Multi-Stage Ensemble and Feature Engineering for MOOC Dropout Prediction

Jeong-Yoon Lee
Conversion Logic
12300 Wilshire Blvd. Los Angeles, CA 90025, USA
jeong@conversionlogic.com

Andreas Toescher
Opera Solutions
Hauptplatz 12, 8580 Koeflach, Austria
andreas.toescher@commendo.at

Michael Jahrer
Opera Solutions
Hauptplatz 12, 8580 Koeflach, Austria
michael.jahrer@commendo.at

Kohei Ozaki
AIG Japan Holdings KK
Kamiyacho MT Bldg 18F, 4-3-20 Toranomon, Minato-ku, Tokyo 105-0001, Japan
ozaki.kohei@aig.co.jp

Mert Bay
Conversion Logic
12300 Wilshire Blvd. Los Angeles, CA 90025, USA
mert@conversionlogic.com

Peng Yan
NetEase Youdao
Chuangye Building, Tsinghua Science Park, Beijing, 100084, China
yanpeng@rd.netease.com

Song Chen
American International Group
175 Water Street, New York, NY 10038, USA
song.chen@aig.com

Tam T. Nguyen
Institute for Infocomm Research, A*STAR
1 Fusionopolis Way, #21-01 Connexis, Singapore 138632
nguyentt@i2r.a-star.edu.sg

Xiaocong Zhou
Tsinghua University
Haidian District, Beijing, 100084, China
infinitezxc@gmail.com

ABSTRACT

This paper describes the winning solution of KDD Cup 2015. The competition aims to predict dropouts in Massive Open Online Courses (MOOCs). Our approach begins with feature engineering to extract predictive features from activity logs of students and meta data. Then, we train sixty three individual classifiers with different subsets of features and seven algorithms. Lastly, we blend predictions of individual classifiers with the multi-stage ensemble framework. Our solution achieves AUC scores of 0.90918 and 0.90744 on the public and private leaderboards respectively.

Categories and Subject Descriptors

I.5.4 [**Pattern Recognition**]: Application

General Terms

Application

Keywords

KDD Cup, Feature Engineering, Ensemble Learning

1. INTRODUCTION

The task of KDD Cup 2015 is to predict the likelihood of dropout for students on XuetangX, one of the largest Massive Open Online Course (MOOC) platforms in China.

Activity logs of 200,906 enrollments from 112,448 students across 39 courses are provided. Each activity is described by 6 fields of the username, course ID, timestamp, source, event, and object. For each object, 3 additional fields of the category, children, and start date are provided. The training set consists of 8,157,278 logs from 120,543 enrollments with the target variable indicating if a student dropped out. The test set consists of 5,387,848 logs from 80,363 enrollments. The full description of the data sets is available in [?]

Our final solution is a joint work from 9 data scientists, distributed around the world. The pipeline from raw data to final solution is as follows:

- Hand crafted feature engineering (most of hard work)
- Automatic feature design (autoencoder)
- Individual models (gbm, nn, factor model,..)
- Stage-I ensemble (blends individual models)
- Stage-II ensemble (blends stage-I ensemble models)
- Stage-III ensemble (blends stage-II ensemble models)

2. FEATURE ENGINEERING

All features.

2.1 Feature SK

Features generated by Song and Kohei can be classified as follows:

- Enrollment-based features (No.1-8)
- Username-based features (No.9-18)
- Username-based features for each courses (No.19-25)

- Features based on 10 days after the end date of course (No.26-35)
- Features based on 1 day after the end date of a course (No.36-45)
- Day-level features (No.46)
- Day-level features using target variables (No.47-58)

Full list of features generated by Song and Kohei are described in Table 1. (just listing them for now. TBD in detail).

2.2 Feature RW

Peng and Xiaocong features are comprised of the following parts:

- Visit time(hour, day) set features (including time span and max absent days)
- Act(event, object) counting features (some uses missed content counts)
- Course drop rate
- Number of courses the user enrolled
- Minimum time interval between time points(first visit, last visit, course begin, course end, 10 days after course end) of current course and another enrolled course
- Active days between course end and 10 days after course end
- Active days between last visit and course end
- Number of courses ended after current course end

The full feature list could be found in Table 2.

