!

Feature Engineering - User Side

	userId	user_rating_freq	user_rating_mean
0	0	-0.558471	-2.351626
1	1	-0.316104	-0.362525
2	2	-0.424303	-0.188878
3	3	0.237878	1.465967
4	4	-0.212232	0.535923

```
data.groupby(“userId”).rating.agg([‘size’, ‘mean’])
```

- ❏ user_rating_freq: User過去rating過多少電影
- ❏ user_rating_mean: User過去rating的平均

Feature Engineering - Movie Side

genres	genres_len	avg_rating	freq_rating	year	candidate_movie_id	rating
[8]	1	1.102099	1.102099	-0.153507	931	4.0
[1, 6, 17]	3	0.830070	0.830070	-1.083561	1515	4.0
[9, 11, 15, 17]	4	0.006851	0.006851	0.001502	1083	3.5
[3, 4, 8, 13]	4	0.466777	0.466777	-2.633649	833	3.0
[17]	1	0.288261	0.288261	0.208180	859	3.0

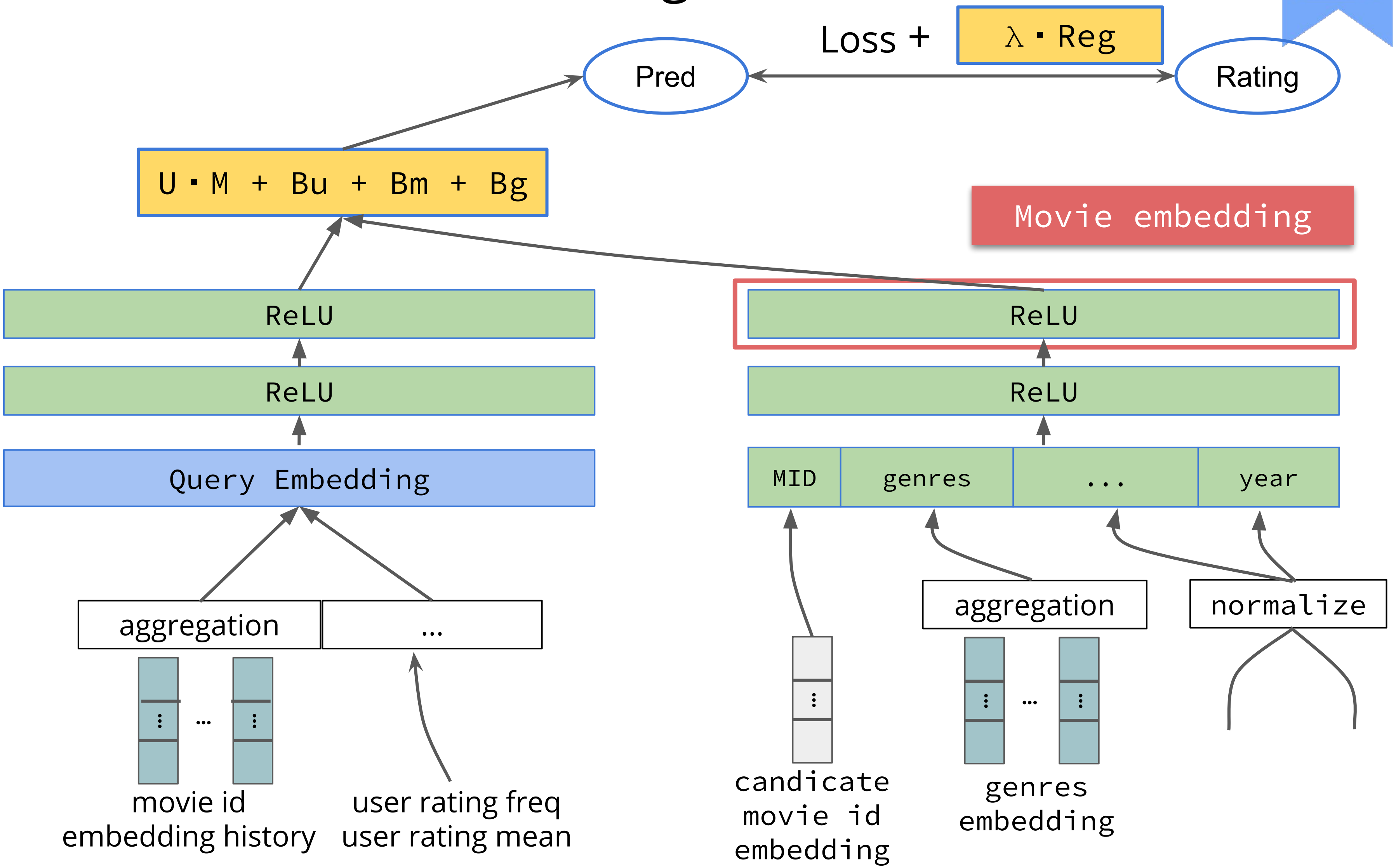
```
data.groupby(“movidId”).rating.agg([‘size’, ‘mean’])
```

```
movies.title.str.findall("\(\s*(\d+)\s*\)")\
      .map(lambda lst: int(lst[-1]) if len(lst) else None)
```

