Solutions and Experiences from KDD Cup 2011

Track 1: A Linear Ensemble of Individual and Blended Models for Music Rating Prediction

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What is KDD Cup?

Background

- an annual competition on KDD (knowledge discovery and data mining)
- organized by ACM SIGKDD, starting from 1997, now **the most prestigious data mining competition**
- usually lasts 3-4 months
- participants include famous research labs (IBM, AT&T) and top universities (Stanford, Berkeley)

Aim

- bridge the gap between theory and **practice**
- define the **state-of-the-art**

KDD Cup 2011

from

YAHOO! LABS

Music Recommendation Systems

- host: Yahoo!
- **11 years** of Yahoo! music data
- **2 tracks** of competition
- official dates: **March 15 to June 30**
- 1878 teams submitted to track 1;
  1854 teams submitted to track 2

NTU Team for KDD Cup 2011

- 3 faculties:
  Profs. Chih-Jen Lin, Hsuan-Tien Lin and Shou-De Lin
- 1 course (similar to what was done in 2010):
  Data Mining and Machine Learning: Theory and Practice
- 3 TAs and 19 students:
  most were **inexperienced in music recommendation in the beginning**
- official classes: April to June;
  actual classes: December to June

our motto: study state-of-the-art approaches
and then **creatively improve them**

The Track 1 Problem (1/2)

Given Data

263M examples (user u, item i, rating r_{ui}, date t_{ui}, time τ_{ui})

user	item	rating	date	time
1	21	10	102	23:52
1	213	90	1032	21:01
4	45	95	768	09:15
...				

- u, i: abstract IDs
- r_{ui}: integer between 0 and 100, **mostly multiples of** 10

Additional Information: Item Hierarchy

- track (46.85%)
- album (19.01%)
- artist (28.84%)
- genre (5.30%)

The Track 1 Problem (2/2)

Data Partitioned by Organizers

- training: $253M$; validation: $4M$;
  test (w/o rating): $6M$
- per user, **training < validation < test in time**
  - $\geq$ 20 examples total
  - 4 examples in validation; 6 in test
- **fixed random half of test: leaderboard**;
  another half: award decision

Goal

predictions $\hat{r}_{ui} \approx r_{ui}$ on the test set, measured by

$$RMSE = \sqrt{\text{average}(\hat{r}_{ui} - r_{ui})^2}$$

note: one submission allowed **every eight hours**

Three Properties of Track 1 Data

$\mathbf{R} =$

	track_1	track_2	album_3	author_4	$\cdots$	genre_I
user_1	100	80	70	?	$\cdots$	–
user_2	–	0	?	80	$\cdots$	–
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
user_U	?	–	20	–	$\cdots$	0

similar to Netflix data, but with the following differences.....

- scale: larger data

  training: study mature models that are computationally feasible

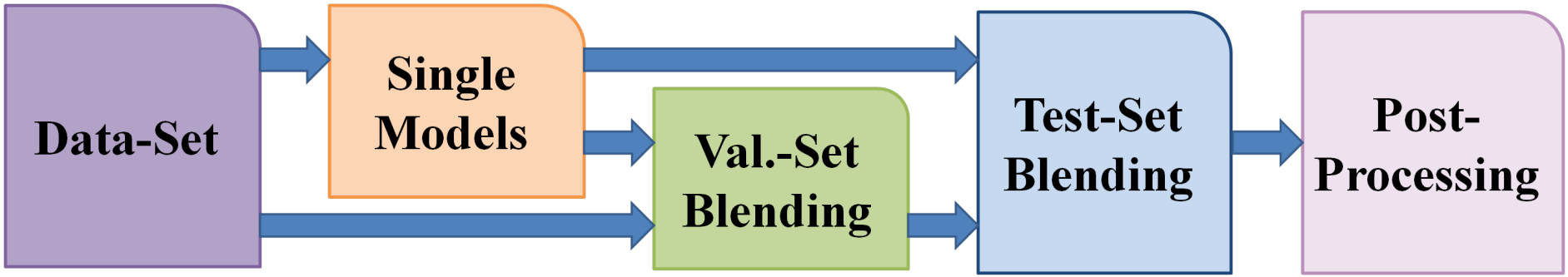
- taxonomy: relation graph of tracks, albums, authors and genres

