Predicting conversions in display advertising based on URL embeddings

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ABSTRACT

Online display advertising is growing rapidly in recent years thanks to the automation of the ad buying process. Real-time bidding (RTB) allows the automated trading of ad impressions between advertisers and publishers through real-time auctions. In order to increase the effectiveness of their campaigns, advertisers should deliver ads to the users who are highly likely to be interested (i.e., purchase, registration, website visit, etc.) in the near future. In this study, we introduce and examine different models for estimating the probability of a user converting, given their history of visited URLs. Inspired by natural language processing, we introduce three URL embedding models to compute semantically meaningful URL representations. To demonstrate the effectiveness of the different proposed representation and conversion prediction models, we have conducted experiments on real logged events collected from an advertising platform.

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1 INTRODUCTION

In online display advertising [24], advertisers promote their products by embedding ads on the publisher’s web page. The majority of all these online display ads are served through Real-Time Bidding (RTB) [7]. RTB allows the publishers to sell their ad placements via the Supply-Side Platform (SSP) and the advertisers to purchase these via the Demand-Side Platform (DSP). More specifically, each time a user visits a website that contains a banner placement, an auction is triggered. The publisher sends user’s information to the SSP, which forwards this information to the Ad exchange (AdX), and finally the AdX sends a request to the DSPs. Then each DSP decides if it will submit or not a bid for this impression, based on its information about user, advertisement, urls, etc. Once the DSPs send back to the AdX their bids, a public auction takes place with the impression to be sold to the highest bidder. Figure 1 briefly illustrates the procedure of online display advertising.

DSPs are agent platforms that help advertisers optimise their advertising strategies. Roughly speaking, DSPs try to estimate the optimal bid price for an ad impression in order to maximise the audience of the campaigns of their advertisers, given some budget constraints. The bid price of an ad impression is highly related to the additive value that this impression could have on the advertising campaign (i.e., the number of ad impressions, clicks or conversions, etc.). In this context, advertisers have at their disposal a number of different pricing models. In the case where the objective of the advertisers is to maximise the exposure of their advertising message to a targeted audience, paying per impression, referred as cost-per-mille (CPM), is probably the best option for them. Nevertheless, in most of the cases, performance display advertising is more attractive to advertisers that are interested in accomplishing specific goals reducing their risks. In this case, advertisers are willing to pay for an ad impression if and only if that impression will drive the user to take a predefined action/conversion [15], such as a visit on the advertiser’s website, a purchase of a product, etc. Two performance payment models have been introduced for this purpose, referred as cost-per-click (CPC) and cost-per-action (CPA).

In performance-driven display advertising, DSPs submit a bid for a given ad impression based on the CPC or CPA that the advertiser is willing to pay. To determine the optimal bid price for an ad impression, DSPs estimate the expected cost per impression, called eCPI, which is either equal to the click-through-rate (CTR) for this impression multiplied by the value of CPC, or the conversion rate (CVR) multiplied by the value of CPA [5]. As a result, accurate CTR/CVR prediction plays an important role in the success of online advertising. For this purpose, DSPs build CTR/CVR prediction models able to estimate the probability a user converting after their exposure to an advertisement. The accuracy of these models is of high importance for the success of the campaign as if we overestimate click or conversation rates, we will probably submit quite higher bids than we should do, winning possible useless ad impressions. On the other hand, if these rates are underestimated, we will probably miss ad impressions likely to lead to a user action.
In this work we examine the user conversion problem, where given an advertiser, we want to predict if a user will be converted or not based on their history. In contrast to previous works that use a number of features related to the user profile, ad information and context information, we consider only the user’s browsing history. More specifically, each user is represented as a sequence of URLs visited by the user in a single day. Therefore, the problem examined in this paper can be formally described as: given a user’s sequence of URLs from a single day, predict the probability this user to take a predefined action on the next day. In our case, a user is considered as converted if they visit the advertiser’s website. Due to the high cardinality and diversity of URLs, a compact semantically meaningful representation of URLs is of high importance. For this purpose, we build and examine three URL embedding models following the idea of word embeddings [18]. The sequential dependency between user’s browsing history has also been considered by using a Recurrent Neural Network (RNN) [9]. In total, ten different prediction conversion models have been introduced. A number of large scale experiments have been executed on a data collected from a real-world advertising platform in order to reveal and compare the prediction abilities of the proposed prediction schemes. Finally, our empirical analysis validates our claims about the effectiveness of our representation models showing that they achieve to group together URLs of the same category. It means that URLs with the same or similar context are also close on the embedding space.

2 RELATED WORK

As the performance of a campaign is directly related on how precisely the CVR/CTR is estimated, it has been the object of considerable research in the past few years. Typically, the problem of CVR/CTR estimation is formulated as a standard binary classification problem. Logistic regression has been extensively used to accurately identify conversion events [4, 16, 20]. [8] introduced a Bayesian learning model, called Bayesian probit regression, which quantifies the uncertainty over a model’s parameters and hence about the CTR of a given ad-impression. A precise user representation (a set of features describing user behaviour) constitutes also the foundation for building a linear model able to estimate CVR with high accuracy. Nevertheless, in most cases it requires a lot of feature engineering effort and the knowledge of the domain. Moreover, linear models are not capable to reveal the relationship among feature. To overcome this problem, a number of non-linear models such as factorisation machines [19, 22] and gradient boosted regression trees [11] have been also proposed to capture higher order information among features. A number of different deep learning methods have been also proposed recently for CTR prediction [3, 14, 25, 26].

Representation learning has been applied with success in several applications and has become a field in itself [1] in the recent years. The URL representation architectures presented in this manuscript have been inspired by those used in natural language processing (NLP) tasks. Learning high-quality representations of phrases or documents is a long-standing problem in a wide range of NLP tasks. Word2Vec [18] is one of the most well-known word embeddings algorithms. The main idea behind Word2Vec is that words that appear in similar contexts should be close in the learned embedding space. For this purpose, a (shallow) neural network language model is applied that consists of an input, a projection, and an output layer. Its simple architecture makes the training extremely efficient. [10] proposed search2vec model that learns user search action representations based on contextual co-occurrence in user search sessions. To the best of our knowledge, URLNet [13] is the only work that learns a URL representation but for the task of malicious URL detection. In contrast to our unsupervised representation scheme that considers the sequential order of URLs, URLNet is an end-to-end (supervised) deep learning framework where its character-level and word-level CNNs are jointly optimized to learn the prediction model.

