Practical Lessons for Job Recommendations in the Cold-Start Scenario

Jianxun Lian
University of Science and Technology of China
Hefei, China
jianxun.lian@outlook.com

Fuzheng Zhang
Microsoft Research
Beijing, China
fuzzhang@microsoft.com

Min Hou
University of Science and Technology of China
Hefei, China
hmhoumin@gmail.com

Hongwei Wang
Shanghai Jiao Tong University
Shanghai, China
wanghongwei55@gmail.com

Xing Xie
Microsoft Research
Beijing, China
xingx@microsoft.com

Guangzhong Sun
University of Science and Technology of China
gzsun@ustc.edu.cn

ABSTRACT

The ACM RecSys Challenge 2017 focuses on the problem of job recommendations on XING in a cold-start scenario. In this paper we describe our solution as well as some practical lessons we learned from the competition. Similar to some classical tasks like click-through rate (CTR), we model this task as a binary classification problem. Negative candidates selection seems to be the first key phase in this task. We design a negative sampling strategy which perform significantly better than taking users' deleted or unclicked items as negative candidates. We then extract comprehensive features to model the relationship between a user-job candidate, including the direct profile similarity between the user and the job, and the profile similarity between the user's historical interested jobs and the target job. To make the whole pipeline scalable and easy to deploy online, we decide to use a single boosting tree model as the final discriminative model, instead of using a stacking ensemble of multiple models. Overall we ranked 5th in the leaderboard, and our last model kept the 2nd rank during the last two online weeks.

CCS CONCEPTS

•Information systems →Personalization; Recommender systems; *Retrieval efficiency;* Collaborative filtering;

KEYWORDS

job recommendations, cold start, recsys challenge 2017, recommendation systems, content-based filtering

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1 INTRODUCTION

The ACM RecSys challenge 2017 focuses on the problem of job recommendations on XING. XING is a social network for business and has attracted more than 18 million users and has typically around 1 million active job posting on the platform. In order to better connect job seekers and recruiters, the RecSys challenge 2017 requests participants to build recommender systems to solve the following task: given a new job posting, identify those users that (a) may be interested in receiving the job posting as a push recomnedation and (b) that are also appropriate candidates for the given job.

Actually, the job recommendation task is very close to the traditional click-through rate (CTR) prediction tasks such as ad click prediction or app download prediction, and the critical part of them is to estimate the probability that a user will click on the target item. However, one special thing in job recommendation task is that we need to model not only the preference of the user over the item, but also the relevance between the user and the item. For example, some apps such as WeChat and Office 365 may be liked and downloaded by most of the people, while normally no jobs can be applied commonly by the overwhelming majority of the people. This is due to the fact that usually a job seeker is only interested in the jobs which he/she is qualified for. So the first key point is to model both relevance and preference of a user-item pair. In this paper, we introduce a simple, efficient and effective candidate sampling method to handle this problem. And in the discussion section we further propose an integrated model which can incorporate both relevance and preference.

Just like some related CTR tasks [3, 5, 10, 15], we formulate the job recommendation as a binary classification problem, where a positive label indicates that the user has ever clicked/bookmarked/replied the item, and negative label indicates the user has deleted or no action on the item. Not surprisingly, the most important thing is feature engineering. Although some research works [4, 12] aim at develop models which can be trained end-to-end without feature engineering, for this job recommendation task, the use of elaborated hand-craft features can achieve far better scores. We split the features into three pillars: (1) features derived from the similarity between the user's profile and the target item's profile; (2)features derived from the similarity between the user's history interested items and the target item; (3) features using words and tags directly

Table 1: Fields in the user profile file.

field	type	comments
id	categorical	anonymized ID of the user
job roles	bag of words	list of jobrole terms that were extracted from the user's current job titles
career level	categorical	career level ID , e.g. Beginner or Experienced
discipline	categorical	anonymized IDs represent disciplines such as "Consulting", "HR", etc.
industry	categorical	anonymized IDs represent industries such as "Internet", "Automotive", etc.
country	categorical	describes the country in which the user is currently working.
region	categorical	specified for some users who was in Germany.
experience_01	numerical	the number of CV entries that the user has listed as work experiences
experience_02	numerical	the estimated number of years of work experience that the user has
experience_03	numerical	the estimated number of years that the user is already working in her current job
edu degree	categorical	estimated university degree of the user
edu fields	bag of words	fields of studies that the user studied
wtcj	categorical	estimation regarding the user's willingness to change job
premium	categorical	the user subscribed to XING's payed premium membership

from the profiles. We find that the most important features come from the second pillar, and it is in line with the intuition: for the cold-start recommendation content-based fitering is the most efficient method, and it is essential build a better profile via the user's historical activities.

