

Personalized Machine Learning

Every day we interact with machine learning systems offering individualized predictions for our entertainment, social connections, purchases, or health. These involve several modalities of data, from sequences of clicks to text, images, and social interactions. This book introduces common principles and methods that underpin the design of personalized predictive models for a variety of settings and modalities.

The book begins by revising 'traditional' machine learning models, focusing on how to adapt them to settings involving user data; then presents techniques based on advanced principles such as matrix factorization, deep learning, and generative modeling; and concludes with a detailed study of the consequences and risks of deploying personalized predictive systems.

A series of case studies in domains ranging from e-commerce to health plus handson projects and code examples will give readers understanding and experience with large-scale real-world datasets and the ability to design models and systems for a wide range of applications.

JULIAN MCAULEY has been a Professor at the University of California San Diego since 2014. Personalized Machine Learning is the main research area of his lab, with applications ranging from personalized recommendation to dialog, health care, and fashion design. He regularly collaborates with industry on these topics, including Amazon, Facebook, Microsoft, Salesforce, and Etsy. His work has been selected for several awards including an NSF CAREER award, and faculty awards from Amazon, Salesforce, Facebook, and Qualcomm, among others.





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vector of labels

Notation

Common Mathematical Symbols

Machine Learning

v	and in Containing
X	matrix of features
x_i	feature vector for the <i>i</i> th sample
$f(x_i)$	model prediction for the <i>i</i> th sample
r_i	residual (error) associated with the <i>i</i> th prediction, $r_i = (y_i - f(x_i))$
θ	vector of model parameters
σ	sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$
$ x _p$	p -norm, $ x _p = (\sum_i x_i ^p)^{1/p}$
$\ell_1;\ell_2$	regularizers $\ \theta\ _1$ and $\ \theta\ _2$
λ	regularization hyperparameter
$\mathcal{L};\ell$	likelihood and log-likelihood
	Users and Items
$u \in U$	user u in user set U
$i \in I$	item i in item set I
I_u	set of items rated (or interacted with) by user u
U_i	set of users who have rated (or interacted with) item i
U ; $ I $	number of users and number of items
$R_{u,i}$	measurement (e.g., a rating) associated with an interaction
	between user u and item i
$x_{u,i}$	
$u_{i,l}$	model estimate of the compatibility between user u and item i
seu,i	
,	Recommender Systems
eta_u eta_i	



 $egin{array}{lll} x & Notation \\ egin{array}{lll} \gamma_u & ext{vector of parameters describing a single user } u \\ \gamma_i & ext{vector of parameters describing a single item } i \\ \gamma_U; \gamma_I & ext{parameters for all users } U ext{ or all items } I \\ K & ext{feature dimensionality (or number of latent factors)} \\ \end{array}$

Common Abbreviations

AUC area under the ROC curve (eq. (5.26)) BER balanced error rate (eq. (3.20)) BPR Bayesian personalized ranking (sec. 5.2.2) **CNN** convolutional neural network (sec. 5.5.4) **FVU** fraction of variance unexplained (eq. (2.32)) FN/FNR false negatives/false negative rate (sec. 3.3.1) FP/FPR false positives/false positive rate (sec. 3.3.1) **GAN** generative adversarial network (sec. 9.4) LSTM long short-term memory model (sec. 7.6) MAE mean absolute error (eq. (2.17)) MLE maximum likelihood estimation (sec. 2.2.3) MLP. multilayer perceptron (sec. 5.5.2) **MMR** maximal marginal relevance (sec. 10.3.1) MRR mean reciprocal rank (sec. 5.4.2) MSE mean squared error (sec. 2.2.1) **NDCG** normalized discounted cumulative gain (sec. 5.4.3) **RNN** recurrent neural network (sec. 7.6) ROC receiver-operating characteristic (sec. 3.3.3) **SVM** support vector machine (sec. 3.2) TF-IDF term frequency and inverse document frequency (eq. (8.8)) TN/TNR true negatives/true negative rate (sec. 3.3.1) TP/TPR true positives/true positive rate (sec. 3.3.1)