3 PROPOSED CONVERSION PREDICTION ARCHITECTURE

The goal of this paper is to predict the probability a user to be converted one day after, given their browsing history on a single day. More specifically, we consider each user as an ordered sequence of URLs, sorted chronologically. The notion of conversion corresponds to an action of interest for the advertiser, such as visit on the landing page, purchase of a product, registration, etc. Therefore, we can treat the problem of predicting the user conversion as a binary classification problem [2], where given a sequence of URLs visited by a user $U_n = \{url_1^n, \ldots, url_T^n\}$, $n = 1, 2, \ldots, N$, we want to predict if $U_n$ will be converted or not, $y_n \in \{0, 1\}$. The length of the URL sequence, $T_n$, may be different for each user.

As an analogy to text classification, we view a sequence of URLs as a document, or a sequence of sentences. In our case, a URL is itself a sequence of tokens, of length at most three (we ignore the rest tokens as they are quite noisy). Each URL is split with a ‘/’ (slash) character, where the first token corresponds to the domain name. For instance, https://en.wikipedia.org/wiki/Main_Place is mapped to [en.wikipedia.org, wiki, Main_Place].

In order to apply any supervised classification model, such as logistic regression, etc., a semantically meaningful representation of each URL is needed. Therefore, a key intermediate step in our model is the learning of a URL representation. More precisely, the proposed conversion prediction scheme is composed of two consecutive training phases. The first one corresponds to the learning of the URL representations, while the second one corresponds to the training of a classifier. It should be mentioned that the training processes of these two models are independent.

Due to the high cardinality of URLs, we learn the URL representations implicitly by learning and aggregating their tokens representations. In this study, we present and examine four different URL representation models, $f_r$: $url \rightarrow x$, where $x \in \mathbb{R}^d$ and $d$ is the dimensionality of the embedding space. The first one is the simple one-hot encoding that treats tokens as atomic units. The main limitation of this representation is that the representation size grows linearly with the corpus and it doesn’t consider the similarity between URLs. To overcome these issues, we propose three different URL embedding models (see Section 4).

After having trained a representation model, $f_r$, and given a training set $D = \{(U_n, y_n)\}_{n=1}^{N}$ we produce a new dataset $D' = \{(X_n, y_n)\}_{n=1}^{N}$ where $X_n = \{x_1^n, \ldots, x_{T_n}^n\}$ is a sequence of length $T_n$

1The http(s):// and www parts of each URL are stripped.
with elements $x_i^n = f_r(url_i^n)$. In a nutshell, $\mathcal{D}'$ contains sequences of URL embedding vectors along with their labels. Then, we apply mapping $f_m: X \rightarrow z$ that aggregates the URLs embeddings into an embedding vector $z \in \mathbb{R}^m$, where $m$ can be different from $d$. It results in a single compact representation $z$ for each sequence of URLs. Next, our goal is to discover a classification model $f_c: z \rightarrow \hat{y}$ from a set $\mathcal{F}$ of possible models with the minimum empirical risk

$$\min_{f_c \in \mathcal{F}} \mathbb{E}_{(X,y)} \mathcal{L}(\hat{y}, y),$$

where $\ell \in \mathbb{R}$ is a non-negative loss function. In fact, classifier $f_c$ is trained on dataset $\mathcal{D}'' = \{(x_n, y_n)\}_{n=1}^N$. In this work, we use logistic regression where the conversion conditional probability of user $(n)$ given their browsing history $X_n$, is modeled as:

$$p(y_n = 1|X_n) = \sigma(\theta^T f_m(X_n) + b),$$

where $\theta$ is a vector with the unknown model parameters, $b$ is the bias term and $\sigma()$ is the logistic sigmoid function. From a geometrical point of view, $\theta^T f_m(X_n) + b$ is a hyperplane that separates the two classes. To learn the unknown model parameters, the cross-entropy loss is applied:

$$\mathcal{L} = -\mathbb{E}_{(X,y)} \mathcal{L}(y \log f_c(f_m(X)) + (1-y) \log(1-f_c(f_m(X))))].$$

Next, we are describing the three different mapping functions $f_m$ adopted in our work. The first one returns the average of the URLs embedding vectors along with their labels. Then, we apply the embedding vector returned by the first mapping function. To be more precise, the third mapping function is an LSTM network able to map an input sequence of URL embeddings $X$ to a fixed-sized vector $z$, that can be considered as the representation of the whole sequence. In all cases, we are feeding the produced vector $z$ to a final dense layer with sigmoid activation function. In the rest of the paper, we denote as LR, DLR and RNN the prediction conversion models which are using the "average", "dense" and 'LSTM" mapping functions, respectively. A graphical illustration of the proposed conversion prediction model architecture is presented at Fig.6.

4 URL REPRESENTATION SCHEMES

This section introduces the four URL representation models proposed in our work. These models can be divided in two categories: i) one-hot encoding, and ii) embedding representation. There is no need for learning in the case of one-hot encoding. On the other hand, the embedding representations of URL tokens are learned in advance and then used to form the final URL representation. A representation is also learned for the so-called "rare" and "none" tokens, respectively. A token is considered "rare" if it is present less than a predefined number (we set it equal to 20) of times in our data. We denote the token embedding vectors as $e$.

**One-hot encoding.** First, we introduce a variant of the standard one-hot encoding for representing URLs that is our baseline. As already mentioned, the token representations are used to get the URL representation. Therefore, in our case, the cardinality of the one-hot encoding is equal to the number of all possible tokens appearing in our data. Given a one-hot encoding $\{e_{url_i}\}_{i=1}^{n_tokens}$, for each one of the tokens appearing in $url$, we take their average to encode it: $f_r(url) = \frac{1}{n_tokens} \sum_{i=1}^{n_tokens} e_{url_i}$.