We have compared different classifiers and find that the gradient boosting decision tree (GBDT) model are the best one, with is inline with most of the winning solutions from various data mining competitions [7, 9, 13]. And usually blending the results of multiple models, as known as model ensemble, can further improves the scores. However, given that it is necessary for online systems to keep simple and efficient for good scalability and maintainability, we decide to use a single GBDT model through the offline and online period without model ensemble. Our initial model ranked 6th in the first two weeks, and after we updated our model, we ranked 2nd in the last consecutive weeks. On average we ranked 5th in the leaderboard.

2 PROBLEM STATEMENT

The Recsys challenge 2017 consists of offline phase and online phase. For offline phase, target users and items are fixed, participants are requested to recommend at most 100 users for each target item, the ground-truth labels are made from the historical activities. For online phase, each team will receive a new group of target users and items daily, and the recommendation submitted by the teams will actually be rolled out to the real users in XING's live system. The training dataset includes users' profiles, items' profiles, and historical transactions between users and items. The details of user profile information is listed in Table 1. Most of the fields in item profile are the same as the fields in user profile, except that items have the additional latitude and longitude information for the location information. The interaction file has four fields, including user id, item id, timestamp, and the type of interaction.

Typically, the user response prediction problem can be regarded as binary classification or ranking problem. In this paper we mainly discuss the binary classification models, while we also compare them with one ranking model. A positive label indicates that a user has some explicit positive action on an item, such as clicks on or replies it; and a negative label indicates that a user neglects or explicitly deletes an item.

Evaluation metrics. The official evaluation metrics [1] is calculated according to the user/item's premium level and the interaction type. For better demonstration and comparison of various models, we use the following evaluation metrics throughout the paper:

(1) reward. This is the official evaluation metrics. We predict 10% of the offline test dataset (selected by $item\_id \ mod \ 10 = 1$) and submit to the platform for judgement.
(2) reward@1. Since online phase requires that each target user can at most receive one recommendation, we follow this constraint and only keep the top 1 prediction for each user.
(3) p@1. Success user rate at top 1 predictions. Calcualted by $\frac{|success(user@1)|}{|users|}$, where $success(user@1)$ is the set of users that have positive interactions on the top 1 prediction.
(4) p@5. Success user rate at top 5 predictions. Calcualted by $\frac{|success(user@5)|}{|users|}$.
(5) AUC. Area under the ROC curve.

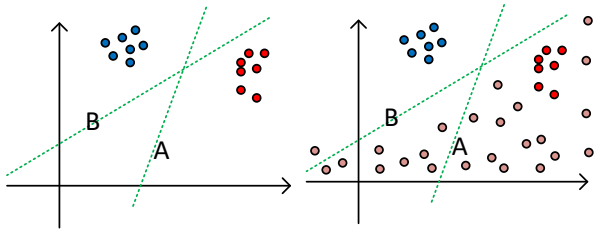
We reserve 1000 items from the training set as validation set to simulate the cold-start scenario. *reward* and *reward@1* are evaluated on 10% of the official offline test dataset, while *p@1*, *p@5* and *AUC* are evaluated on the validation set.

3 NEGATIVE CANDIDATES SELECTION

We find that for job recommendation task, the selection of negative candidates is highly important. At the first beginning we use the items which are deleted by the user or receive no interaction after impression as negative candidates. We soon find the model trained based on this training instances yield very poor performance as shown in row *negative action* in Table 2. Although the performance can be improved by adding a filter to remove those user-job pairs which do not have common words in the user's and item's titles,

[1] The details can be found here: http://2017.recsyschallenge.com

the scores (as shown in row *negative action filtered*) is still far less than a simply random sampling for negative candidates (as shown in row *random small*). It is not hard to understand the cause: every historical item that showed to the user is proposed by XING's recommender system, which means the item is at least relevant to the user to some extent. If all the training data come from the user's historical interaction logs provided by XING, the trained model is biased to the user's relevant area. However, in the real world prediction step, we are dealing with an open target item set, which contains far more items that are not relevant to the user. The trained model do not have knowledge in this new area, thus it will produce a lot of false positive cases. We further illustrate this with Fiture 1. To sum up, classifier usually fails to work if the data distribution of training set and test set is different.