2.3 Feature TN

Tam feature.

2.4 Feature MJ

Features generated by Michael Jahrer are in sparse format:

- uID (0-112,447)
- cID (112,448-112,486)
- uIDcnt (112,487-112,487)
- eIDcnt (112,488-112,488)
- eID $\rightarrow$ sID (112,489-112,490)
- eID $\rightarrow$ evID (11,2491-112,497)
- eID $\rightarrow$ oIDCnt (112,498-139,443)
- eID $\rightarrow$ tIDCnt (139,444-139,635)
- uID: floor(log(dateSpan^2+1)) (139,636-140,635)
- uID $\rightarrow$ log(time diff to obj start+1) (140,636-140,636)
- eID $\rightarrow$ dateVec diff stats (140,637-140,649)

2.5 Feature MB

- Course ID - One-hot-encoded course_id
- Source time counts by enrollment - The log count of each source type per day for each enrollment
- Source time counts by course id - The log count of each source type per day for each course id
- Event time counts by enrollment - The log count of each event type per day for each enrollment
- Event time counts by course id - The log count of each event type per day for each course id

2.6 Feature JL

Features generated by Jeong-Yoon Lee are as follows:

- User ID (20,113) - One-hot-encoded username. Usernames appearing less than 100 times in training log data are grouped together as one user ID.
- Course ID (39) - One-hot-encoded course_id.
- Source Event (10) - One-hot-encoded combination of source and event.
- Object ID (3,554) - One-hot-encoded object. Objects appearing less than 100 times in training log data are grouped together as one object ID.
- Count (1) - Number of log entries for an hour_id.
- Object Category (6) - Number of log entries with an object category for an enrollment_id.
- Number of Children Objects (7) - One-hot-encoded total number of object's children for an enrollment_id.
- Object Timespan (10) - One-hot-encoded timespan in days between object's start date and last day of the class
- Day of Class (30) - One-hot-encoded day of the class
- Week of Class (4) - One-hot-encoded week of the class
- End Month of Class (7) - One-hot-encoded end month of the class
- Object Started in Dropout Period (2) - Binary variable that is 1 if object started after but before 10 days after last day of the class and 0 otherwise.

3. MODEL VALIDATION

We use stratified 5-fold cross validation to estimate the performance of single and ensemble models: Training data are split into five folds while the sample size and dropout rate are preserved across folds.

For validation, each of single and ensemble models is trained five times. Each time, one fold is held out and the remaining four folds are used for training. Then, predictions for the hold-out folds are combined and form the model's CV prediction. CV predictions are used in AUC score calculation and/or as inputs in ensemble model training.

For test, each of single and ensemble models is retrained with whole training data. Then predictions for test data are used for submission and/or as inputs in ensemble model prediction.

4. SINGLE MODELS

something like this.

4.1 Learning Algorithms

- Logistic Regression (LR)
- Kernel Ridge Regression (KRR)
- Factorization Machine/Field-aware Factorization Machine (FM/FFM)
- Neural Networks (NN)
- Extreme Trees (ET)
- Gradient Boosting Decision Trees (GBDT)

4.2 Single Models

- Model 1: RandomForest(R). Dataset: X
- Model 2: Logistic Regression(scikit). Dataset: Log(X+1)
- Model 3: Extra Trees Classifier(scikit). Dataset: Log(X+1) (but could be raw)
- Model 4: KNeighborsClassifier(scikit). Dataset: Scale(Log(X+1))
- Model 5: libfm. Dataset: Sparse(X). Each feature value is a unique level.

5. MULTI-STAGE ENSEMBLE

Stratified 5-fold cross validation (CV). We used xgboost [?], neural nets and linear regression for stage-II ensembling.

5.1 Stage-I Ensemble

We trained 15 stage-I ensemble classifiers with different subsets of CV predictions of 64 individual classifiers.

5.2 Stage-II Ensemble

We trained 2 stage-II ensemble classifiers with different subsets of CV predictions of 15 stage-I ensemble classifiers.

5.3 Stage-III Ensemble

We trained a stage-III ensemble classifier with CV predictions of 5 classifiers: 1 stage-II ensemble, 3 stage-I ensemble, and 1 individual classifiers.