- genres: multivalent variable ⇒ embedding ⇒ average
- genres_len: 描述genres長度
- avg_rating: 電影的平均評分(已normalize)
- freq_rating: 電影的平均評分(已normalize)
- year: 從title extract出來(已normalize)

Variant of Matrix Factorization

Model - MF with DNN (Regression)



Variant of Matrix Factorization

The Regression and Classification

- Functions of Regression

  Model prediction function

  $$f_{u,m}(x) = u_i \cdot m_j + b_u + b_m + b_{global}$$

  Loss function: mean squared error

  $$L = \sum (f_{u,m}(x) - r_{ij})^2 + \lambda \cdot \frac{1}{2}(\sum u^2 + \sum m^2 + \sum b_u^2 + \sum b_m^2)$$

- Functions of Classification

  Model prediction function

  $$f_{u,m}(x) = \sigma(u_i \cdot m_j + b_u + b_m + b_{global})$$

  Loss function: cross entropy

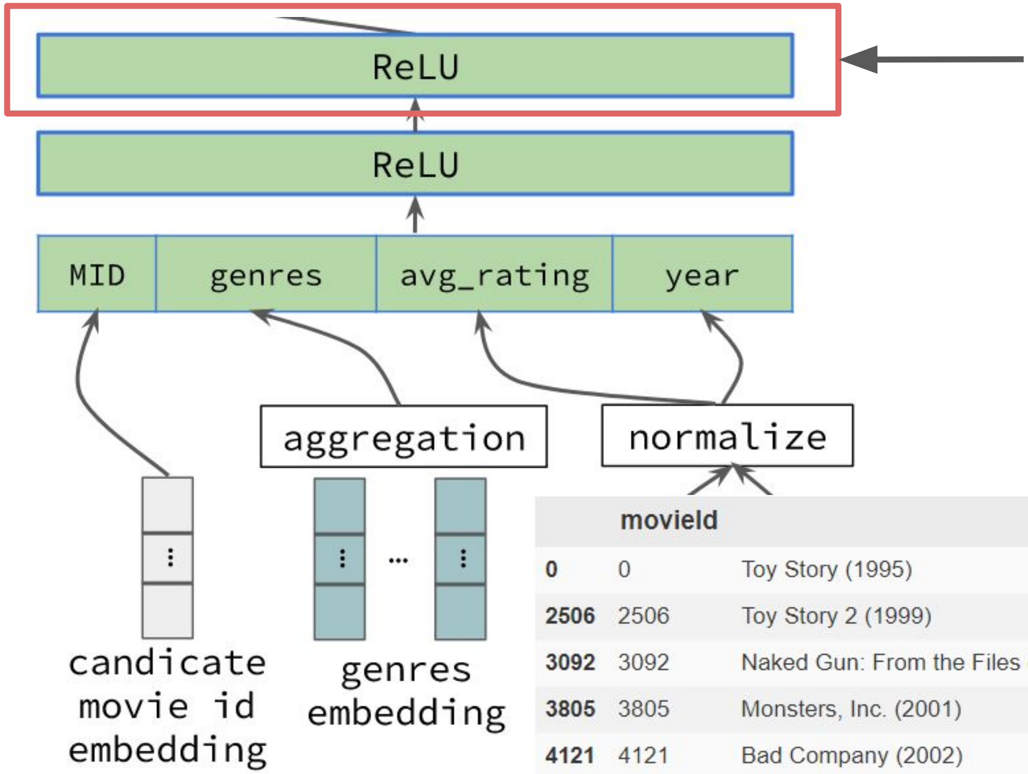
  $$L = -\sum (\hat{y} \cdot lnf_{u,m}(x) + (1-\hat{y})(1 - lnf_{u,m}(x))) + \lambda \cdot \frac{1}{2}(\sum u^2 + \sum m^2 + \sum b_u^2 + \sum b_m^2)$$

