Click Maximization in Online Social Networks Using Optimal Choice of Targeted Interests

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Abstract—Click-through rate (CTR) prediction of advertisements on online social network platforms to optimize advertising is of much interest. Prior works build machine learning models that take a user-centric approach in terms of training — using predominantly user data to classify whether a user will click on an advertisement or not. While this approach has proven effective, it is inaccessible to most entities and relies heavily on user data. To accommodate for this, we first consider a large set of advertisement data on Facebook and use natural language processing (NLP) to extract key concepts that we call conceptual nodes. To predict the value of CTR for a combination of conceptual nodes, we use the advertisement data to train four machine learning (ML) models. We then cast the problem of finding the optimal combination of conceptual nodes as an optimization problem. Given a certain budget k, we are interested in finding the optimal combination of conceptual nodes that maximize the CTR. A discussion of the hardness and possible NP-hardness of the optimization problem is provided. Then, we propose a greedy algorithm and a genetic algorithm to find near-optimal combinations of conceptual nodes in polynomial time, with the genetic algorithm nearly matching the optimal solution. We observe that Decision Tree Regressor and Random Forest Regressor exhibit the highest Pearson correlation coefficients w.r.t. click predictions and real click values. Additionally, we find that the conceptual nodes of “politics”, “celebrity”, and “organization” are notably more influential than other considered conceptual nodes.

Index Terms—click prediction, online social networks, optimization, machine learning

I. INTRODUCTION

Social media platforms allow for accessible, immediate, and wide-spanning interactions with people across the globe — allowing for social interaction not previously possible. With the wide adoption of these platforms, much effort is made, in part, by businesses and corporations to market products on these platforms to reach potential customers [1], [2], [3]. Increasingly, political organizations and outside nations may also seek to influence political attitudes and voting behavior, using these platforms [4]. In order to increase their influence across a platform, stakeholders will target certain interests, demographics, topics, etc. to promote their product or cause [5], [6]. With this vested need to try to more effectively market information and products to users of these platforms, there is an interest in understanding how and why people interact with certain information on these social media platforms [7], [8]. A better understanding of how to design advertisements to attract more clicks from users has many practical applications. For instance, this can be used to more effectively propagate vital information throughout a population or to better sell a product. It could also give us some insight as to how misinformation spreads on social media platforms so that further research can be committed to preventing such phenomena.

Click-through rate (CTR) prediction is a domain of research invested in developing systems that can predict how users will respond, in the measure of clicks, to given content (though usually advertisements). Contextual advertising is where advertisements are placed in contexts specific to an individual user, so decisions as to which advertisement to display in CTR prediction is often based on user data [9], [10], [11]. These works rely heavily on having direct access to rich user data to train their learning models and improve their accuracy over time. Some of the state-of-the-art works modeling approaches to these problems are described in detail in Section II. However, for our work, we are more interested in understanding how features related to the advertisements themselves can be used to perform CTR prediction, and which features attract more CTR. From there, this work studies selecting the optimal combination of targeted interests as an optimization problem and proposes algorithms to maximize expected clicks using an approach to CTR prediction that does not touch sensitive user data and maintains user privacy. Additionally, there is interest as to which topics, themes, sentiments, etc. drive more people to click advertisements.

To support this work, we use data provided by the U.S. Congress. These data contain controversial, misleading, and/or hyperbolic advertisements distributed on Facebook as part of Russia’s (mis)information campaign leading up to and after the U.S. 2016 presidential election. These data containing advertisements purchased by the Internet Research Agency (IRA) — a notorious Russian “troll” farm — were made freely and publicly available by the U.S. Congress [12]. To the best of our knowledge, this is the only investigatory study of CTR prediction using this dataset. Using these data, we perform a novel approach to CTR prediction. What separates our method for CTR prediction from the state-of-the-art CTR prediction models (in contextual advertising) is the lack of access to user data. For this work, we are not interested in asking whether a user will click on an advertisement or not; instead we are interested in understanding which features of advertisements lead to high CTR. The contributions of this paper can be summarized in the following points:
• Model the problem of CTR maximization as an optimization problem, “OCNC” problem, and discuss the NP-hardness of OCNC.
• Introduce the notion of conceptual nodes to encapsulate themes of targeted interests to perform CTR prediction whilst preserving user privacy by not using user data.
• Propose efficient genetic and greedy algorithms to optimally select conceptual node combinations to maximize expected clicks of advertisements.
• Social insights on which conceptual nodes were the most effective at attracting users to click advertisements on Facebook. These insights provide some guidelines on potentially effective advertisement strategies, and can be used for designing more efficient advertisements.