**Embedding learning.** Despite its simplicity, the aforementioned one-hot encoding does not take into account the similarity between URLs, while on the same time the representation size grows linearly with the corpus. In fact, one-hot encoding is sparse (curse of dimensionality) and it is not able to capture the distance between individual urls. To tackle this problem, we propose three representation schemes inspired by the idea of Word2Vec [18]. More specifically, our representation schemes use the skip-gram model that given a target word (URL in our case) tries to predict its context words. More formally, the skip-gram model tries to find word representations that can be used for predicting the words in its neighborhood. Therefore, given a sequence of words (URLs) $url_1, \ldots, url_T$, our objective is the maximisation of the average log probability

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j < c, j \neq 0} \log p(url_{i+j}|url_i),$$

where $c$ specifies the neighborhood of target URL. The conditional probability is defined by using the softmax function, as $p(url_{i+j}|url_i) \triangleq \frac{e^{\theta^T f_m(url_{i+j})}}{\sum_{k \neq i} e^{\theta^T f_m(url_k)}}$, where $\theta$ is a vector with the unknown model parameters, $b$ is the bias term and $\sigma()$ is the logistic sigmoid function. From a geometrical point of view, $\theta^T f_m(url_i) + b$ is a hyperplane that separates the two classes. To learn the unknown model parameters, the cross-entropy loss is applied:

$$\mathcal{L} = -\mathbb{E}_{(X,y)} \mathcal{L}(y \log f_c(f_m(X)) + (1-y) \log(1-f_c(f_m(X))))].$$
\[ \text{exp}(x_i, x_j) \]
\[ \sum_{c \in C} \text{exp}(x_i, x_j, c) \]

where \( x_i \) and \( x_j \) are the representations for context and target URLs respectively, and \( C \) is the set of unique words.

As the direct optimisation of Eq. 4 is computationally expensive, we are adopting the negative sampling approach [18]. In negative sampling, we treat the word’s representation learning as a binary classification task where we try to distinguish the target-context pairs of words presented on the training data from those that are not. Following the suggestions of [18], for each positive pair we are creating \( k \) negative (target-context) pairs.

In contrast to the original Word2Vec model, the proposed representation learning architectures try to learn the tokens representations, instead of the URL representations directly. A token representation is also learned for the case of a Pad token. For instance, https://en.wikipedia.org/ is mapped to \( \text{[Pad]} \).

sentiment learning architectures try to learn the tokens representations, instead of the URL representations directly. A token representation takes the average of the token embedding vectors to represent the URL. In this case, the dimension of the URL embedding vector is three times the dimension of the token embedding vectors.

For instance, let \( \{e_1\}^{3}_{i=1} \) be the token embedding vectors of the three tokens presented on url = [token1, token2, token3]. Then, the Domain_onely representation is equal to \( e_1 \), the Token_avg representation is equal to \( \frac{1}{3} \sum_{i=1}^{3} e_i \), and the Token_concat representation is given as \( [e^T_1, e^T_2, e^T_3] \). A graphical illustration of the proposed embedding learning architecture is provided in appendix.

5 EXPERIMENTS

This section presents the results of our empirical analysis. A real-world RTB dataset was used to train and analyse the performance of the ten proposed prediction models. We built our dataset by using the auction system logs from campaigns launched in France. It should be also mentioned that our dataset is anonymised, and only visited URLs are considered. In this way, each record of the dataset corresponds to a chronologically ordered sequence of visited URLs along with a binary label (specific to the advertiser) that indicates whether or not a conversion has happened on the advertiser’s website on the next day. More precisely, the data composed of sequences of URLs along with their labels of three successive dates, \( D_d, D_{d+1}, \) and \( D_{d+2} \) where \( D_d \) is used for learning representations, and \( D_{d+1} \) and \( D_{d+2} \) for training and testing the prediction models, respectively. Moreover, the maximum length of a URL sequence is set equal to 500, where only the most recently visited URLs are kept in each sequence, \( T_n \leq 500, \forall n \in [1, N] \). In total we examine the performance of the models on five advertisers, belonging to four different categories: banking, e-shop, newspaper, and telecommunications (see Table 1). Details about the statistics of the data are provided in the appendix [url link] (https://bit.ly/3SNFXU).

5.1 Settings

All our predictors assume the existence of a URL representation model in order to vectorise the sequence of URLs for each one of the dataset records. Our baseline, One_hot/LR, represents the URL sequences using a one-hot encoding vector of size 193,409, where the first two entries correspond to the “unknown” and “rare” tokens, respectively. The other models rely on an already trained embedding matrix. Each token is embedding into a 100-dimensional vector. The first three rows correspond to the “unknown”, “rare”, and Pad tokens, respectively. The rest rows contain the embedding vector of all non-rare tokens observed in the dataset \( D_d \). The number of non-rare tokens is 22,098 for the Domain_onely, and 187,916 for both the Token_Average and Token_Concatenation. To train representations, we have considered two different \( \text{[pos:neg]} \) ratios (\( \{1:1\} \) and \( \{1:4\} \)). Due to page limitations, only the results of the \( \{1:4\} \) ratio are presented in this manuscript. See supplementary material [url link] for a full comparison between these two ratios.

The number of units of the hidden dense layer (dimensionality of its output space) of DLR model is set to 30. Furthermore, the number of hidden units of LSTM is set to 10 on the RNN model. A dense layer with a sigmoid activation function is applied at the end of each one of the three mapping functions \( f_m \) (“average”, “dense”, “LSTM”) in order to form a binary classifier. Through our empirical analysis we have observed that the DLR and RNN prediction models are prone to overfitting. To enhance the generalization capabilities of these two models, we are using dropout that is set to 0.5. To be more precise, a dropout layer is added right after the \( f_m \) layer of the DLR model, while both the dropout and the recurrent_dropout parameter of LSTM layer are set equal to 0.5 on the RNN model.

For the training of all representation and prediction models, the mini-batch stochastic optimization has been applied by using Adam optimizer with the default TensorFlow 2.0 settings (i.e., \( \text{lr}=0.001 \), \( \beta_1 = 0.9 \), \( \beta_2 = 0.999 \)). More precisely, to train the representation models we are doing one full pass over the whole data that is divided to 200 parquet files. The total number of epochs is 200, equal to the number of parquet files. At each epoch we are producing the positive and negative pairs based on the data contained on a single parquet file and are feeding them to the representation model. On the other hand, the size of batches for training prediction models is 64, while the number of epochs and number of steps per epoch is set to 100 in both cases. To tackle the problem of our unbalanced dataset (see Table 1), the ratio of positive and negative records is \( \{1:1\} \) in the batches used for the training of the classifiers.