  include as features for combining models nonlinearly

- time: detailed; training earlier than validation earlier than test

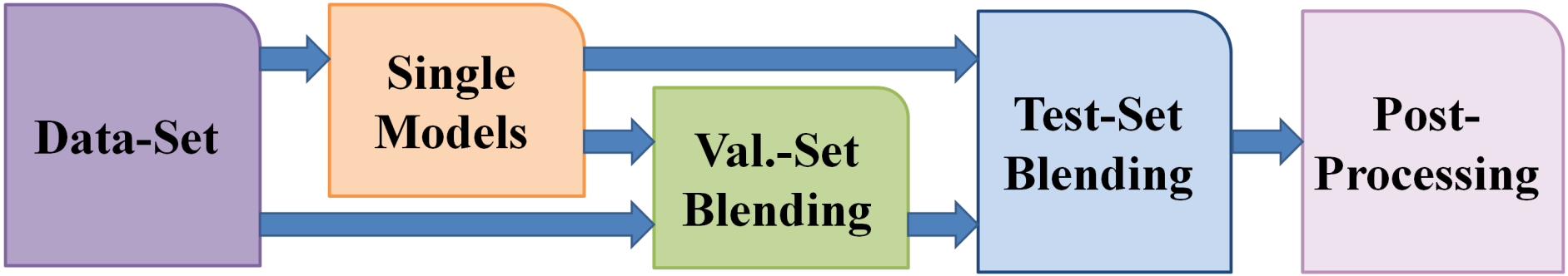
  include as features for combining models nonlinearly;
  respect time-closeness during training

Framework of Our Solution



- single models—computationally feasible models that are diverse:
  - individual models: matrix factorization (& pPCA), pLSA
  - residual models: R-Boltz. machine, *k*-NN
  - derivative model: regression with statistical & model-based features
- validation-set blending:
  combine models nonlinearly while respecting time-closeness
- test-set blending:
  combine models linearly while fitting the leaderboard feedback
- post processing:
  polish predictions using findings during data analysis

RMSE Performance at Each Stage of Framework



- single models: 22.7915
  - individual models: best RMSE 22.9022 (MF)
  - residual models: best RMSE 22.7915 (k-NN + MF)
  - derivative model: best RMSE 24.1251 (but helps in later stages)
- validation-set blending: 21.3598 [improvement 1.4317]
- test-set blending: (estimated) 21.0253 [improvement 0.3345]
- post processing: 21.0147 [improvement 0.0106]

both blending stages: key to the system

Single Model: Matrix Factorization (1/2)

Basic Idea

$$\mathbf{R} \approx \hat{\mathbf{R}} = \mathbf{P}^T\mathbf{Q} \text{ on the known examples}$$

- $\mathbf{P}^T$: U (number of user) by F (number of factor) user-factor matrix
- $\mathbf{Q}$: F (number of factor) by I (number of item) item-factor matrix
- one of the **most commonly-used** single models

Training

- learn $\mathbf{P}$ and $\mathbf{Q}$ from data

$$\min_{\mathbf{P},\mathbf{Q}} \sum_{(u,i)\in\text{data}} \underbrace{(\hat{r}_{ui} - r_{ui})^2}_{E_{ui}(\cdot)} \text{ s.t. } \hat{r}_{ui} = \mathbf{p}_u^T\mathbf{q}_i$$

- large-scale optimization tool: stochastic gradient descent (SGD)
  1. randomly pick one example (u, i)
  2. $\mathbf{P} \leftarrow \mathbf{P} - \eta \cdot \nabla E_{ui}(\mathbf{P})$ (similar for $\mathbf{Q}$)

Single Model: Matrix Factorization (2/2)

Matrix Factorization Variants

$$\min_{\mathbf{P},\mathbf{Q},\cdots} \quad \text{regularization} + \sum_{(u,i)\in\text{data}} (\hat{r}_{ui} - r_{ui})^2$$

$$\text{s.t.} \quad \hat{r}_{ui} = \mathbf{p}_u^T \mathbf{q}_i + \bar{r} + \mu_u^{\text{user}} + \mu_i^{\text{item}} + \sigma_i \cdot \frac{\delta}{\delta + (t_{ui} - t_i^{\text{begin}})}$$