(a) distribution of training data **(b) distribution of test data**

Figure 1: Illustration of classifier fail to work when distributions of training data and test data are different. In the left figure, a max-margin classifier will choose A as the optimal discriminative plane. However, in the real test set, there are many hidden unrelevant data points, which make B to be a better splitting plane.

Since random sampling performs well, now we are curious about two questions: (1) how many negative candidates are enough for the sampling? (2) Is there a better strategy rather than the brute-force sampling over the complete $N \times M$ space? Question (1) is related to the class unbalance problem. Usually we can train a better model if we collect more instances. However, since we have a limited number of positive instances, the increase of negative instances aggravates the unbalance between positive and negative labels. We propose an effective and efficient negative sampling algorithm as shown in Algorith 1, in order to control the total number of negative instances while keep as much information as possible in the open space. Basically it consists two parts: the wide part and the deep part. The wide part aims to cover a large number of items, while each item is only connected to a small number of users; on the contrary, the deep part aims to explore exhaustive candidates for one item. The total number of sampled negative candidates is 80 million. To demonstrate the necessity of both the deep part and the wide part, we sample negative candidates using only wide part or deep part, while keep the total number of negative candidates remains 80 million. The performance comparison is shown in Table 2. We find that by using the wide & deep part we can get the best model.

Algorithm 1 Wide & Deep Negative Sampling

Require: user set **U**, item set **V**, and interactions **I**.
Ensure: training candidates **D**.
  D $\leftarrow \varnothing$
  Add pairs from **I** with activity $\{1,2,3,5\}$ to **D** as positive candidates
  Add pairs from **I** with activity $\{4\}$ to **D** as negative candidates
  %% the wide part
  $\mathbf{V}_1 \leftarrow$ sample 100000 items from **V**
  for each item $v \in \mathbf{V}_1$ **do**
    for $i = 0 \rightarrow 500$ **do**
      sample one user $u \in \mathbf{U}$
      Add $< u, v >$ to **D** as negative candidate if not exists
    end for
  end for
  %% the deep part
  $\mathbf{V}_2 \leftarrow$ sample 1000 items from **V**
  for each item $v \in \mathbf{V}_2$ **do**
    for $i = 0 \rightarrow 30000$ **do**
      sample one user $u \in \mathbf{U}$
      Add $< u, v >$ to **D** as negative candidate if not exists
    end for
  end for
  return D

4 FEATURE EXPLORATION

4.1 feature engineering

Our entire feature set can be split into three pillars: profile matching, historical matching, and bag of words.

4.1.1 profile matching. Job relevance can be measured through comparing user's profile and the item's profile. The numerical and categorical fields in the user's profile and the item's profile are used directly as features, such as discipline, industry, number of words in job roles. Next we use some boolean variables to record whether the corresponding field of user's profile and item's profile matches, e.g. the user's industry v.s. the item's industry, and the user's country v.s. the item's country. We further intersect some fields from the user's profile and the item's profile, considering that using each base field separately may not be enough to explain the relationship. For example, intersect the user's *career_level* field with the item's *career_level* field will yield a new categorical column with $n \times m$ possible values, where n, m stands for the possible values for user's *career_level* field and the item's *career_level* field, respectively.