Table 1: Number of converted vs. non-converted records for each one of the 5 advertisers on the training and testing data.

| Advertiser Category | Training | Testing |
|---------------------|----------|---------|
| Banking             | (3,746 – 5,448,831) | (8,539 – 7,155,570) |
| E-shop              | (1,463 – 5,451,114) | (1,821 – 7,162,288) |
| Newspaper_1         | (1,406 – 5,451,171) | (2,923 – 7,161,186) |
| Newspaper_2         | (1,261 – 5,451,316) | (1,291 – 7,162,818) |
| Telecom             | (1,781 – 5,450,796) | (2,201 – 7,161,908) |
5.2 Results

In this section, we formally present the results of our empirical analysis. Firstly, to get an intuition about the ability of the three introduced URL embedding schemes (Sec. 4) to group together URLs that belong to the same category (i.e., sports, news, etc.), we will visualise (Fig. 12) the embedding vectors of 24 selected domains along with those of the thirty closest URLs of each one of them. To be more precise, we are using the embedding matrix learned by the Domain_only model. Cosine similarity has been used to measure the similarity between the embedding vectors of two URLs. To project the original high-dimensional embedding vectors on a 2-dimensional space, we apply the Barnes-Hut t-SNE algorithm [23].

To be guaranteed that the URLs belong to the same category with that of their closest domain, Table 2 provides the 10-nearest URLs for each one of the 24 domains (see appendix for the full list of the 30-nearest neighbors). For instance, all URLs that are on the neighborhood of expedia.fr are about travelling. Moreover, all the neighbors of sport.fr (16) are URLs about sports. The visualization of Fig. 12 illustrates the ability of our model to produce semantically meaningful embeddings. Actually, it becomes apparent that we are getting 24 clearly distinguished clusters. Moreover, we can see that the clusters of ‘similar’ domains are also close on the embedding space. For instance, the URLs embeddings of clusters (10) [auto-moto.com] and (19) [renault-laguna.com] are close as they are related to the automobile category. The same also holds for the URLs embeddings of clusters (2) [lesechos.fr], (4) [leparisien.fr], and (23) [vogue.fr] that belong to the news category.

Next, we formally present the numerical results of the ten prediction models on five different advertisers. The first part of the name of each model specifies the type of URL representation used, while the second one indicates the classifier type. To evaluate and compare the effectiveness of the models we are using the area under ROC curve (AUC) metric. More specifically, we consider the average (%) AUC across five independent runs (see Table 4), where each run corresponds to a specific seed used for the models initialisation. Moreover, Figure 4 illustrates the average ROC curves of the prediction models for each advertiser. The right plot of Fig. 4 illustrates the AUC of the models on the 25 independent runs (5 advertisers x 5 runs for each advertiser).

Based on the results presented in Table 4, the Token_avg/RNN model is more effective in predicting user’s conversions compared to the rest models. Precisely, the Token_avg/RNN model has the highest average AUC in all advertisers. All models achieve their highest performance on the newspaper advertisers. It is also worth noticing that the performances of Domain_only/LR, Token_avg/LR, and Token_concat/LR are highly competitive, compared to our baseline, One_hot/LR. More specifically, Token_concat/LR clearly outperforms One_hot/LR in 2 out of 5 advertisers (E-shop, Newspaper_1), and has slightly better performance in one of them (Newspaper_2). That remark validates our claims that the proposed representation models produce meaningful embeddings, by distinguishing URLs of the same category and placing them close to the embedding space. Taking a closer look at the standard deviations, we can see that the performance of One_hot/LR is quite stable performance in all advertisers. The right plot of Fig. 4 illustrates the AUC of the models on the 25 independent runs (5 advertisers x 5 runs for each advertiser).

Table 3: Avg (%) and std of the area under ROC curves (5 independent runs) of the 10 prediction models on 5 advertisers.

| Method                  | Adv      | Banking | E-shop | Newspaper_1 | Newspaper_2 | Telecom |
|-------------------------|----------|---------|--------|-------------|-------------|---------|
| One_hot/LR              | 65.7 ± 0.985 | 64.4 ± 0.053 | 74.1 ± 0.379 | 71.6 ± 0.400 | 65.4 ± 0.085 |
| Domain_only/LR          | 69.0 ± 2.184 | 67.2 ± 0.248 | 79.8 ± 0.342 | 75.7 ± 0.658 | 66.0 ± 3.014 |
| Domain_only/RNN         | 71.4 ± 0.144 | 76.9 ± 0.422 | 80.0 ± 0.168 | 77.4 ± 0.261 | 71.2 ± 0.230 |
| Token_avg/LR            | 64.3 ± 0.241 | 67.2 ± 0.396 | 76.6 ± 0.132 | 73.1 ± 0.184 | 62.9 ± 0.468 |
| Token_avg/RNN           | 67.4 ± 0.295 | 72.1 ± 0.263 | 79.2 ± 0.242 | 77.7 ± 0.274 | 67.9 ± 0.348 |
| Token_concat/LR         | 71.9 ± 0.082 | 74.1 ± 0.246 | 81.2 ± 0.155 | 80.2 ± 0.322 | 71.4 ± 0.154 |
| Token_concat/RNN        | 64.3 ± 0.241 | 67.2 ± 0.060 | 76.7 ± 0.179 | 73.4 ± 0.273 | 63.6 ± 0.425 |
| Domain_only/LR          | 69.1 ± 0.224 | 75.5 ± 0.460 | 80.5 ± 0.192 | 79.1 ± 0.130 | 70.5 ± 0.278 |

Table 2: The 10-nearest neighbors of 24 different domains according to our trained Domain_only representation model.

| URL                  | Domain | Category   | Token_concat/RNN | Domain_only/LR | One_hot/LR | Token_concat/LR | Token_avg/LR | Token_avg/RNN | Domain_only/RNN |
|----------------------|--------|------------|------------------|----------------|------------|-----------------|--------------|---------------|-----------------|
| tempsdecuisson.net   | 24     | Food       | 0.69             | 0.67           | 0.70       | 0.68            | 0.69         | 0.68          | 0.69            |
| tempsdecuisson.info  | 24     | Food       | 0.69             | 0.67           | 0.70       | 0.68            | 0.69         | 0.68          | 0.69            |
| tempsdecuisson.fr    | 24     | Food       | 0.69             | 0.67           | 0.70       | 0.68            | 0.69         | 0.68          | 0.69            |
Let us now compare the impact of the type of classifier on the performance of the prediction model. The overall comparison presented at Fig. 4 demonstrates that both DLR and RNN performs significantly better compared to LR, with the RNN to be the best one. More precisely, the AUC of RNN is around ~7% and ~3% higher compared to those of LR and DLR, respectively. This means that the consideration of the chronological order in which the URLs appeared on the sequence is of high importance. On the other hand, choosing DLR over LR improves around ~4% the performance of the prediction models independent to the representation model.