- extended terms (overall bias, user bias, item bias, time factor, etc.): enhance the power of model
- regularization: control the complexity of model
- parameter selection: tried **Automatic Parameter Tuning** tool

included many variants in the final solution for diversity

Selected Ideas that Worked (1/5): Time Emphasis in Stochastic Gradient Descent

Background

SGD for minimizing sum of per-example $E_{ui}(\mathbf{P})$:

- randomly pick one example (u, i)
- $\mathbf{P} \leftarrow \mathbf{P} - \eta \cdot \nabla E_{ui}(\mathbf{P})$

Idea

- last M steps of SGD: effectively considering only the last M examples picked—**final P *as if* biased towards those**
- need: **P** respects time-closeness to the test examples
- heuristic: deterministically pick the "newer" examples as last

consistent ≈ 0.05 **RMSE improvement** for MF

Single Model: Probabilistic Principle Component Analysis

Basic Idea

$$P(r|u,i) = \mathcal{N}(\mathbf{p}_u^T \mathbf{r}_i + \bar{r}_u, \sigma^2)$$

- $\bar{r}_u$: user rating average
- can be viewed as probabilistic MF
- prediction $\hat{r}_{ui}$: expected rating over $P(r|u,i)$

Training

- Expectation Maximization (EM) over maximum likelihood formulation

very similar to MF in the final solution

Single Model: Probabilistic Latent Semantic Analysis

Basic Idea

$$P(r|u,i) = \sum_{\kappa=1}^{k} P(r|i,z=\kappa)P(z=\kappa|u).$$

- z: the hidden variable representing user type
- can be viewed as **another way of factorization**
- prediction $\hat{r}_{ui}$: expected rating over $P(r|u,i)$

Training

- basic: EM over maximum likelihood formulation
- improvement: **tempered EM**—EM + annealing (0.468 RMSE improvement)

not strong individually,
but quite different from MF solutions

Residual Model: Restricted Boltzmann Machine

Basic Idea

discrete hidden factors	
↑	↑↓
per-user incomplete discrete ratings	predicted continuous ratings

- a recursive NNet
- popularly used in Netflix competition

Training

- find the fixed point of the NNet weights by **contrastive divergence**

not better than MF individually,
but can be used to process residuals (see below)

Selected Ideas that Worked (2/5): Gaussian RBM as Residual Model

Background

- RBM: a recursive NNet; can be used as an individual model by

discrete hidden factors	
↑	↑↓
per-user incomplete discrete ratings	predicted continuous ratings

- as individual: RMSE 24.7433, worse than MF (22.9974)

Idea

- MF (a first-order model) efficiently gets better performance, but can RBM digest something different?
- need: RBM that learns from the residuals of MF $r_{ui} - \hat{r}_{ui}^{\text{MF}}$ (continuous values)

Selected Ideas that Worked (2/5): Gaussian RBM as Residual Model

Background

discrete hidden factors	
↑	↑↓
per-user incomplete discrete ratings	predicted continuous ratings

Idea

- need: RBM that learns from the residuals of MF
- choice: Gaussian RBM (gRBM)

discrete hidden factors	
↑	↑↓
per-user incomplete continuous residuals	predicted continuous residuals

MF+gRBM: 22.8008;
better than individual MF (22.9974) or RBM (24.7433)

Residual Model: k-Nearest Neighbor

Basic Idea

$$\hat{r}_{ui} = \frac{\sum_{j \in G_k(u,i)} w_{ij} \cdot r_{uj}}{\sum_{j \in G_k(u,i)} w_{ij}}$$

- $G_k(u, i)$: item-neighbors of item i (for user u)
- w_{ij}: correlation between items i and j