4.1.2 historical matching. The user's profile is filled explicitly by the user. Actually, a fixed number of fields is not enough to introduce a user exhaustively. What is more, sometimes the user does not enter too much message in the online platform and his/her profile is very brief, or some fields are even fake. By contrast, the user's historical activities are ideal implicit supplement to the profile. So we try to build the user's secondary profile from his/her historical interacted items. We design several numerical variables by matching the user's secondary profile and the target item's profile, covering title similarity, industry similarity, career level similarity, employment similarity, and location similarity. Typically, *similarity* here means the percentage of items in the secondary

Table 2: Evaluation of different negative candidates selection methods. The classification model is GBDT.

method	reward	reward@1	p@1	p@5	AUC
negative action	1502	8	0.0050	0.0193	0.6659
negative action (filtered)	2474	430	0.1546	0.2978	0.6128
random (small)	5089	1805	0.4148	0.6572	0.9656
random(small) + negative action	3015	1205	0.2648	0.4172	0.8686
random (wide)	6013	2804	0.4755	0.7056	0.9736
random (deep)	5025	945	0.1251	0.3030	0.9291
random (wide & deep)	**7286**	**3005**	**0.6419**	**0.8264**	**0.9825**

Table 3: Evaluation of different feature set. The classification model is GBDT.

feature set	reward	change	reward@1	p@1	p@5	AUC
ALL	**7286**	-	**3005**	**0.6419**	**0.8264**	**0.9825**
- profile	5999	↓ 17.6%	1795	0.4428	0.6363	0.9479
- history	1883	↓ 74.2%	848	0.2816	0.5391	0.9190
- BOW	6790	↓ 6.81%	2919	0.5347	0.7501	0.9764
- car & loc	5603	↓ 23.1%	2306	0.5195	0.7453	0.9724
- location	6640	↓ 8.87%	2734	0.5421	0.7573	0.9758

profile share the same corresponding field with the target item. And for location similarity, we also calculate the min/avg/max distance between the target item and items in the user's secondary profile via latitude and longitude.

4.1.3 bag of words. Up to now we compact the profile into some numerical variables to describe the similarity. Usually it is necessary to treat the profile as a document and learn its latent representation to retain as much information as possible. Some popular methods are latent topic models [1] and deep learning techniques [14]. However, due to time limitation, we do not have enough time to build and tune parameters for these models, so we adopt the most simple bag-of-words feature to retain the raw document. To reduce dimension, we only use the top 20k frequent words.

4.2 feature evaluation

To study the importance of each feature pillar, we remove one of them and see how the performance changes. Results are shown in Table 3, where - *profile* indicates removing the entire *profile matching* pillar; - *history* indicates removing the entire *historical matching* pillar; - *BOW* indicates removing the entire *bag of words* pillar. We can observe that all of the three pillar contribute to the best model, and the *historical matching* features are the most important features, without which the performance drops severely by 74.2%. Thus we are curious to further explore the features within the *historical matching* pillar. Row - *car & loc* in Table 3 means for the *historical matching* pillar we only keep similarity variables extract from titles and tags, and remove those similarity variables extract from career level, employment, and location. Row - *location* in Table 3 indicates that we exclude all location related variables in the *historical matching* pillar. By doing this we want to verify whether only one or two historical fields are enough to explain the data. Results demonstrate that every field is important, and the more fields we have in the profile, the better precise the model can be.

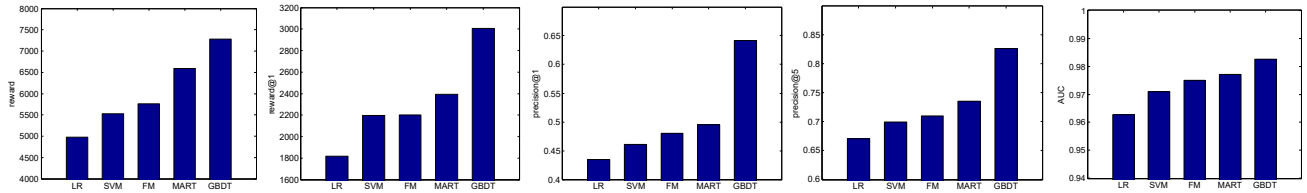
Table 4: Feature importance from GBDT.

feature	importance	pillar
sum_clicked_item_sim	1	historical matching
nearest_clicked_item	0.34	historical matching
avg_city_match	0.32	historical matching
sum_city_match	0.31	historical matching
nearest_clicked_item	0.28	historical matching
avg_clicked_item_sim	0.21	historical matching
region_match	0.21	profile matching
sum_distance	0.19	historical matching
item_is_paid	0.19	profile matching
tag_similarity	0.12	profile matching

Table 4 lists the top 10 most important features ranked by GBDT. The vast vast majority top features come from the *historical matching* pillar, which again demonstrates that implicit profiles better describe the user. The best feature is *sum_clicked_item_sim*, which means the sum of similarities between the user's clicked items and the target item. Intuitively, the more similar the user's historical interested items with the target item, the more likely the user will click on the target item.

