Algorithms and Architecture for Real-time Recommendations at News UK

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Abstract. Recommendation systems are recognised as being hugely important in industry, and the area is now well understood. At News UK, there is a requirement to be able to quickly generate recommendations for users on news items as they are published. However, little has been published about systems that can generate recommendations in response to changes in recommendable items and user behaviour in a very short space of time. In this paper we describe a new algorithm for updating collaborative filtering models incrementally, and demonstrate its effectiveness on clickstream data from The Times. We also describe the architecture that allows recommendations to be generated on the fly, and how we have made each component scalable. The system is currently being used in production at News UK.

Keywords: Recommendation Systems · Real-Time · Text Mining

1 Introduction

Two years ago News UK completed a refresh of our data platforms and brought this process in-house. Now that we had greater access to our data we wanted to provide our customers with a premium digital experience based on their individual habits and behaviours. Other competitors in the market offer this, and we believe it will help us improve engagement and reduce churn. There are a number of products in the market that attempt to achieve this, however, we required a platform that was able to adapt to the constant changing news cycle and not centred around evergreen or e-commerce data. The decision was made to develop a platform tailored to our unique business models. We have two major News Titles with two different business models, The Times & The Sunday Times and The Sun. On the Times, we are in the unique position of knowing a lot about our users, their behaviours, their preferences and their level of engagement with our products due to the digital product suite being behind a paywall.
The Times & The Sunday Times currently has over 400,000 subscribers. The Sun is a brand that is going for major reach across all of its products; since removing its paywall last year it has become the second largest UK newspaper [8].

The platform we designed is intended to improve the numbers above and increase retention by employing personalization techniques where it makes sense for users. We want to maintain the current editorial package, but use the information we have at our disposal to present content relevant to the user, which provides a more engaging product experience.

Our paper is structured as follows. In the remainder of this section we outline related work, our approach and the datasets used. In Section 2 we describe the algorithms we used and the offline evaluations we performed. This includes the major contribution of this paper, a novel algorithm for updating collaborative filtering models incrementally. In Section 3 we describe our evaluation, and in Section 4 we give our results. We show that the incremental approach works as well as non-incremental under the right conditions. In Section 5 we describe the architecture of our system, concluding in Section 6.

1.1 Related Work

Diaz-Aviles et al. [3] describe an algorithm for real-time recommendations called Stream-Ranking Matrix Factorization (RMFX) in the context of recommending for social media. This performs matrix factorization and ranking of recommendations on streaming data. However their system requires specifying the set of users and items in advance, which is not appropriate in our setting where we must handle new users and items (in our case new articles) all the time.

The xStreams system of Siddiqui et al. [9] does handle new users and items, however it does not incorporate the matrix factorization algorithms which provide the current state-of-the art recommendations.

The system used for real-time recommendations on YouTube is described by Covington et el. [2], which uses a sophisticated deep-learning model built on TensorFlow [1]. However the focus of the paper is on the deep learning model used rather than the real-time aspect of the system.

1.2 Approach

Our approach has been a pragmatic one. We performed an offline evaluation of a number of standard approaches to recommendation generation. We then chose the best performing systems to implement in production. The initial requirement for recommendations was to send an email to users once a day with personalised recommendations. Our first implementation precomputed recommendations for all users. These were then sent to users via email at a preconfigured time. We found that it took a long time to precompute and store the recommendations for all users: with a Spark cluster of forty machines, the recommendations could take up to half an hour to generate.
We decided to re-architect our system when we were tasked with building a system to serve recommendations on demand for The Times and The Sun websites. In particular, for The Sun, new content is generated throughout the day, and we wanted that content to be recommendable as soon as possible. In our new architecture, we no longer precompute recommendations. Instead, models are updated continuously as new information about users is received. The models are stored in a database that allows them to be very quickly retrieved, and recommendations are generated at the point that they are needed via an HTTP request to our API.

This approach not only means that recommendations are always up-to-date, but also means that we do not need to generate and store recommendations for all users, a process which is both time and space intensive.