To sum up, the main conclusions of our empirical analysis are: i) all three proposed URL embedding models are able to learn high-quality vector representations that precisely capture the URL relationships, ii) the performance of the LR model is relatively invariant to the selection of the representation model, iii) among the three representation models, Token_avg is more adequate to capture the relationship between URLs, with the Token_concat second best, iv) the consideration of the chronological order of the visited URLs (RNN) and the learning of dependencies among the embedding features (DLR) are also of high importance as both improve significantly the performance of the prediction model.

6 CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we considered the problem of user response prediction in display advertising. Ten conversion prediction models were proposed to predict user response based on their browsing history. To represent the sequence of visited URLs, four different compact URL representations were examined. The effectiveness of the proposed models has been experimentally demonstrated offline in a real-world RTB dataset for five different advertisers. The impact of the sequential dependency between users’ visited URLs on the performance of the predictors has been also examined. The main conclusions of our empirical analysis were that all three proposed representation models produce a meaningful URL representation, and considering the chronological order of the visited URLs by using RNN significantly improves the model’s performance. In the future, we intend to propose an online version of our framework and to extend our empirical analysis to a real-world online scenario.

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SUPPLEMENTARY MATERIAL

The purpose of this Supplementary Material is to provide more details about: i) the proposed representation and prediction conversion model architectures, ii) the statistics of data, and iii) present additional experimental results. First in Section A, we illustrate graphically and explain the architecture of the prediction model. Next, Section B presents some statistics for the three data used for the representation training and for the training and testing of the representation and prediction models. Finally, Section C reports some additional experiments where we examine the impact of the \( \{\text{pos: neg}\} \) ratio (used for representation training) on the learning of meaningful URL representations and on the performance of the final prediction model.

A PREDICTION CONVERSION MODEL ARCHITECTURE

A graphical illustration of the proposed prediction conversion model architecture is presented in this section. The objective of the proposed model is to predict with high accuracy if a user will be converted or not given his browsing history. Actually, the proposed conversion prediction scheme is composed of two consecutive training phases. The first one corresponds to the learning of the URL representations, while the second one corresponds to the training of a classifier. It should be mentioned that the training processes of these two models are independent. A high-level overview of the pipelines of these two training phases is illustrated at Fig.5.

Figure 5: URL representation and conversion classifier learning pipeline. The binary labels are not needed for training the URL representation model.

Figure 6 shows the three basic ‘blocks’ of our prediction model. First, the URL representation layer, \( f_r: \text{url} \rightarrow x \), maps a single \text{url} into a vector on the embedding space. For this purpose, a URL representation model is trained in advance to learn meaningful \text{url} representations. Second, the mapping \( f_m: X \rightarrow z \) aggregates the URLs embeddings and produces a single compact representation \( z \) for the sequence of the URLs. Three different mapping functions \( f_m \) examined in our work: the first one \( f_m^{(1)} \) just returns the average of the URLs embedding vector, the second one \( f_m^{(2)} \) considers the dependencies among the features of the embedding vector returned by the first mapping function, and the third one \( f_m^{(3)} \) uses an LSTM network \([6, 12]\). Finally, standard logistic regression (dense layer with a sigmoid activation function) is applied to estimate the user conversion probability.

Figure 7 illustrates a variant of the negative sampling skip-gram model \([17, 18]\) used for learning url semantic meaningful representations. In general, skip-gram produces embedding vectors such that the embedding vector of \text{url}_t is close to the embedding vectors of the URLs of its neighborhood. Therefore, the url’s representation learning is treated as a binary classification task where we try to distinguish the pairs of URLs presented close on the sequences. The main difference between our architecture with the standard one is the Target URL embedding layer (and the Context URL embedding layer). This layer combines the token representations and forms the final URL representation. Roughly speaking, the proposed representation model learns an embedding matrix where each row corresponds to a token appearing in the URLs of our data. To form the URL representation, we are combining the embedding vectors of each token appearing in the URL. In this work, we examine three different ways for combining token representations to form the final URL embedding vector (for more details, check Sec. 4 of the paper).

B DATASET STATISTICS

Figure 8 presents an analysis of the URL sequence lengths for \( \mathcal{D}_d \), \( \mathcal{D}_{d+1} \), and \( \mathcal{D}_{d+2} \). To be more precise, the distribution of the URL sequence lengths is given. As it can be easily observed, the length of the URL sequences for most of the records is less than 500. Due to this fact, for the training and testing of our prediction models we are using the 500 most recent visited URLs of each sequence. On the other hand, for the training of the representation the whole sequences are used.

In our setting, a URL is split with a ‘/’ (slash) character and it is supposed to consist of at most three tokens. Figure 9 shows the token frequency distribution of the first three URL tokens for each dataset. As it was expected, the tokens at the last two spots are more rare in the data. Also, the number of unique tokens in the first place \( \text{(domain token)} \) is significantly smaller than the number of unique tokens on the other two spots. In our analysis, we consider a token “rare” if it appears less than 20 times.