II. RELATED WORKS

Much work has been devoted to predicting click-through rates (CTR) of online advertisements. In this domain of study, there are typically two different flavors of online advertisements considered: sponsored search and contextual advertising. The former deals with static webpages and placing advertisements w.r.t. to a search query provided by a user [7], [8]. The latter deals with more user-centric approaches that select advertisements that are more appropriate for a given user based on historic data, categorized interests, etc. When considering CTR prediction for advertisements in social media platforms, contextual advertising is more appropriate.

For contextual advertising on social media platforms, much work has been done to accurately predict CTR for advertisements. He et al. in [9] considered interests and demographics of users on Facebook for their classifier models that are built on top of decision tree and logistic regressor models. Their model is then incorporated in a recurrent architecture to continually improve accuracy over time as the model continues to get feedback from users. The authors in [10] introduced a learning-to-rank model to predict CTR of advertisements placed in a unique online Twitter stream, composed of Tweets shared by a user’s followees. Predictions made by this model are based on user-specific input features. Researchers at Alibaba in [11] introduced a novel Deep Interest Network model that uses historical user data that adaptively learns user interests over time to improve CTR prediction. A central commonality of these works is that they all are user-centric — where their model is most interested in classifying whether an individual user will click a given advertisement or not. The models these works describe all rely on user data (interests, demographics, historical data, etc.) to predict whether a given user will click an advertisement before deciding whether to display the advertisement for the user under consideration.

While these works are very interesting and make great steps forward for CTR prediction for contextual advertising, for our work we are interested in conducting an content-aware approach. Rather than investigate how to best predict whether a user will click an advertisement based on user features, we are interested in predicting how many clicks an advertisement will receive based on input features specific for that advertisement’s content, targeted interests, etc., while ignoring user data entirely. This work is motivated by the increasing sensitivity surrounding how user data is used by OSN platforms to support many necessary for these services. We are additionally motivated to gain high-level insights to better understand what interests lead to higher CTR across advertisements and, more generally, across information shared on online social media platforms.

III. DATA DESCRIPTION

For this work, we study and analyze data provided by the U.S. Congress — which, from now on, we will refer to as the IRA data. Here, we provide some important measures of the data and describe our interest in it. The IRA data contains 3,519 PDF documents, with each PDF document containing information pertaining to a single advertisement. More than 11.4 million Americans were exposed to the advertisements featured in the IRA data [13] that we will be using for the bedrock of our analysis.

IV. CONCEPTUAL NODES

As mentioned in Section III, each advertisement in the IRA data provides some important features to consider. One of the most interesting features to consider is targeted interests. This feature provides a list of curated interests that allow an advertisement to focus on people with interests in this list. For analysis, we wish to abstract the wide variety of targeted interests the entirety of this data-set includes. To do this, we introduce the notion of conceptual nodes. We
consider conceptual nodes to essentially serve as categorical markers for these interests. Using individual targeted interests to train machine learning models to predict CTR would be too granular. So, we use conceptual nodes to provide some level of abstraction and, essentially, clump together targeted interests into groups — irrespective of how (in)frequently a targeted interest appears in the IRA data. Under this construct, “LGBTQ+” and “African American” can both belong to the same conceptual node because of their possible thematic similarities. For this work, we consider a fixed set of conceptual nodes. The set of conceptual nodes considered for this work \( \mathcal{N} \) are as follows: celebrity, identity, news, organization, politics, and religion. We chose these conceptual nodes to be general enough to accommodate the diversity of the targeted interests upon reading through a large number of advertisements in the IRA data. Further, these conceptual nodes were decided upon experimenting with different sets of conceptual nodes and seeing that these generally performed well at encapsulating the targeted interests — of course, this could always be reconsidered for future works.

To map targeted interests to conceptual nodes, we employ natural language processing (NLP) models to learn word embeddings to approximately map targeted interests to appropriate conceptual nodes. The NLP model we employ for this work is Facebook’s fastText model \([13, 15]\). This model is an extension of the well-studied Word2Vec model \([16]\). Both models are unsupervised learning models, meaning that they can learn and recognize semantic features of words without the extra step of someone manually providing labeled data. An advantage that fastText has over Word2Vec is that it can learn and recognize semantic features of words without the extra step of someone manually providing labeled data. An advantage that fastText has over Word2Vec is that it decomposes words it does not immediately recognize into smaller \( n \)-grams such that it can then approximate semantic values. For instance, if a fastText model’s vocabulary does not include the word “colors”, but it does contain the word “color”, the fastText model will then break up the word into the following \( n \)-grams to calculate an approximate semantic value: “color” and “s”. To generate a large set of training corpus, we employ a recursive scraper we call \( \mu \)-Scraper. This approach to scraping text data is elaborated in detail in Section IV-A.