1.3 Datasets
We collected ten days’ worth of Times user behaviour from web logs. For each pair of user and item, we collated the user events as follows:

- **Dwell time**: this was estimated based on time between subsequent clicks. If the time between subsequent clicks by the same user was less than 30 minutes, it was assumed that the user spent that time on the first item clicked on. Thus the last item clicked on by a user would never receive a dwell time event.
- **Shares**: the number of times that the user shared the item.
- **Comments**: the number of times the user commented on the item.

These data were translated using a simple rule to determine whether or not there was an implicit expression of interest in the item by the user. We call such interactions “significant”. We defined a significant interaction to be a dwell time of more than ten seconds, or any positive number of shares or comments. Reducing the data to this simple binary signal simplified the choices we had to make in designing and evaluating the algorithms. We plan to investigate more sophisticated possibilities in future work.

2 Algorithms
We evaluated two recommendation algorithms, one collaborative in nature and one content based, and two baselines that we wished to improve upon: global popularity ranking and randomly chosen articles. The first chooses the articles that have the highest number of significant actions in the training set, and the second chooses from articles seen in the training set at random.

2.1 Incremental Updates for Collaborative Recommendations
Our main contribution is an algorithm for updating collaborative models incrementally, described in Figure 1. In theory, the model could work with any
users ← empty dictionary;
items ← empty dictionary;
ratings ← empty dictionary;

while more batches exist do
    read new batch with \( n_u \) users and \( n_i \) items;
    foreach user \( u \) in batch do
        // initialise unseen user vectors to a new random vector:
        if \( u \) not in users then
            users[\( u \)] ← new initial user vector;
        else
            ratings[\( u \)] ← empty set;
        end
        // keep track of all user ratings so far:
        ratings[\( u \)] ← ratings[\( u \)] ∪ new items with significant actions for \( u \) in this batch;
    end
    // initialise unseen item vectors to a new random vector:
    foreach item \( i \) in batch do
        if \( i \) not in items then
            items[\( i \)] ← new initial item vector;
        end
    end
    // perform a learning iteration:
    \( R \) ← matrix of shape \( n_u \times n_i \) with values from ratings;
    \( X \) ← matrix of shape \( n_u \times k \) with values from users;
    \( Y \) ← matrix of shape \( n_i \times k \) with values from items;
    LatentFactorUpdate(\( R \), \( X \), \( Y \));
    update ratings, users and items with values from \( R \), \( X \) and \( Y \);
end

Fig. 1: Incrementally updating a collaborative filtering model. Each batch is a streamed collection of user actions. The positive integer \( k \) is a parameter of the underlying collaborative filtering algorithm specifying the dimensionality of the factorization. The matrices \( X \), \( Y \) and \( R \) are built from dictionaries of ratings, users and items by defining an order on users and items and iterating the maps in that order. The function \texttt{LatentFactorUpdate} updates \( X \) and \( Y \) from \( R \) using the underlying collaborative filtering algorithm.
Fig. 2: Depiction of the matrix factorization algorithm, and how a user can be added or removed by adjusting the matrices. The matrix at the top depicts the matrix of user preferences, with users in rows and items in columns. This is approximately factored into two matrices, one for items and one for users. Removing a user from the preference matrix results in removing the corresponding row in the users matrix. In our algorithm we do the converse by adding a randomly initialised vector to the users matrix along with the user’s actions to the preference matrix.

collaborative filtering algorithm that allows user and item vectors to be updated from some initial state.

The algorithm is based on the observation that in collaborative filtering algorithms that decompose a matrix into products of latent factors, the set of users and items under consideration can easily be altered by adding or removing rows or columns from the matrices (see Figure 2). It works by processing batches of user actions, updating the vectors only for users in each batch. We found that it was necessary to keep track of all user actions performed to date; for each user in the batch, we retrieve these actions and perform a model update using the underlying collaborative algorithm.

Some concerns when implementing this algorithm are:

– determining the size of the batch: if batches are too small, the algorithm does not work reliably. This was mitigated by adding in some randomly chosen users if there were not enough in the batch. The number of users needed in the batch was determined empirically.
– processing batches in parallel: if the level of parallelism is too high, the algorithm does not converge to an optimal solution.
Storing and retrieving user actions and user and item vectors becomes a major concern when implementing this algorithm at scale. Most of our effort has been around designing an architecture to do this reliably, described in Section 5.