C ADDITIONAL RESULTS

Next, we report the results of our complete empirical analysis, where we examine the impact of the selection of the \( \{\text{pos: neg}\} \) ratio (representation training) on the performance of the prediction model. More specifically, we present the performance of nineteen prediction models on the five advertisers described in the manuscript. In order to distinguish the nineteen different models, their names consist of three parts separated by a slash ('/') character apart from the \text{One_hot/LR} model. The first part indicates the type of representation \( \text{(Domain_only, Token_avg, Token_concat)} \), the second defines the kind of prediction model \( \text{(LR, DLR, RNN)} \), and the last one shows the \( \{\text{pos: neg}\} \) ratio \((1:1), (1:4)\) used for the training of the representation model.
Figure 6: Proposed conversion prediction model architecture. It consists of three main parts: i) URL embedding layer \( f_r \), ii) URL sequence embedding layer \( f_m \), and iii) Logistic regression classifier \( f_c \). Only the unknown classifier parameters, \( \theta \) and \( b \), (see Eq. 2 of the paper) of the dense layer and these of LSTM and "dense" mappings are trainable.

As already highlighted at the paper, the area under ROC curve (AUC) is the metric that used to evaluate the prediction capabilities of each model. Table 4 presents the average AUC of each model across five independent runs (five randomly selected seeds). Moreover, Figures 10 and 11 illustrate the average ROC curves of the ten prediction models for each advertiser, where \( \{1:1\} \) and \( \{1:4\} \) \{pos:neg\} ratios used for training representation models, respectively. Next, we present the main conclusions of our "full" empirical analysis:

- All three proposed URL embedding models are able to learn high-quality vector representations that capture precisely the URL relationships. Even the \( \text{Domain\ only}/LR \), \( \text{Token\ avg}/LR \), and \( \text{Token\ concat}/LR \) models are able to predict with high accuracy the probability a user to be converted, and their performance is quite close or better compared to that of our baseline \( \text{One\ hot}/LR \).
- It can be easily verified by the reported results that the prediction model performance is not so sensitive on the \{pos:neg\} ratio used for training representation models.
- \( \{1:1\} \) performs better on the \( \text{Domain\ only} \) representation compared to \( \{1:4\} \) that performs better on Token\_avg. On the other hand, the performance of both \{pos:neg\} ratios are almost equivalent for the Token\_concat model.
- Among the three representation models, Token\_avg seems to be more adequate to capture the relationships between URLs, with the Token\_concat to be the second best. Moreover, the performance of Domain\_only representation is quite close to that of Token\_concat.
- The consideration of the chronological order of the visited URLs (RNN) and the learning of dependencies among the embedding features (DLR) are also of high importance as both improve significantly the performance of the conversion prediction model. To be more precise, it is clear (see bottom right plot of Fig. 10 and Fig. 11) that the RNN model surpass the performance of the rest two classifiers, while DLR performs better compared to LR.
- The best prediction conversion models are \( \text{Domain\ only}/RNN \) and \( \text{Token\ avg}/RNN \) for \( \{1:1\} \) and \( \{1:4\} \) \{pos:neg\} ratios, respectively (see bottom right plot of Figs. 10 and Fig. 11).

C.1 Representation Visualisation

In this section we visualise the embedding vectors of 24 selected domains along with those of the thirty closest URLs of each one of them, which have been learned by \( \text{Domain}/1:1 \) (Fig. 12a) and \( \text{Domain}/1:4 \) (Fig. 12b) representation models. Looking carefully
Figure 7: The Skip-gram model architecture used for learning token embeddings. Only the (unknown) parameters of the red blocks are trainable. The dimensionality of the embedding matrices is equal to the number of tokens \( \times \) the preferable size of the embedding space.

Figure 8: Analysis of the URL sequences lengths for the data, \( D_d \), \( D_{d+1} \), and \( D_{d+2} \).
Figure 9: Analysis of URL tokens frequencies. X-axis represents the number of times a token is present in the dataset and y-axis shows the number of tokens. In parentheses we give the number of unique tokens.
Table 4: Average (%) and standard deviation of the area under ROC curves (5 independent runs) of the 10 prediction models on 5 different campaigns.

| Method            | Bankings | E-shop | Newspaper_1 | Newspaper_2 | Telecom |
|-------------------|----------|--------|-------------|-------------|---------|
| One_hot/LR        | 65.7 ± 0.093 | 66.4 ± 0.053 | 75.5 ± 0.379 | 73.3 ± 0.400 | 65.4 ± 0.085 |
| Domain_only/LR/1:1| 64.9 ± 0.138 | 66.7 ± 0.237 | 76.1 ± 0.109 | 72.9 ± 0.219 | 63.4 ± 0.479 |
| Domain_only/LR/1:4| 64.6 ± 0.300 | 66.6 ± 0.217 | 75.7 ± 0.507 | 73.2 ± 0.345 | 63.2 ± 0.168 |
| Domain_only/DR/1:1| 69.2 ± 0.268 | 70.3 ± 0.383 | 77.4 ± 0.397 | 76.7 ± 0.333 | 67.0 ± 0.370 |
| Domain_only/DR/1:4| 69.0 ± 0.214 | 69.7 ± 0.234 | 76.8 ± 0.342 | 75.7 ± 0.658 | 66.6 ± 0.303 |
| Domain_only/RNN/1:1| 71.9 ± 0.258 | 72.9 ± 0.149 | 80.3 ± 0.149 | 79.7 ± 0.146 | 71.7 ± 0.252 |
| Domain_only/RNN/1:4| 71.4 ± 0.144 | 72.6 ± 0.422 | 80.3 ± 0.168 | 79.4 ± 0.281 | 71.2 ± 0.250 |
| Token_avg/LR/1:1  | 63.6 ± 0.188 | 66.4 ± 0.438 | 76.1 ± 0.076 | 72.3 ± 0.466 | 62.3 ± 0.380 |
| Token_avg/LR/1:4  | 64.5 ± 0.241 | 67.2 ± 0.390 | 76.4 ± 0.152 | 73.1 ± 0.184 | 62.9 ± 0.468 |
| Token_avg/DR/1:1  | 68.9 ± 0.148 | 71.5 ± 0.219 | 78.9 ± 0.175 | 77.3 ± 0.279 | 67.3 ± 0.263 |
| Token_avg/DR/1:4  | 69.4 ± 0.294 | 72.1 ± 0.263 | 79.2 ± 0.242 | 77.7 ± 0.274 | 67.9 ± 0.348 |
| Token_avg/RNN/1:1 | 71.7 ± 0.116 | 72.9 ± 0.184 | 80.8 ± 0.121 | 79.5 ± 0.119 | 71.4 ± 0.209 |
| Token_avg/RNN/1:4 | 71.9 ± 0.082 | 73.1 ± 0.246 | 81.2 ± 0.153 | 80.2 ± 0.322 | 71.8 ± 0.153 |
| Token_concat/LR/1:1| 64.5 ± 0.142 | 67.3 ± 0.149 | 76.6 ± 0.174 | 73.3 ± 0.216 | 63.3 ± 0.672 |
| Token_concat/LR/1:4| 64.8 ± 0.241 | 67.2 ± 0.060 | 76.7 ± 0.179 | 73.4 ± 0.273 | 63.6 ± 0.425 |
| Token_concat/DR/1:1| 69.0 ± 0.187 | 71.2 ± 0.274 | 78.7 ± 0.304 | 76.7 ± 0.232 | 67.0 ± 0.469 |
| Token_concat/DR/1:4| 69.1 ± 0.222 | 70.8 ± 0.400 | 78.2 ± 0.285 | 76.7 ± 0.255 | 66.9 ± 0.310 |
| Token_concat/RNN/1:1| 71.5 ± 0.214 | 72.5 ± 0.264 | 80.9 ± 0.286 | 79.4 ± 0.318 | 71.2 ± 0.180 |
| Token_concat/RNN/1:4| 71.5 ± 0.224 | 72.5 ± 0.460 | 80.5 ± 0.192 | 79.1 ± 0.130 | 70.5 ± 0.278 |