Each considered conceptual node will have a fastText model trained with its own training corpus. Upon having a trained fastText model for each conceptual node, a targeted interest \( i \) will be passed into each conceptual node’s model to generate a value of semantic similarity. A targeted interest is then mapped to the conceptual node whose fastText model produces the highest semantic similarity value.

**A. Textual Data Collection**

In order to collect a large amount of pertinent natural language data to train a fastText model, we use a recursive scraper that strips text data from Wikipedia articles using their open-source Python API \([\text{https://pypi.org/project/wikipedia/}]\). The procedure for the scraping algorithm takes arguments of a starting article title and some integer, \( \mu \), and can be described as follows:

1) Given an initially empty set \( V \), add the root Wikipedia article title \( t \).
2) If \( \mu > 0 \), then repeat the process for each Wikipedia article link \( l \) in the article provided by \( t \) but for \( \mu - 1 \) and with the now non-empty \( V \).
3) Upon collecting all Wikipedia article titles in the scraping process, then pull the text data from each Wikipedia article in \( V \) and output the entirety of this data to a text file to be used for training.

For our work, we consider the following set of starting article titles on Wikipedia and perform the described procedure for each starting article: “celebrity”, “identity”, “news”, “organization”, “politics”, and “religion”. These Wikipedia starting articles correspond with a single conceptual node and are used to generate corresponding text files to train corresponding fastText models to classify targeted interests into conceptual nodes. It is intuitively obvious that the run-time of this algorithm exponentially increases with respect to \( \mu \). We can grossly consider this algorithm to have a run-time of approximately \( O(n^\mu) \) where \( n \) is the largest number of linked articles among all the articles explored.

It is important to note that this algorithm may require trial-and-error. While scraping, we found the training text data generated when \( \mu = 0 \) to result in models that produced seemingly random conceptual node classifications. Intuitively, if we increase \( \mu \) to \( \mu = 1 \), the fastText models would be provided with more text and thus more accurate results would be produced. We found that in the case of \( \mu = 1 \), 92.857% of targeted interests were classified as belonging to the same conceptual node. However, upon letting \( \mu = 2 \), we saw more appropriate results and a more expected distribution of conceptual node assignments. Note: scraping for when \( \mu = 2 \) took several days to finish. For context, the machine we performed scraping with was equipped with an Intel Core i7-7700 quad-core processor with 32 GB of RAM.

**V. LEARNING MODELS**

A prominent aim of this work is to explore methods that effectively approximate the CTR of advertisements on Facebook based on the conceptual nodes of targeted interests. To do this, we employ the following learning models: AdaBoost regressor (ABR) \([17]\), decision tree regressor (DTR) \([18]\), multi-layer perceptron regressor (MLP) \([19]\), and random forest regressor (RFR) \([20]\). For this work, we use the implementations of these machine learning models supplied by the SciKit-Learn API \([21]\). The ABR model fits a regressor on an original data-set, fitting additional copies under the same regressor, while adjusting weights of instances according to error of the current prediction. The DTR model fits data under a sine curve and learns local linear regressions by approximating the sine curve. The MLP model is a supervised model that learns a non-linear function \( f(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^n \) by training on a data-set under a set of provided features. The RFR model is an ensemble technique that incorporates the notion of “bagging” across training examples and features when training a set of
decision trees, rather than a single decision tree, to perform regression.

For the input features for our machine learning models, we consider three cases of input. **Case A** considers counts of each conceptual node. **Case B** considers spend (in Russian rubles) and counts of each conceptual node. **Case C** number of days online, spend, and counts of each conceptual node. The decision to consider three cases of input for our machine learning models was motivated by the initiative to see how our conceptual nodes, on their own, compare to including other simple features for our learning models in terms of CTR prediction accuracy. We discuss the accuracy of the learning models, under each case, in Section [VII]. In each of the three cases considered, we consider the input provided to the learning models to be vectors. For instance, in Case A we consider the input vector \([0, 1, 0, 2, 0, 0]\) to be the combination of the conceptual nodes — corresponding respectively with celebrity, identity, news, organization, politics, and religion. For Case B, an additional leftmost element is included for spend; for Case C, two additional leftmost elements are included for spend and days online respectively.