Training

- efficiently compute suitable neighbor and correlation functions

like RBM, not better than MF individually,
but can be used to process residuals

Derivative Model: Regression

Basic Idea

$$\hat{r}_{ui} = g(\mathbf{x}_{ui})$$

- $\mathbf{x}_{ui} \in \mathbb{R}^d$: some features related to user u and item i
  - **statistical**: number of ratings from u, number of genre of item i, etc.
  - **model**: $\mathbf{p}_u$ in MF, w_{ij} in k-NN, etc.
- g: a regressor from $\mathbb{R}^d$ to $\mathbb{R}$
  - linear regression
  - NNet
  - gradient boosting regression tree

can be flexibly used to include "side information" like hierarchy and time

Glance of Single Model RMSE

model	# used	best	average	worst	contribution
MF	81	22.90	23.92	26.94	**0.3645**
pPCA	2	24.46	24.61	24.75	0.0014
pLSA	7	24.83	25.53	26.09	0.0042
R-Boltz. machine	8	22.80	24.75	26.08	0.0314
k-NN	18	22.79	25.06	42.94	0.0298
regression	10	24.13	28.01	35.14	0.0261

- contribution (**before val.-set blending**):
  estimated RMSE diff. via leave-the-model-out in test-set blending
- MF: most important (absorbing pPCA)
- residual models: both quite important
- derivative model: individually weak but adds diversity

val.-set blending:

95 models, best 21.36, average 23.53, worst 31.70

Selected Ideas that Worked (3/5) in Val.-Set Blending: Multi-Feature and Multi-Stage Binned Lin. Reg.

Background

- Binned Linear Regression: a conditional aggregation model
- different model strength on different "types" of examples
- different blending weights for different types (**bins**) to utilize strength

bins	# rating $\leq \theta_1$	$\theta_1 <$ # rating $\leq \theta_2$	others
weight of MF-1	0.4	0.7	1.0
weight of RBM-1	0.5	0.1	0.0
weight of RBM-2	0.1	0.2	0.0

- a simplified regression tree with one level (on one feature)

Selected Ideas that Worked (3/5) in Val.-Set Blending: Multi-Feature and Multi-Stage Binned Lin. Reg.

Background

- Binned Linear Regression
  —different blending weights for different (types) bins of examples

Idea: **multi-feature** BLR

- rationale: “type” more sophisticated than 1-feature bin
- a special multi-level decision tree
- prevent overfitting by limiting height and bin size
- heuristic algorithm instead of traditional decision tree:
  due to simplicity by extending from one-feature BLR

multi-feature	1-feature	4-feature	6-feature
RMSE	22.0829	21.8605	21.8128

Selected Ideas that Worked (3/5) in Val.-Set Blending: Multi-Feature and Multi-Stage Binned Lin. Reg.

Background

- Binned Linear Regression
  —different blending weights for different (types) bins of examples

Idea: **multi-stage** BLR

- rationale: more diverse but good models before test-set blending

bins	1	2	3
weight of MF-1	...	...	...
weight of RBM-1	...	...	...
weight of RBM-2	...	...	...
weight of BLR-1	...	...	...
weight of BLR-2	...	...	...

multi-stage	1-stage	2-stage	3-stage
RMSE	21.7140	21.4591	21.4287

Selected Ideas that Worked (4/5) in Test-Set Blending: Offline Test Performance Predictor

Background

- given: columns $\mathbf{z}_m$ = test-set prediction of model m
- test-set linear regression:

$$\mathbf{w}(\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_M, \lambda) = (\mathbf{Z}^T\mathbf{Z} + \lambda\mathbf{I})^{-1}\mathbf{Z}^T\mathbf{r}$$

- true ratings $\mathbf{r}$ unknown but $\mathbf{z}^T\mathbf{r}$ can be estimated by

$$\begin{aligned} 2\mathbf{z}^T\mathbf{r} &= \mathbf{z}^T\mathbf{z} + \mathbf{r}^T\mathbf{r} - (\mathbf{z}-\mathbf{r})^T(\mathbf{z}-\mathbf{r}) \\ &\approx \mathbf{z}^T\mathbf{z} + N \cdot \text{RMSE}(\mathbf{0})^2 - N \cdot \text{RMSE}(\mathbf{z})^2 \end{aligned}$$

- common technique for RMSE ever since Netflix competition

Selected Ideas that Worked (4/5) in Test-Set Blending: Offline Test Performance Predictor