5 MODEL SECTION

With all the features, we train models using logistic regression (LR), support vector machine (SVM), factorization machine (FM), gradient boosting decision trees (GBDT), and LambdaMART. LR, SVM, FM, GBDT are classification model, while LambdaMART [2] is a ranking model. We find the best parameters for each model using grid-searching and report their best scores. Figure 2 shows



(a) reward **(b) reward@1** **(c) Precision@1** **(d) Precision@5** **(e) AUC**

Figure 2: Performance comparison among logistic regression (LR), support vector machine (SVM), factorization machine (FM), LambdaMART (MARK), and gradient boosted decision tree (GBDT).

Table 5: Results of complexity reduction.

	reward@1	AUC	test size	test time
initial	3005	0.9825	4 TB	2.6 h
LR preprocess	2998	0.9824	250 GB	0.2 h

that under all evaluation metrics, GBDT performs best. Another interesting observation is that although GBDT provides only slightly better improvement than the other models in terms of AUC, it performs far ahead in terms of reward@1 and precision@1. Actually, reward@1 and precision@1 are more realistic metrics because the real users usually view only a small number of items.

We also have tried two ways to ensemble several model to further improve the performance. The first way is to blend the best output from LR/SVM/FM/MART/GBDT by harmonic average or stacking ensemble. Other way is to train GBDT with different parameters and different bags of features, and then blend the results. We can get about 1.5% improvement through model ensemble. However, this step make the running pipeline being more complex and time-consuming. To make the pipeline efficient, we decide to give up model ensemble during the challenge.

6 COMPLEXITY REDUCTION

In Section 3 we generate about 80 million candidates for training set, and the entire test set for offline stage has 46k × 74k possible candidates. After extracting features we find the size of test file is about 4 TB, the training and test process together costs about 12 hours. The data is really big and we are curious about reducing the data volume. We notice that in fact many items proposed by Algorithm 1 is not relevant to the user. Inspired by [7], we decide to use a weak classification model to filter out low quality candidates. Since we have found that LR is the relatively weakest learner and GBDT is the best one, we use LR to filter instances with probability lower than 0.01 in both training set and test set, then train a GBDT model using the filtered training set. Finally we make prediction on the filtered test set. Table 5 indicates that with the LR preprocessing, there is no significant loss in evaluation metrics, while the file size and running time are reduced significantly.

7 RESULTS OF CHALLENGE

Since the final leaderboard is evaluated according to the online stage, here we only report our growth history in the online stage

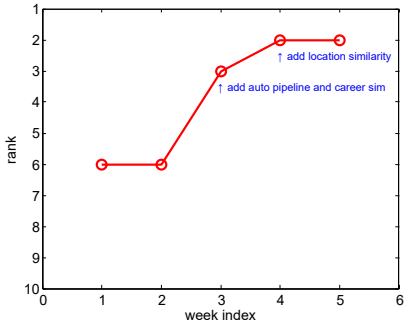


Figure 3: The trend chart of our rank during online phase.

[2]. At the first two weeks we only use the model without historical career and location similarity features (as shown in row - *car & loc* of Table 3). And we manually start the programs and submit the prediction file. Since we are in UTC+8 time zone, the time when new data will be released happens to be our midnight. So every time after we come to office to finish the pipeline, about 16 hours have passed since the new data was released. Thus we decide to build an automatic pipeline to daily pull data via API, extract features, make predictions, and then submit the prediction file. This automatic pipeline saved us 12 hours to submit the prediction file. We enabled the pipeline in week 3, along with some new features related to historical career matching. As shown in Figure 3 our rank increased to 3rd at this week. We further added historical location matching features in week 4, and our model kept ranking 2nd since we used the latest model.