VI. OPTIMAL CONCEPTUAL NODE COMBINATIONS

Here, we present the formulation for finding optimal combination of conceptual nodes that maximizes the CTR under a given machine learning model trained to perform CTR prediction. We then present a greedy algorithm and a genetic algorithm that run in linear time. It is worth mentioning that the proposed algorithms for conceptual node allocation only consider learning models under Case A.

**Optimization Formulation.** The Optimal Conceptual Node Combination (OCNC) problem can be formally described using an integer nonlinear program (INLP) formulation. The INLP formulation, provided below, considers a value function \(f(\cdot)\), a conceptual node combination \(C = [C_1, \ldots, C_|N|]\), and a budget \(k\),

\[
\begin{align*}
\text{maximize} & \quad f(C) \\
\text{subject to} & \quad C_i \in \mathbb{N} \\
& \quad 1 \leq i \leq |N| \\
& \quad \sum_{i=1}^{|N|} C_i \leq k \\
& \quad k \in \mathbb{N}
\end{align*}
\]

where, as a reminder, \(N\) is the set of conceptual nodes and \(\mathbb{N}\) is the set of natural numbers (including 0). The objective function \(f(C)\) in Eq. (1) represents the click prediction function returned by some trained machine learning model. Constraint (2) restricts a conceptual node combination to be comprised of numbers belonging to the natural number set (i.e., no negative amount of conceptual nodes). Finally, constraint (3) ensures that the number of conceptual nodes allocated to \(C\) do not exceed the considered budget \(k\). From here, we discuss the hardness of solving this problem under some assumptions regarding the value function \(f(\cdot)\).

**NP-Hardness.** The hardness of the OCNC problem is dependent on the class \(f(\cdot)\) belongs to — which relies on which ML model is used, the training data, the training hyperparameters, etc. For example, with a linear regression model, the function is linear and makes the problem trivially easy to solve: simply select whichever conceptual node has the largest coefficient and spend all your budget \(k\) on that conceptual node. However, for more advanced models, such linearity is likely not possible. For instance, in MLP models, that can result in a composition of convex/concave functions that can make the resulting function \(f(\cdot)\) demonstrate non-convexity/concavity \([22]\). No guarantees can be made about the nature of the resulting \(f(\cdot)\). If it demonstrates non-convexity/concavity or some other rigorous behavior, the OCNC problem could then be considered as NP-hard. This can be suggested under the observation that global optimization of a non-convex/concave function is found to be NP-hard \([23, 24]\). A robust proof for the models considered in this work is beyond the scope of this paper.

A. Proposed Greedy Algorithm

The greedy algorithm uses a machine learning model as a heuristic to incrementally allot conceptual nodes. Essentially, it starts off by selecting 0 conceptual nodes, then will generate children combinations where 1 more conceptual node is considered (e.g., \([0, 0, 1] \rightarrow \{[1, 0, 1], [0, 1, 1], [0, 0, 2]\}\). For each of these children combinations, it will predict the number of clicks using the provided model. It then repeats this process for the combination that produced the highest predicted click values until it exhausts its budget. The pseudocode for this algorithm can be found in Algorithm [1].

**Algorithm 1:** Greedy algorithm.

In : value function \(f\), budget \(k\), conceptual node set \(N\), current combination \(C\) (initially empty).

Out: Solution to OCNC problem.

1. if \(k \leq 0\) then
2. return \(C\);
3. if \(C = \emptyset\) then
4. \(C \leftarrow [0]^{\times |N|};\) /* CHILDREN([0, 0, 1]) \rightarrow \{[1, 0, 1], [0, 1, 1], [0, 0, 2]\} */
5. \(C' \leftarrow \text{CHILDREN}(C);\)
6. \(\text{child} \leftarrow \arg \max_{c \subseteq C'} f(c);\)
7. return \(\text{GREEDY}(f, k - 1, N, \text{child});\)

B. Genetic Algorithm

We implemented a genetic algorithm for conceptual node allocation that is given a trained learning model for its fitness function. Additionally, the genetic algorithm is given a budget \(k\) for node allocation to ensure that mutated DNA strands and randomly generated children in an initial population do not exceed the budget for conceptual nodes considered. For our genetic algorithm, we considered 1000 generations and populations of 35 individuals. No advanced hyper-parametric tuning was performed to arrive at these parameters. We do not provide the genetic algorithm in this paper because the advent genetic algorithms is general enough to be applied to a wide variety of problems \([25]\).
VII. RESULTS