At Fig. 12, we observe that clusters close on the embedding space produced by Domain/1:1 are also close on the embedding space of Domain/1:4. For instance, clusters 6 [expedia.fr] and 24 [tripadvisor.fr] are close in both cases. That is normal, as these two clusters contain URLs about travelling. The same also holds for the URLs embeddings of clusters (2) [lesechos.fr], (4) [leparisien.fr], and (23) [vogue.fr] that belong to the news category. Moreover, clusters (10) [auto-moto.com] and (19) [renault-laguna.com] are also close as both are related to automobile. Another example is that of clusters 16 [anti-crise.fr] and 17 [auchan.fr] that are about promotions. To be sure that the URLs belong to the same category (and are not just random URLs) with that of their closest domain, Tables 5 and 6 provide the 30-nearest URLs for each one of the 24 domains for the Domain/1:1 and Domain/1:4, respectively. Finally, Fig. 13 illustrates the t-SNE visualization of the embedding matrix (22101 × 100) trained by Domain_only/1:4 representation model after 0, 50, 100, 150, and 200 epochs, respectively.
Table 5: The 30-nearest neighbors of 24 different domains according to our trained Domain_only/1:1 representation model.

| Domain                                                                 | 30-nearest neighbors (URLs)                                                                                     |
|----------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| huffpostpostes                                                        | sevilla.abc.es; ricicloudicentro.com; stodata elpais.com; verne epasa.com; elmon.cat; tietores.com; expansion.com; infotribu.es; vozpopuli.com; blogs.elconfidencial.com; eldiario.com; copex.es; eldia.es; elpais.es; espaulew.com; ekasa.cat; noticias.emv.com; telecinque.com; telecinquetv.com; tvtoday.com; viva.com |
### Table 6: The 30-nearest neighbors of 24 different domains according to our trained Domain-only/1:4 representation model.