8 DISCUSSION

In Section 3 we have demonstrated that random sampling negative candidates performs far better than using the user's none-click impressions as negative candidates. However, removing the latter may to some extent cause information loss. If we regard the user's clicked items as positive candidates, random sampling items as negative candidates, and the user's none-click impressions as negative ranking candidates (for which we do not know their true label, however, we know that their score should not be higher than positive candidates), now we can incorporate classification and

[2]Until the time we submit this paper, our best single GBDT model ranks 3rd in the latest offline leaderboard with score 62110.

Table 6: Score comparison between the *relevance & preference* model and base LR model.

	P@1	P@5	AUC
LR	0.3541	0.4801	0.8672
relevance & preference	0.3581	0.4991	0.8683

ranking into one unified model, which we call *relevance & preference model*. Formally, let $\mathbf{D}_+$ denotes the positive candidates in $\mathbf{D}$ from Section 3, $\mathbf{D}_-$ denotes the negative candidates in $\mathbf{D}$, $\mathbf{R}$ denotes the interactions history, and $\mathbf{\Theta}$ denotes the model parameters. We want to maximize the following posterior:

$$Pr(\mathbf{\Theta}; \mathbf{D}_+, \mathbf{D}_-, \mathbf{R}) = P(\mathbf{D}_+|\mathbf{\Theta})P(\mathbf{D}_-|\mathbf{\Theta})P(\mathbf{R}|\mathbf{\Theta})P(\mathbf{\Theta}) \quad (1)$$

where $P(\mathbf{D}_+|\mathbf{\Theta})$ classifies positive candidates:

$$P(\mathbf{D}_+|\mathbf{\Theta}) = \prod_{i \in \mathbf{D}_+} f(i|\mathbf{\Theta}) \quad (2)$$

and $P(\mathbf{D}_-|\mathbf{\Theta})$ classifies negative candidates:

$$P(\mathbf{D}_-|\mathbf{\Theta}) = \prod_{i \in \mathbf{D}_-} (1 - f(i|\mathbf{\Theta})) \quad (3)$$

and $P(\mathbf{R}|\mathbf{\Theta})$ models the preference among the user's interaction history, c is a hyper-parameter controlling the weight of the preference module:

$$P(\mathbf{R}|\mathbf{\Theta}) = \prod_{(+,-) \in \mathbf{R}} \frac{c}{1 + e^{-(f_+ - f_-)}} \quad (4)$$

$f(,;\mathbf{\Theta})$ can be arbitrary discriminative learner. Due to time limit, we only implement it with LR and conduct experiments over a small subset. Table 6 demonstrates that the proposed *relevance & preference* model is promising. In the future we will implement the model with GBDT and conduct experiment in the complete dataset.

9 RELATED WORKS

Compared to the Recsys Challenge 2016, the Recsys Challenge 2017 focus more on the online scenario. All recommendations submitted by the teams are pushed to the real users, which requires us to build efficient pipeline for make timely recommendations. Different with the winning solutions from last year [11, 13, 16], our pipeline is simple and does not include any model ensemble, which make the online logic efficient and easy to maintain.

The most popular method for recommender system is collaborative filtering (CF). However, since the Recsys Challenge 2017 aims at making recommendations for new items, which is known as the cold-start problem, CF is not applicable in this task. Thus we have to abandon a lot of good models related to CF [6, 8, 14], and mainly consider models with content-based filtering. We find the job recommendation task is very close to click-through rate prediction tasks, where the most popular way is to model it as a binary classification problem [5, 10]. Generalized linear algorithms such as FTRL [10] proves to be efficient and effect in practice. Recently, some researchers try to enhance the non-linear ability of the models with deep neural networks [4, 12, 15]. However, these deep learning-based models are still not fast enough to make real-time predictions.

10 CONCLUSIONS

In this paper, we have introduce our pipeline for the Recsys Challenge 2016. There are mainly three key components, i.e. negative candidates selection, feature engineering, and model selection. We have demonstrated that in each component there are some elaborate designs which improve the performance significantly. For new jobs recommendation task, the user's historical activities are the best features for profiling the user. We also propose a unified model to incorporate both relevance and preference together. In the future, we are going to conduct more comprehensive experiments for the proposed relevance & preference model.

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