Accuracy of Machine Learning Models. In order to make the case that our approach to CTR prediction using our conceptual nodes has merit, we must affirm that at least one of the trained learning models used to predict clicks is reasonably close to real click values. To verify this, we train each of the four considered learning models on a random set consisting of 95% of the IRA data, dedicating the remaining 5% of data to testing accuracy. Figure 1 shows the accuracy of the four learning models, under Case C, in terms of how predicted click values $\hat{Y}_i$ correlate with the real click values $Y_i$ for each advertisement $i$ in the testing subset of advertisements. In these plots, it is evident that each model maintains a positive correlation between predicted and real click values. To more thoroughly analyze the accuracy of these models, Table I provides the Pearson correlation coefficients between $Y_i$ and $\hat{Y}_i$ for each model under each case. We see significant gains in terms of correlation under Case C for all learning models with the exception of MLP. The RFR and DTR models feature the highest correlation coefficients, demonstrating their reliability for CTR prediction in this approach. Further, across the results, the RFR and DTR demonstrate the highest efficacy in terms of Pearson correlation coefficient.

Performance of Proposed Algorithms. To reiterate, this approach to CTR prediction is unorthodox when compared to other approaches in the literature. Standard approaches to CTR prediction typically incorporate heavy use of user-based input features. Since rich user input features are difficult to get for entities other than OSN platforms themselves, this is an inaccessible approach for most researchers. Having said that, to the best of our knowledge, there are not any reasonable baseline algorithms to compare our approach against. Thus, we compare our greedy and genetic algorithms against two other algorithms, brute force and random allocation. Brute force allocation will serve as our upper bound. It simply runs through all possible allocations of conceptual nodes and returns the allocation that provides the highest click prediction. To reiterate, the run-time for this algorithm is $\Theta(k^{|\mathcal{N}|})$ where $\mathcal{N}$ is the set of conceptual nodes — making it very computationally expensive. Our random algorithm simply allocates a random allocation of conceptual nodes within budget, making it the lower bound for comparison.

First, we train our learning models with all of the IRA data. For each budget value $k = 0, 1, \ldots, 20$, we allocate conceptual nodes for $k$ using each of the four algorithms and then predict CTR using each learning model. We keep track of the CTR predictions for each value of $k$ under each model to generate a curve that will be used to plot the performance of the algorithms in maximizing clicks. To adequately compare the results of this process, we perform this task 100 times and average the results over the 100 iterations to account for any random behaviors when training our learning models.

Under the ABR, DTR, and RFR learning models, we observe that the genetic algorithm performs the best among the three non-brute-force solutions — with performance being very close to the optimal brute force solution. Under the MLP model, we observe that the greedy algorithm outperforms the genetic algorithm and performs very close to the optimal brute-force solution. The performance of these algorithms under the four learning models and Case A, can be seen in Figure 2. It is worth noting that the genetic algorithm reaches near-optimal solutions with the learning models that exhibit the highest accuracy in terms of Pearson correlation coefficients.

Most Influential Conceptual Nodes. For this work, we wanted to be able to draw some social intuition as to which conceptual nodes among the six considered proved to be more influential in attracting clicks from users. First, we normalize the data to account for spend. This is necessary because advertisements with more spend are prioritized more in Facebook’s system. To do this, we disregard all advertisements that had 0 rubles spent on them. From there, we normalize values for spend and clicks of the remaining advertisements by grabbing the top 10% of advertisements with the most clicks per spend. Table II provides the average occurrence of each conceptual node among the top 10% of clicks-per-ruble advertisements. From these results, we can clearly observe that the conceptual nodes of politics, organization, and celebrity are the most influential conceptual nodes by a considerable margin. Interestingly, the news conceptual node has very insignificant influence according to these results.

| Input Case | ABR   | DTR   | MLP   | RFR   |
|------------|-------|-------|-------|-------|
| A          | 0.184 | 0.357 | 0.199 | 0.427 |
| B          | 0.167 | 0.687 | 0.406 | 0.681 |
| C          | 0.508 | 0.724 | 0.052 | 0.755 |

Table I

PEARMON CORRELATION COEFFICIENTS OF EACH MODEL.
VIII. Conclusions & Future Directions

In this work, we perform an content-aware approach to CTR prediction using machine learning models with our notion of conceptual nodes and a relatively small data-set. Through this approach for CTR prediction, our learning models achieve impressive efficacy. Also, we introduce a greedy algorithm and implement a genetic algorithm to find optimal conceptual node combinations to solve the considered optimization problem under our trained learning models, with our genetic algorithm performing near optimal solutions under three of our four models. Lastly, we acquire some social insights that politics, celebrity, and organization are the most influential conceptual nodes for attracting user clicks while news is the least effective.

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