ID	Model	Type	5-CV	Weight
S1	xgb_rf.ko_new_feat	Single	0.906721	1.1703
E4	at.esb50v2+ko	Stage I	0.907878	1.9626
E8	esb58v5+magic.dae+nn	Stage I	0.907567	0.7871
E18	et_esb58v5_rank	Stage I	0.906207	0.4580
E2	lr_forward_0.01_esb.esb15v3	Stage II	0.907968	1.6146

A linear combination of the 5 models from table 5.3 results in train AUC=0.908072 and accuracy=0.887334. Which leads to 0.90910 public leaderboard score. By adding 39 courseID correction factors train AUC=0.908194 and public score improved to 0.90918.

6. CONCLUSIONS

Our final AUC score of 0.90918 results from a complex pipeline from raw data to final score. Every part of that pipe needs to be (sub-)optimal implemented by our team to get the best score at the end. The first part “feature design” is the most important one and needs expertise, experience and of course a bit luck to capture all signals in the data.

7. ACKNOWLEDGEMENTS

Thanks to dropbox, github and skype to enable easy communication around the globe.

No.	Description
1	Course_id encoded by 1-of-N coding
2	Number of requests by an enrollment_id
3	Number of unique object by an enrollment_id
4	Number of unique problem object of event by an enrollment_id
5	Number of active days by an enrollment_id
6	Number of active hours by an enrollment_id
7	Time of first access in hours by an enrollment_id
8	Time of last access in hours by an enrollment_id
9	Number of enrollments by an username
10	Number of requests by an username
11	Number of unique objects by an username
12	Number of unique problem object of event by an username
13	Number of active days by an username
14	Number of active hours by an username
15	Time of first access in hours by an username
16	Time of last access in hours by an username
17	Time of first problem access in hours by an username
18	Time of last problem access in hours by an username
19	For each course, number of requests by an username
20	For each course, number of unique object by an username
21	For each course, number of unique problem object by an username
22	For each course, number of active days by an username
23	For each course, number of active hours by an username
24	For each course, time of first access in hours
25	For each course, time of last access in hours
26	Number of enrollment_ids during 10 days after the end date of course by an username
27	For each course, number of access logs during 10 days after the end date of course by an username
28	For each course, number of unique objects during 10 days after the end date of course by an username
29	For each course, number of unique problem objects during 10 days after the end date of course by an username
30	For each course, number of active hours during 10 days after the end date of course by an username
31	For each course, difference between first and last access during 10 days after the end date of course by an username
32	For each course, time of first access in hours during 10 days after the end date of course by an username
33	For each course, time of last access in hours during 10 days after the end date of course by an username
34	For each course, time of first access to an problem object in hours during 10 days after the end date of course by an username
35	For each course, time of last access to an problem object in hours during 10 days after the end date of course by an username
36	Number of enrollment_ids during 1 day after the end date of course by an username
37	For each course, number of access logs during 1 day after the end date of course by an username
38	For each course, number of unique objects during 1 day after the end date of course by an username
39	For each course, number of unique problem objects during 1 day after the end date of course by an username
40	For each course, number of active hours during 1 day after the end date of course by an username
41	For each course, difference between first and last access during 1 day after the end date of course by an username
42	For each course, time of first access in hours during 1 day after the end date of course by an username
43	For each course, time of last access in hours during 1 day after the end date of course by an username
44	For each course, time of first access to an problem object in hours during 1 day after the end date of course by an username
45	For each course, time of last access to an problem object in hours during 1 day after the end date of course by an username
46	For each days of the course, which date is provided in date.csv, number of unique active courses by an username
47	For each 10 days after the end date of the course, number of active enrollment_id, which target variables are 1 in the training set, enrolled by
48	For each 10 days after the end date of the course, number of active enrollment_id, which target variables are 0 in the training set, enrolled by
49	For each 10 days after the end date of the course, number of active enrollment_id (in this case, days between last access and the end date of t
50	For each 10 days after the end date of the course, number of active enrollment_id (in this case, days between last access and the end date of t
51	For each 14 days before the end date of the coruses, number of active enrollment_id, which target variables are 1 in the training set, enrolled
52	For each 14 days before the end date of the coruses, number of active enrollment_id, which target variables are 0 in the training set, enrolled
53	For each 14 days before the end date of the coruses, number of active enrollment_id (in this case, days between last access and the end date o
54	For each 14 days before the end date of the coruses, number of active enrollment_id (in this case, days between last access and the end date o

Table 1: List of features generated by Song and Kohei.