Background

$$\begin{aligned} 2\mathbf{z}^T\mathbf{r} &= \mathbf{z}^T\mathbf{z} + \mathbf{r}^T\mathbf{r} - (\mathbf{z}-\mathbf{r})^T(\mathbf{z}-\mathbf{r}) \\ &\approx \mathbf{z}^T\mathbf{z} + N \cdot \text{RMSE}(\mathbf{0})^2 - N \cdot \text{RMSE}(\mathbf{z})^2 \end{aligned}$$

Idea

- want: decide which $\mathbf{z}_m$'s and λ to use
- restriction: one submission every eight hours
- solution: estimate RMSE of $\mathbf{w}$ without submitting more than $\mathbf{z}_m$

$$N \cdot \text{RMSE}(\mathbf{w})^2 = (\mathbf{Z}\mathbf{w}-\mathbf{r})^T(\mathbf{Z}\mathbf{w}-\mathbf{r}) = \mathbf{w}^T\mathbf{Z}^T\mathbf{Z}\mathbf{w} - 2\mathbf{w}^T\mathbf{Z}^T\mathbf{r} + \mathbf{r}^T\mathbf{r}$$

compute the contribution of models;
choose 221 from $\approx$ 300 models & decide $\lambda = 10^{-6}$ offline

Selected Ideas that Worked (5/5) in Post-Processing: Clipping for Old Four-Star Days

Background

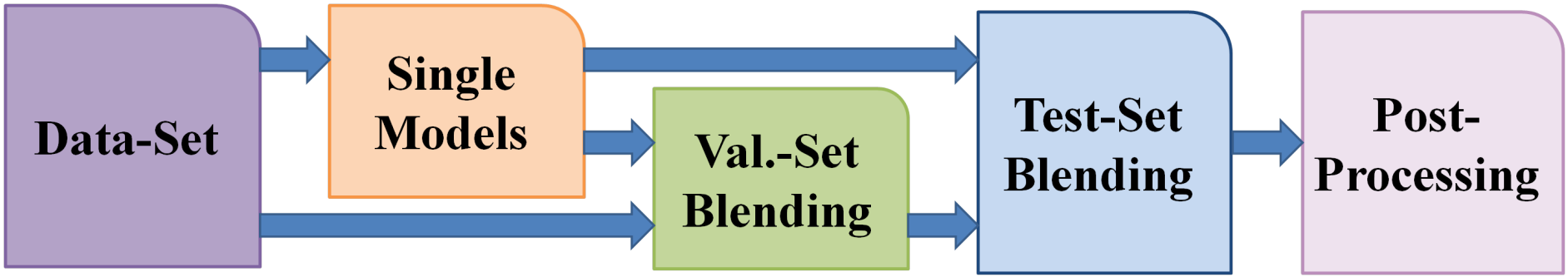
- some very different rating systems observed during data analysis:
  - four-star rating? $\{0, 30, 50, 70, 90\}$
  - five-star rating? $\{0, 20, 40, 60, 80, 100\}$
  - 100-point scale
- suspect changes in the user interface of Yahoo! Music

Idea

- existing: in five-star or 100-point scale, clip prediction to $[0, 100]$
- new: for four-star, clip prediction to $[0, 90]$
- what dates? $[3365, 5982]$ (7 years) or $[4281, 6170]$ (5 years)

$\approx$ 0.02 RMSE improvement on most models

Revisit: RMSE Performance at Each Stage of Framework



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both blending stages: key to the system

Selected Ideas that Did Not Work: Deal with Zero-Variance Users

Background

- zero-variance users (7% of all users)
  —if a user gives 60, 60, 60, $\cdots$ in all training ratings, how'd she rate the next item?
- Occam's razor prediction: 60
  —only true for 80% of users, 20% changed their mind!

Idea

- conditionally (the 80%) post-process the predictions
- difficult to distinguish and thus failed

Track 1 Mini-Summary

- individual models
  - single: **MF** (& pPCA), pLSA
  - residual: RBM, k-NN
  - derivative: regression

  —concept of diversity important
- blending
  - validation: deeply and non-linear to improve model power
  - test: broadly and linear to use leaderboard feedback properly (**with good estimation**)

Next: Track 2 by Prof. Shou-De Lin