Model - MF with DNN

filename	lab_reco_model_mf_dnn.ipynb
number of users	671
number of movies	9125
rating range	0.5 ~ 5分, ❏ 4分以上算正評 ❏ 未滿4分認為是負評或是不列入推薦名單
neural network	matrix factorization with dnn

Variant of Matrix Factorization

MF with DNN - 活用Laten Factor(Embedding)!



找出跟Toy Story相似的電影

- ❑ Toy Story2
- ❑ Monsters, Inc
- ❑ …

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2506	2506	Toy Story 2 (1999)	Adventure|Animation|Children|Comedy|Fantasy
3092	3092	Naked Gun: From the Files of Police Squad!, Th...	Action|Comedy|Crime|Romance
3805	3805	Monsters, Inc. (2001)	Adventure|Animation|Children|Comedy|Fantasy
4121	4121	Bad Company (2002)	Action|Comedy|Crime
607	607	Wallace & Gromit: The Best of Aardman Animatio...	Adventure|Animation|Comedy
7850	7850	Mike's New Car (2002)	Animation|Comedy
4139	4139	Minority Report (2002)	Action|Crime|Mystery|Sci-Fi|Thriller
6423	6423	Protector, The (a.k.a. Warrior King) (Tom yum ...	Action|Comedy|Crime|Thriller
6248	6248	Kiss Kiss Bang Bang (2005)	Comedy|Crime|Mystery|Thriller
4558	4558	Cowboy Bebop: The Movie (Cowboy Bebop: Tengoku...	Action|Animation|Sci-Fi|Thriller

Model - 實際上使用Embedding的例子

使用User embedding找出該user偏好的衣服類型

甚至可以找不同類型的搭配(馬克思禮服找到一堆寬腿褲)

https://making.dia.com/embedding-everything-for-anything2anything-recommendations-fca7f58f53ff

MF with DNN - Metrics and Comparison

Model	MF	MF with DNN(MSE)	MF with DNN (Cross Entropy)
RMSE Loss	0.92	**0.82**	1.44 **cross entropy loss: 0.53(無法與RMSE相比)**
ROC AUC	0.74	0.80	**0.81**
NDCG	strict: 0.63 normal: 0.76	**strict: 0.73** **normal: 0.83**	strict: 0.72 normal: 0.82
Precision at 10	strict: 0.50 normal: 0.63	**strict: 0.59** **normal: 0.68**	**strict: 0.59** **normal: 0.68**

Model MF with DNN 彈性的應用

- 對於新的user
  - 無使用紀錄
    - 推薦最受歡迎商品
  - 一點點使用紀錄
    - Content base recommendation (movied embedding cosine similarity)
  - 大量使用紀錄
    - Model recommendation

- 對於新進來的電影
  - 將metadata帶入model取得embedding就可以使用
    - ex: genres、avg_rating、year、director、actors(actresses)...
  - 不使用指向性的Feature ⇒ Ex: Movie ID