No.	Description
1	act counts
2	hourset length in last 2 days
3	last month
4	max absent days
5	day set length
6	hour set length
7	average hours per day
8	event wiki counts
9	event discussion counts
10	event access counts
11	event video counts
12	event problem counts
13	obj chapter not visited
14	obj chapter visited ratio
15	obj video not visited
16	obj video visited ratio
17	obj problem not visited
18	obj problem visited ratio
19	obj set length
20	total time span
21	days from last act to course end
22	course drop rate
23	number of courses enrolled
24	min days between first visit and next course begin
25	min days between 10 days after last visit and next course begin
26	min days between last visit and next course end
27	min days between previous course end and last visit
28	min days between 10 days after current course end and next course begin
29	min days between 10 days after current course end and next course end
30	min days between current course end and next visit
31	number of active days between last visit and course end
32	number of active days in 10 days after course end
33	number of courses ended after current course end

Table 2: List of features generated by Peng and Xiaocong.

ID	Model	Feature	5-CV	Publ
S1	xgb_rf_ko_new_feat	-	0.906721	0.90
S2	ko_v83	Feature RW + Feature SK + Feature JL + ko_feat3	0.906729	0.90
S3	bag_10_xgb_rf.xiv	Feature RW + Feature SK + Feature TN	0.905875	0.90
S4	xgb_rf.xvi	Feature RW + Feature TN + Feature JL	0.905543	0.90
S5	xgb_rf.xix	Feature RW + Feature SK + Feature TN + Feature MB	0.905356	-
S6	rw_sk_xgb	Feature RW + Feature SK	0.905312	-
S7	xgb_rf.xv	Feature RW + Feature TN	0.904935	0.90
S8	xgb_rw_sk	Feature RW + Feature SK	0.904914	-
S9	mjahrer.feat.tam+rw+sk+tam2+sk2+azure.dae+nn	Feature RW + Feature SK + Feature TN + Feature MJ	0.904235	-
S10	mjahrer.featmjahrer+Tam+RW+KoheiSong.nn	Feature RW + Feature SK + Feature TN + Feature MJ	0.903736	-
S11	mjahrer.featTam+RW+KoheiSong.dae+nn	Feature RW + Feature SK + Feature TN	0.903669	-
S12	pred_train_sk_feature_ffm_rw	-	0.903560	0.90
S13	mjahrer.featTam+RW+KoheiSong.nn	Feature RW + Feature SK + Feature TN	0.903428	-
S14	xg_400_4_0.05_feature_rw	Feature RW + Feature JL	0.903385	-
S15	kohei_song	Feature SK	0.902918	-
S16	xgb_cv_rw	Feature RW	0.902287	-
S17	ffm_cv_rw	Feature RW	0.901983	-
S18	mjahrer.dae+nn.RWfeat	Feature RW	0.901846	0.90
S19	mjahrer.featmjahrer+Tam+RW+KoheiSong.dae+krr	Feature RW + Feature SK + Feature TN + Feature MJ	0.901522	-
S20	mjahrer.feat.tam+rw+sk+tam2+sk2+azure.BIN	Feature RW + Feature SK + Feature TN	0.900982	-
S21	xg_400_4_0.05_feature_sk	Feature SK	0.900906	-
S22	xgb_rf.xiv	Feature TN	0.899239	-
S23	xgb_rf.xiv	Feature TN	0.899167	-
S24	xgb_rf.xiv	Feature TN	0.898969	-