2.2 Algorithmic Complexity

Keeping the model constantly up-to-date comes with an associated computational cost. Let $f(n)$ be a function describing the time complexity of the underlying matrix factorization algorithm, where $n$ is the number of user-article pairs in the dataset, i.e. the number of non-zero entries in the matrix. Our algorithm splits the $n$ datapoints into batches of size $b$. In the worst case (when there is a very small number of users), all the data from the previous batches needs to be included in each batch. Thus the complexity is

$$O\left(\sum_{i=1}^{n/b} f(ib)\right)$$

In the case where $f$ is linear, this becomes $O(n/2 + n^2/2b) = O(n^2/b)$. Making $b$ bigger mitigates the additional cost, and if $b = n$ we recover $O(n)$ complexity.

2.3 Collaborative System

The collaborative filtering algorithm we use for the latent factor update step is based on an approach to implicit feedback datasets [5]. This suggests an alternative to treating a rating matrix $R$ as a set of explicit ratings given by the user. Each value is considered as a rating together with a confidence in that rating. In their scheme, items with a low rating are given a low confidence.

The implementation we use makes use of conjugate gradient descent to perform the updates [10]. This is a faster algorithm with time complexity $O(nEk^2)$ where $E$ is the number of iterations and $k$ the number of latent factors. The original algorithm has cubic time complexity with respect to $k$ [7].

Intuitively, it makes sense to consider algorithms for implicit feedback. This approach is in theory perfectly suited to our case, since we have only implicit signals of interest in articles from users and no reliable signal that the user is not interested in an article. Thus, if we know that a user has shared an article or read it for five minutes, we can be fairly confident that the user is interested in it. However, if the user did not read the article we can be much less certain that the user is not interested in it. In order to verify this hypothesis, we performed some initial experiments in which we found that algorithms designed for implicit signals gave much higher accuracy on our datasets than those designed for explicit signals.

We used Ben Frederickson’s open source implementation [4] which is written in Python and Cython, which compiles to C. The library makes use of the low-level BLAS library for vector operations, which makes it very fast.

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[4] https://github.com/benfred/implicit
On top of this, we implemented the weighted regularization scheme described in [11] in the Cython version of the library, which we found provided a modest improvement in accuracy in our preliminary experiments.

The algorithm assumes that for each user \( u \) and item \( i \) we have values \( p_{ui} \in \{0, 1\} \) which describes whether or not the user has implicitly expressed a preference for the item and \( c_{ui} \in \mathbb{R} \) that expresses our confidence in the user’s preference for that item [5]. These values are assumed to be derived from the implicit rating \( r_{ui} \) given by the user for the item in such a way that \( p_{ui} = 1 \) if and only if \( r_{ui} > 0 \), and \( c_{ui} = 1 \) if and only if \( r_{ui} = 0 \), with \( c_{ui} > 1 \) otherwise. One suggestion is that \( c_{ui} = 1 + \alpha r_{ui} \) for some parameter \( \alpha \) to be tuned. The intuition behind this is that items for which we have no information from a user are treated as a negative signal with low confidence, while implicit signals from a user are treated as a positive signal with higher confidence. In practice, the values are chosen to have this form to make the vectors in the intermediate computations sparse.

Given these matrices, the goal is to learn vectors \( x_u \) for each user and \( y_i \) for each item such that we minimize the following:

\[
\min_{x_u, y_i} \sum_{u,i} c_{ui} (p_{ui} - x_u^T y_i)^2 + \lambda \left( \sum_u n_{x_u} \|x_u\|^2 + \sum_i n_{y_i} \|y_i\|^2 \right)
\]

where \( \lambda \) is a regularization constant and \( n_{x_u} \) and \( n_{y_i} \) are the number of non-zero entries in the vectors \( x_u \) and \( y_i \) respectively. This is solved using the conjugate-gradient approach described in [10].

In the experiments we report here we used a dimensionality of 50 for the factor vectors; we found this worked well in initial experiments.

### 2.4 Content-based Learning to Rank

The content-based system is based on the Learning to Rank model [6], which treats the task of ranking pages as a supervised learning problem. We consider two “classes” of articles: those that interest the user and those that do not. Since we do not make use of any explicit signals from users, for the purpose of training a model, we identify these two classes with the following sets of articles:

- The “positive” articles are those that the user has had a significant interaction with.
- The “negative” articles are a random sample of articles that the user has not interacted with at all.

