

MovieLens—Predicting and Analysing User Ratings of Movies

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Motivation

Prediction

- Build a predictive model for user ratings
- Inspired from the Netflix prize (Bennett, Lanning, et al. 2007)
- Incorporate external information
- Actionable: could be part of a recommender system

Exploratory analysis

- Analyze how user and movie information relate to model predictions
- Cluster users and movies and identify relationships with ratings
- Actionable: improve production and marketing decisions



MovieLens Datasets User ratings

		user_id	movie_id	rating
Harper and Konstan 2015	0	196	242	3
 Collected in 1997-1998 	1	186	302	3
- 1001/	2	22	377	1
• 100K user ratings of movies (94692	3	244	51	2
after tidying)	4	166	346	1
 Ratings 1-5 	•••			
 1682 movies (935 after tidying) 	99995	880	476	3
• 943 users	99996	716	204	5
	99997	276	1090	1
• Extra information	99998	13	225	2
	99999	12	203	3

MovieLens Datasets Movie information—Movie genres

		Genre(19)		
movie_id	movie_title	Action		Western
1	Toy Story (1995)	0		0
2	GoldenEye (1995)	1		0
3	Four Rooms (1995)	0		0
4	Get Shorty (1995)	1		0
5	Copycat (1995)	0		0
		•••		
1678	Mat' i syn (1997)	0		0
1679	B. Monkey (1998)	0		0
1680	Sliding Doors (1998)	0		0
1681	You So Crazy (1994)	0		0
1682	Scream of Stone (Schrei aus Stein) (1991)	0		0

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MovieLens Datasets Movie information—Movie tags

movie_id	tag_id	tag_relevance	,	tag_id	tag
1	0	0.032		0	007
	1	0.035		1	007 (series)
	2	0.070		2	18th century
	3	0.114		3	1920s
	4	0.105		4	1930s
	•••			•••	
108932	1123	0.327		1123	writing
	1124	0.030		1124	wuxia
	1125	0.006		1125	wwii
	1126	0.161		1126	zombie
	1127	0.028		1127	zombies

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Predicting and Analysing Movie Ratings

MovieLens Datasets User information

user_id	age	gender	occupation
1	24	М	technician
2	53	F	other
3	23	М	writer
4	24	М	technician
5	33	F	other
	•••		
939	26	F	student
940	32	М	administrator
941	20	М	student
942	48	F	librarian
943	22	М	student



Predictive models *K*-Nearest-Neighbors

- Fuclidean distance between features.
- Standardize features
- Weight groups of features

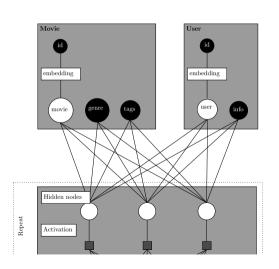
$$\mathbf{x} = (\mathbf{x}_{genres}, \mathbf{x}_{tags}, \mathbf{x}_{user})$$

$$\tilde{\mathbf{x}} := (\mathbf{x}_{qenres}, \alpha_{tags} \mathbf{x}_{tags}, \alpha_{user} \mathbf{x}_{user})$$

- Aggregate neighboring ratings
 - Average (regression)
 - Majority vote (classification)

- Number of neighbors K
- Aggregation function
- Feature weights

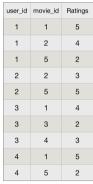
Predictive models Neural Networks



Tuning

- Size of user and movie embeddings
- Whether to use features
- Number and size of hidden layers
- Response transformation and loss function
- Weight decay parameter

Predictive models Matrix completion using SVD



Ratings dataframe



Pivotal matrix

Phylosophy: Lots of people have same taste in movies

Therefore, the pivotal matrix is Low-rank
Use SVD to approximate?

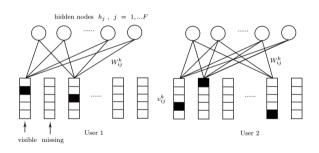
Very famous recommendation algorithm

- Bennett, Lanning, et al. 2007: Netflix prize
- eHarmony: Dating website

Tuning

- Truncated dimension of SVD
- Number of iterations

Predictive models Restricted Boltzmann Machine



- Neural network with hidden input layer.
- Implemented from Salakhutdinov, Mnih, and Hinton 2007

Tuning

- Number of hidden nodes
- Number of Gibbs sampling iterations
- Learning rate



Results Model tuning

K-NN

- + K around 50
- + Averaging ratings
- + $\alpha_{\text{tags}} \approx 0.5$, $\alpha_{\text{user}} \approx 200$

NN

- + Regression transformations
- + Embedding: user(128), movies(128)
- + Two lavers (1024, 128), ReLU
- + Using weight decay
- + Using features

SVD

- Truncated dimension: 4
- Number of iterations around 100.

RBM

- Number of hidden nodes around 15
- Gibbs sampling: 1 (good enough) and fast)
- Learning rate 1.0

Results Model comparison

• The best model of each four methods:

Model	CV MSE	CV Acc.	Test MSE	Test Acc.
K-NN	0.9898	0.3741	0.9737	0.3767
NN	0.9474	0.3886	0.9092	0.3968
SVD	0.9533	0.4116	0.8810	0.4333
RBM	1.0362	0.3609	1.0308	0.3682

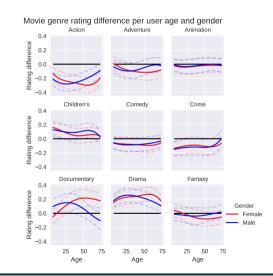
- Matrix completion (SVD) exhibits great generalization performance both in terms of MSE and prediction accuracy
- Fast, simple (almost no tuning) and interpretable model



Exploratory analysis Correlating predictions with features

Using the Matrix completion (SVD) model:

- Make every user rate every movie
- Compute difference between prediction and the average prediction per user
- Subset by movie genre
- Fit a GAM on age for each gender

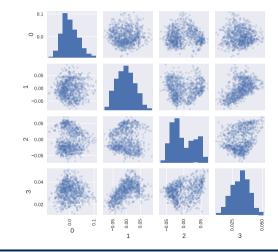


Exploratory analysis Exploring the SVD

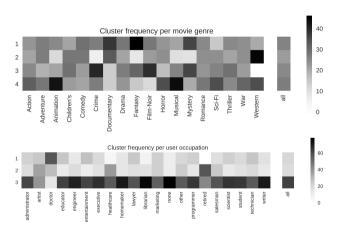
Interpreting U and V in the decomposition

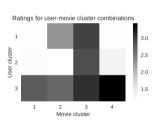
- U and V: principle components for users and movies
- ullet Clustering patterns are visible when plotting U and V
- We can use clustering methods to get the clusters and see how do they correlate to the features

Movie clusters



Exploratory analysis Bi-clustering







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