S25	xgb_rf.xiv	Feature TN	0.898890	-
S26	xgb.xiv	Feature TN	0.898749	-
S27	libfm_100_4_0.002_feature_rw_v2	Feature RW + Feature JL	0.898308	-
S28	xgl_500_0.5_10_10_feature_rw_v2	Feature RW + Feature JL	0.897968	-
S29	xgb_val.xiii	Feature TN	0.897912	-
S30	nn_20_16_0.01_feature_rw_v2	Feature RW + Feature JL	0.897143	-
S31	mb_nn_50_20_feat19	Feature RW + Feature MB	0.896748	-
S32	sm_rw_sk_tam	Feature RW + Feature SK + Feature TN	0.896435	-
S33	ffm_30_20_0.01_feature_rw_v2	Feature RW + Feature JL	0.896160	-
S34	xg_400_4_0.05_feature_tam	Feature TN	0.895754	-
S35	ConfigAMLKRR	Feature MJ	0.894524	-
S36	gbm.xiii	Feature TN	0.893507	-
S37	xg_600_4_0.05_feature10	Feature JL	0.892364	-
S38	xg_600_4_0.05_feature9	Feature JL	0.892253	-
S39	ConfigAML	Feature MJ	0.891217	-
S40	lr_0.01_feature_tam	Feature TN	0.890580	-
S41	ConfigAMLCUDAPreModel	Feature MJ	0.890565	-
S42	ffm_30_20_0.01_feature_tam	Feature TN	0.888418	-
S43	libfm_100_4_0.002_feature_tam	Feature TN	0.888381	-
S44	rf.xiii	Feature TN	0.887583	-
S45	et_1000_20_feature_tam	Feature TN	0.887768	-
S46	ffm_30_20_0.01_feature9	Feature JL	0.887116	-
S47	libfm_100_4_0.002_feature9	Feature JL	0.886866	-
S48	ConfigAML	Feature MJ	0.886705	-
S49	nn_20_16_0.01_feature9	Feature JL	0.886109	-
S50	xg_400_4_0.05_feature6	Feature JL	0.885184	-
S51	xg_400_4_0.05_feature3	Feature JL	0.885124	-
S52	ffm_20_20_0.01_feature6	Feature JL	0.885037	-
S53	ffm_20_20_0.01_feature3	Feature JL	0.884697	-
S54	xg_400_4_0.05_feature_mj	Feature MJ	0.882441	-
S55	et_1000_20_feature_rw_v2	Feature RW + Feature JL	0.881539	-
S56	libfm_100_8_0.01_feature6	Feature JL	0.880878	-
S57	libfm_100_8_0.01_feature3	Feature JL	0.880366	-
S58	nn_20_16_0.005_feature3	Feature JL	0.880219	-
S59	ConfigAMLKNN	Feature MJ	0.877652	-
S60	nn_20_16_0.005_feature5	Feature JL	0.876905	-
S61	lr_0.01_feature_mj	Feature MJ	0.821332	-
S62	lr_0.01_feature9	Feature JL	0.804150	-
S63	lr_0.01_feature3	Feature JL	0.802138	-
S64	lr_0.01_feature6	Feature JL	0.800225	-

ID	Stage	Model	5-CV	Public Leaderboard
E1	III	subBlend_0712v2	0.908194	0.909181
E2	II	lr_forward_0.01_esb.esb15v3	0.907968	-
E3	II	xgl_10_0.01_10_10_esb.esb11v6	0.907379	0.908187
E4	I	at.esb50v2+ko	0.907878	-
E5	I	xg_sk_1800_5_0.004_esb51_rank	0.907734	
E6	I	lr_forward_0.01_esb51_rank_norm	0.907716	-
E7	I	song_train_xgb_esb58v5_ko	0.907668	0.908796
E8	I	esb58v5+magic.dae+nn	0.907567	-
E9	I	esb58v3.trn.final	0.907353	0.908060
E10	I	trn.esb56.blend.at	0.907283	0.908043
E11	I	ConfigAMLCUDAPreModel	0.907076	-
E12	I	xg_sk_1800_5_0.004_esb56_rank_4	0.907036	0.907977
E13	I	esb55.dae+nn	0.906956	-
E14	I	lr_0.01_esb51_rank_norm	0.906746	-
E15	I	nn	0.906714	-
E16	I	xgb_rf_esb55.xix	0.906689	-
E17	I	libfm	0.906537	-
E18	I	et_esb58v5_rank	0.906200	-