For each user, we train a logistic regression model on this data and use it to rank articles as to their likelihood of being of interest to the user.

**Implementation Details** We use the Liblinear implementation [4] of the logistic regression algorithm, and perform a search on the cost parameter for each user, considering costs of 10, 20 and 50, having found that costs below this range are rarely optimal. We perform cross validation on the training set, choosing the value that gives the highest F1 score.
Fig. 3: A *Times* article showing the features used for training the Content-based system (outlined).

**Features** We use the following features (see Figure 3):

- The name of the article section,
- Each term in the “author” text,
- Each term in the article title and body.

All text is tokenized and lower-cased and a simple stop-word list is applied, but no stemming or lemmatization is performed. Tokens from each type of feature (section name, author text and title and body text) are distinguished by adding a unique prefix for each type. Features are treated as binary variables as is typical in document classification. This means we look only at the presence or absence of a feature, rather than counting occurrences.

**Feature selection** We experimented with a variety of feature selection methods, but found the following simple approach worked the best. We train a logistic regression model using all features, then take the top 2,500 and bottom 2,500 features (those with the highest and lowest coefficients) from the learnt model, and set the remaining coefficients to zero. This has the advantage of giving us a
sparse model, which helps to generate recommendations quickly since the model is smaller, but also seems to provide a marginal improvement in recommendation quality.

**Selecting Random Articles** We found that when the ratio of irrelevant to relevant articles was too high, the learning algorithm became unreliable. Restricting the number of negative articles to at most five times the number of positive ones provided a good compromise, representing the underlying imbalance in the dataset whilst still keeping learning reliable.

**Boosting popular articles** We found that the content-based system alone performed poorly compared to the global top items baseline. Boosting the ranking of popular items lead to a significant increase in our evaluation metric. To do this, we computed a score

\[ s_{ui} = p_{ui}(f_i + \beta) \]

where \( p_{ui} \) is the probability output by the logistic regression model for user \( u \) and item \( i \), \( f_i \) is the number of users that have a significant action for item \( i \) and \( \beta \) is a smoothing value which we set at 10. The smoothing value allows for items that have no significant actions to still be recommended.

### 3 Evaluation

#### 3.1 Evaluation metrics

The offline evaluation method we have been using has been designed with the following in mind:

- Make the evaluation representative of how the system will be used in practice
- Design the evaluation so that all types of algorithm can be compared
- Make the evaluation metric intuitively simple

These considerations rule out the normal metrics that are used for example in evaluating matrix factorisation algorithms, since we also want to be able to evaluate classification based approaches. In our first application, we send out an email containing 10 recommendations to users. For this reason we have opted for the “precision at 10” metric.

#### 3.2 Evaluation procedure

The data consists of (user, article, interactions) tuples, where “interactions” consists of all interactions that a user has had with that article, including dwell time, comments and shares. We split these data randomly into a training set consisting of 80% of the data, and the remaining 20% is held out as a test set. We then train a model on the training set, generating recommendations for each
Table 1: Precision at 10 on the held out test set for the systems and baselines we considered.

| System            | Precision at 10 | Standard error |
|-------------------|-----------------|----------------|
| Random baseline   | 0.0056          | 0.0008         |
| Global top items  | 0.0276          | 0.0021         |
| Content           | 0.0281          | 0.0021         |
| Collaborative     | 0.0750          | 0.0043         |

user from articles seen in the training set. For each user we take the top ten recommendations excluding items that occur in the training set for that user, and count the proportion of them that occur for that user in the test set. This is averaged over all users to get the mean precision at 10 score.

4 Results

Results for the systems we evaluated are shown in Table 2. Only the collaborative system was significantly better than the Global Top Items baseline. Figure 4 shows how the precision at 10 score varies with batch size. For batch sizes over 10,000 there is no significant increase in the score. Using a single batch is equivalent to training using the underlying collaborative filtering model; since the score is not significantly different to training with batches of 10,000, it is clear that our incremental approach works, at least with the set-up we have chosen. In initial experiments, we also found that the batch size needed is dependent on the dimensionality of the learnt factors: the higher the dimensionality, the larger the batch size needed to avoid harming the score. One limitation of our approach is that the batch size will need to be tuned for each dataset once an appropriate dimensionality has been chosen.