| Domain |
|--------|
| huffingtonpost.es |
| zeit.de; sueddeutsche.de; faz.net; tagesspiegel.de; sport1.de; kicker.de; saarbruecker-zeitung.de; tz.de; bild.de; promiflash.de; focus.de; transfermarkt.de; finanzen.net; sport.de; flashscore.de; rp-online.de; stylebook.de |
| infomercato.fr; parisfans.fr; topmercato.com; vipsg.fr; footradio.com; mercatolive.fr; footballclubdemarseille.fr; parisunited.fr; football-addict.com; olympique-et-lyonnais.com; football.fr |
| Predicting conversions in display advertising based on URL embeddings AdKDD '20, August 23, 2020, San Diego, CA, USA |
| Table 6: The tempsdecuisson.net |
| farmville2free.com |
| huffingtonpost.es |
| auto-moto.com |
| jeuxvideo.org |
| tripadvisor.fr |
| excel-plus.fr |
| portail-cloture.ooreka.fr |
| arz-online.de |
| portail-cloture.ooreka.fr |
| contacter.unesco.fr |
| arkhamhorrorfr.forumactif.com |
| en.riotpixels.com |
| pexiweb.be |
| petri.com |
| rasage-traditionnel.com |
| tech-connect.info |
| thehackernews.com |
| lecompagnon.info |
| panoptinet.com |
| slice42.com |
| aliasdmc.fr |
| astuces.jeanviet.info |
| faclic.com |
| alvinalexander.com |
| thegeekstuff.com |
| hirensbootcd.org |
| faqword.com |
| openshot.org |
| zoomonapps.com |
| megane3.fr |
| gps-carminat.com |
| megane2.superforum.fr |
| lesamisdudiag.com |
| car-actu.com |
| diagnostic-auto.com |
| tlemcen-electronic.com |
| focusrstteam.com |
| 306inside.com |
| cmonofr.net |
| 207.fr |
| automobile-conseil.fr |
| gamblewiz.com |
| flux-info.fr |
| elmostrador.cl |
| makaan.com |
| univ-montp3.academia.edu |
| e-lawresources.co.uk |
| babycenter.com |
| newocr.com |
| mindtools.com |
| medicoresponde.com.br |
| br.rfi.fr; lazycatkitchen.com |
| realmenrealstyle.com |
| eve-adam.over-blog.com |
| huffingtonpost.es |
| zeit.de; sueddeutsche.de; faz.net; tagesspiegel.de; sport1.de; kicker.de; saarbruecker-zeitung.de; tz.de; bild.de; promiflash.de; focus.de; transfermarkt.de; finanzen.net; sport.de; flashscore.de; rp-online.de; stylebook.de |
| infomercato.fr; parisfans.fr; topmercato.com; vipsg.fr; footradio.com; mercatolive.fr; footballclubdemarseille.fr; parisunited.fr; football-addict.com; olympique-et-lyonnais.com; football.fr |
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| excel-plus.fr |
| portail-cloture.ooreka.fr |
| arz-online.de |
| portail-cloture.ooreka.fr |
| contacter.unesco.fr |
| arkhamhorrorfr.forumactif.com |
| en.riotpixels.com |
| pexiweb.be |
| petri.com |
| rasage-traditionnel.com |
| tech-connect.info |
| thehackernews.com |
| lecompagnon.info |
| panoptinet.com |
| slice42.com |
| aliasdmc.fr |
| astuces.jeanviet.info |
| faclic.com |
| alvinalexander.com |
| thegeekstuff.com |
| hirensbootcd.org |
| faqword.com |
| openshot.org |
| zoomonapps.com |
| megane3.fr |
| gps-carminat.com |
| megane2.superforum.fr |
| lesamisdudiag.com |
| car-actu.com |
| diagnostic-auto.com |
| tlemcen-electronic.com |
| focusrstteam.com |
| 306inside.com |
| cmonofr.net |
| 207.fr |
| automobile-conseil.fr |
| gamblewiz.com |
| flux-info.fr |
| elmostrador.cl |
| makaan.com |
| univ-montp3.academia.edu |
| e-lawresources.co.uk |
| babycenter.com |
| newocr.com |
| mindtools.com |
| medicoresponde.com.br |
| br.rfi.fr; lazycatkitchen.com |
| realmenrealstyle.com |
| eve-adam.over-blog.com |
| huffingtonpost.es |
| zeit.de; sueddeutsche.de; faz.net; tagesspiegel.de; sport1.de; kicker.de; saarbruecker-zeitung.de; tz.de; bild.de; promiflash.de; focus.de; transfermarkt.de; finanzen.net; sport.de; flashscore.de; rp-online.de; stylebook.de |
| infomercato.fr; parisfans.fr; topmercato.com; vipsg.fr; footradio.com; mercatolive.fr; footballclubdemarseille.fr; parisunited.fr; football-addict.com; olympique-et-lyonnais.com; football.fr |
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| excel-plus.fr |
| portail-cloture.ooreka.fr |
| arz-online.de |
| portail-cloture.ooreka.fr |
| contacter.unesco.fr |
| arkhamhorrorfr.forumactif.com |
| en.riotpixels.com |
| pexiweb.be |
| petri.com |
| rasage-traditionnel.com |
| tech-connect.info |
| thehackernews.com |
| lecompagnon.info |
| panoptinet.com |
| slice42.com |
| aliasdmc.fr |
| astuces.jeanviet.info |
| faclic.com |
| alvinalexander.com |
| thegeekstuff.com |
| hirensbootcd.org |
| faqword.com |
| openshot.org |
| zoomonapps.com |
| megane3.fr |
| gps-carminat.com |
| megane2.superforum.fr |
| lesamisdudiag.com |
| car-actu.com |
| diagnostic-auto.com |
| tlemcen-electronic.com |
| focusrstteam.com |
| 306inside.com |
| cmonofr.net |
| 207.fr |
| automobile-conseil.fr |
| gamblewiz.com |
| flux-info.fr |
| elmostrador.cl |
| makaan.com |
| univ-montp3.academia.edu |
| e-lawresources.co.uk |
| babycenter.com |
| newocr.com |
| mindtools.com |
| medicoresponde.com.br |
| br.rfi.fr; lazycatkitchen.com |
| realmenrealstyle.com |
| eve-adam.over-blog.com |
| huffingtonpost.es |
| zeit.de; sueddeutsche.de; faz.net; tagesspiegel.de; sport1.de; kicker.de; saarbruecker-zeitung.de; tz.de; bild.de; promiflash.de; focus.de; transfermarkt.de; finanzen.net; sport.de; flashscore.de; rp-online.de; stylebook.de |
| infomercato.fr; parisfans.fr; topmercato.com; vipsg.fr; footradio.com; mercatolive.fr; footballclubdemarseille.fr; parisunited.fr; football-addict.com; olympique-et-lyonnais.com; football.fr |
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| excel-plus.fr |
| portail-cloture.ooreka.fr |
| arz-online.de |
| portail-cloture.ooreka.fr |
| contacter.unesco.fr |
| arkhamhorrorfr.forumactif.com |
| en.riotpixels.com |
| pexiweb.be |
| petri.com |
| rasage-traditionnel.com |
| tech-connect.info |
| thehackernews.com |
| lecompagnon.info |
| panoptinet.com |
| slice42.com |
| aliasdmc.fr |
| astuces.jeanviet.info |
| faclic.com |
| alvinalexander.com |
| thegeekstuff.com |
| hirensbootcd.org |
| faqword.com |
| openshot.org |
| zoomonapps.com |
| megane3.fr |
| gps-carminat.com |
| megane2.superforum.fr |
| lesamisdudiag.com |
| car-actu.com |
| diagnostic-auto.com |
| tlemcen-electronic.com |
| focusrstteam.com |
| 306inside.com |
| cmonofr.net |
| 207.fr |
| automobile-conseil.fr |
| gamblewiz.com |
| flux-info.fr |
| elmostrador.cl |
| makaan.com |
| univ-montp3.academia.edu |
| e-lawresources.co.uk |
| babycenter.com |
| newocr.com |
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Figure 10: Average ROC curves of the ten conversion prediction (1:1 pos-neg ratio) models on the five advertisers. Shaded regions represent the standard deviations over 5 independent runs. The bottom right plot presents the AUC for each one of the 25 independent runs (5 advertisers × 5 independent runs for each advertiser) of each model. The •, ▼ and × marks indicate the LR, DLR and RNN classification models, respectively.
Figure 11: Average ROC curves of the ten conversion prediction (1:4 pos-neg ratio) models on the five advertisers. Shaded regions represent the standard deviations over 5 independent runs. The bottom right plot presents the AUC for each one of the 25 independent runs (5 advertisers × 5 independent runs for each advertiser) of each model. The •, ▼ and × marks indicate the LR, DLR and RNN classification models, respectively.
Figure 12: t-SNE visualization of the thirty closest neighbors of 24 different domains. The colors of the points indicate the closest domain of each URL.
Figure 13: t-SNE visualization of the embedding matrix trained by Domain_only/1:4 representation model after 0, 50, 100, 150, and 200 epochs, respectively.