Figure 5 shows how the score is affected by processing multiple batches in parallel. As long as the total number of data points being trained simultaneously (the batch size times the number trained in parallel) is much less than the total dataset size, the score is not significantly affected.

4.1 Performance

Tests were created to verify the different performance levels of the Recommendation Engine in terms of the number of concurrent clients, how old the recommended assets could be and how many containers were deployed at the same time (horizontal scalability). We selected Jmeter as the tool to run these tests given its simplicity for creating different scenarios.

Results are shown in table 2. Latency for content-based recommendations is higher because the model size (sparse vectors with up to 5000 non-zero dimensions) is much greater than for the collaborative system (in this test the vectors were 200 dimensional dense vectors); the majority of the time is spent
Fig. 4: Precision at 10 with batch size. Fig. 5: How precision at 10 is affected by the number of batches that are processed in parallel, for a batch size of 100,000.

| System      | Users/sec | Average latency (ms) |
|-------------|-----------|----------------------|
| Collaborative | 663       | 382                  |
| Content     | 412       | 690                  |
| Top articles| 305       | 86                   |

Table 2: Real-time performance results for our system using eight containers for each recommendation algorithm and thirty concurrent clients.

transferring the model from BigTable to the cluster. Top article latency is low because the top articles can be cached between subsequent requests, and all that is needed is to retrieve and exclude seen items for the user.

5 Architecture

Our focus on the architecture was to provide a base structure where the collaborative and content based algorithms had enough resources to ingest and train the data with minimum delay and maximum scalability. Although intended to be used initially on The Times and The Sun, the engine needed to be product agnostic and with delivery model of Software as a Service (SaaS), where a single deployed version of the application is used for all customers.

Given these requirements, each component had to be designed to be horizontally scalable to support huge amounts of data without increasing the recommendation serving latency and freshness. For that, we used a containerised architecture with Docker and Kubernetes to allow easy control of the scalability. Data stores would also have to cope with these variations on the amount of data and be able to scale up and down.

PubSub was used for data ingestion since we can guarantee that all messages are processed using its acknowledgment model and we can configure its bandwidth quota as needed, although the default of 100 mb/s should be sufficient.
Bigtable was selected as the main storage for being a massively scalable NoSQL database with low latency and high throughput. It stores all the user actions, user models and asset models.

Clients of the engine typically will query for the latest recommendations, including the last few hours or days, but we also wanted to support cases where they would need recommendations for much longer periods. Because of that, it was not feasible to load thousands of models from Bigtable, which sits outside the cluster and has much more limited bandwidth compared with the cluster’s internal speed. We created a cache component that would run inside the cluster and initialise all existing recommendable assets models from Bigtable. Each serving API also had its own short-lived in-memory cache for further optimisation.

All the components of the Recommendation Engine can be divided into four layers (see Figure 6):

- Data gathering: collection of user actions and content from our online publications to send to PubSub.
- Data ingestion: messages from PubSub are processed and stored in the engine. User actions are stored in BigTable and feature extraction is performed on article content.
- Data training: use collaborative and content based algorithms to train the ingested data and store the resulting models.
- Recommendation serving - APIs to generate recommendations using query parameters and previously generated assets models and user models.

New algorithms can be incorporated into the Recommendation Engine by creating components fitting into the training and recommendation serving layers.
6 Conclusion

We have described the recommendation system currently used in production at News UK. We make use of a novel algorithm for incrementally updating collaborative filtering models. We demonstrated its effectiveness in an offline evaluation and described the conditions under which the incremental update works reliably for our dataset.

In future work, we hope to combine our content-based and collaborative systems. In our ongoing online tests measuring click-through rates on recommendations, we have found that for some users, content-based recommendations seem to be more effective, while for others, the collaborative filtering recommendations give higher click-through rates. We would like to be able to give the best recommendations possible to each user, so we may try and learn which system works best for users, perhaps using a multi-armed bandit approach. We will also investigate hybrid recommendation techniques.

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