COMPGW02 Web Economics Individual Report (Group 05)

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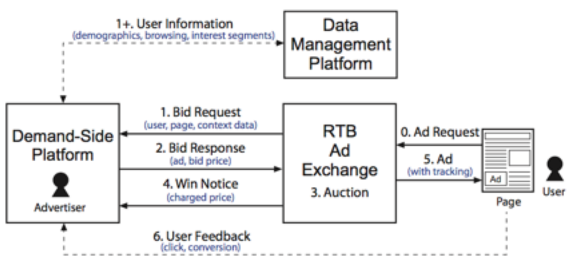
1. INTRODUCTION

Online advertising allows advertisers to bid and place their advertisements onto the web pages that are being visited by users. The process of user landing on a web page to the advertiser bidding and successfully displays their advertisements to the users takes place within a fraction of a second. Such real-time bidding based advertisements requires bidding strategies that would bring in the maximum profit over costs. Figure 1 shows an illustration of the interaction described above. This report proposed a bidding strategy

Figure 1: Real-time advertisements bidding process



consisting of two components, a CTR estimation based on Factorisation Machines (FM) and a Threshold-Sigmoid bidding strategy. The former attempt to learn the chances of a click based on features collected from bid requests of the online advertising system, while the latter formulate an approach to offer the best bid that captures the essence of limited budget, capitalising on higher chances of clicks, bidding from a base and scaling the bid along the probabilities of clicks in a non-linear manner. The strategy was implemented and evaluated against a linear bidding strategy.

The results showed that the FM model with the Threshold-Sigmoid bidding strategy performed better than the linear model. The Threshold-Sigmoid bidding strategy achieved a higher CTR with lower costs as compared to the linear bidding strategy.

The report also discussed issues of class imbalance, and appropriate evaluation measures that were taken for the model during CTR estimation and optimal bidding. All source codes can be found in [9]

2. LITERATURE REVIEW

Prediction of Click-Through-Rate (CTR), or CTR estimation is a widely studied subject. There have been different models and variants developed over it. Some notable examples are Linear Regression (LR) [3], Recurrent Neural Networks (RNN) [5], Boosted Trees [16] and Factorisation Machines [12]. The most popular technique would LR for its simplicity and efficiency. However neural networks tend to provide surprisingly good results despite their difficulty in interpretation. Boosted trees provide very clear interpretation compared to neural networks and can determine its own feature importance. Factorisation Machines perform well on sparse data. It has been previously shown that higher order feature interactions could improve CTR estimation [3]. However, LR models are unable to capture feature interactions with an order higher than one without delicate feature engineering and a resulting explosion of the number of features. Factorisation Machines, first proposed by [13], have shown its ability to model higher order feature interactions with linear complexity. There has been prior research in CTR estimation using Factorisation Machines and its variants [15][8]. These models have been shown to outperform well known LR models. Several Factorisation Machines implementation have since surfaced. The prominent ones are libFM [14], FastFM [2] and Polylearn [11].

Class imbalance has been an inherent characteristic of online advertising [1] in that the ratio of user clicks is extremely small. Several novel approaches [6][10] have been proposed but under-sampling or over-sampling the dataset remains the popular approaches to this issue. Over-sampling would be particularly use if the number of the minority class in the dataset is too small for effective machine learning. Two commonly used algorithms for over-sampling are SMOTE [4] and AYSNA [7].

3. APPROACH AND RESULTS

3.1 Data Exploration

3.1.1 Dataset interpretation

Three different sets of datasets are made available to the students. Broadly, the datasets are named as training, validation and test. An analysis revealed the content of the dataset to be a mash up of logs from the bid requests, bid responses, win notices and user feedbacks data exchanges in and out of the DSP bidding agent indicated in Figure 1. Essentially, all three datasets referred to the same content type, except for the test set which contains only information that would be available prior to bidding. Another noteworthy observation is that almost all the attributes in the datasets are categorical in nature. Due to space constraints, only certain attributs are summarised in Table 1.

Table 1: Interpretation of attributes

Attribute	Interpretation	Remarks
Useragent (Bid request)	String that identifies aspects of the browser such as operating system and internet browser, separated by an underscore.	Categorial. The Operating System and the Internet Browser will be separated into 2 different columns after data preprocessing.
Usertags (Bid request)	Integers representing the segment of the users, separated by commas.	Categorial. This is only available in the DSPâĂŹs proprietary database. Data pre-processing is required to split
Bidprice (Bid response)	An integer representing the price that was bidded by the DSP bidding agent.	Not available in test set.
Payprice (Win notice)	An integer representing the market price, or the second highest bid made in the auction (Second price auction).	Not available in test set.
Click (Win notice)	Integer of 0 or 1 representing a click or not. E.g. 0: No click, 1: Click	Categorial. Not available in test set.

Table 2: Problems on datasets and solutions

Check item	Problems	Solutions
Nulls in columns	Nulls detected in columns domain, keypage, adexchange, usertags.	Nulls will be treated as an additional categorical data for domain, keypage and usertag.
Bidprice < Payprice	3691 such records found in validation set. 33579 such records found in training set.	These records donâĂŹt fit the notion of a second price auction and were thus removed.
Discrepancies between training and validation sets.	useragent, region, city, adexchange, slotvisibility, slotformat and usertag columns have potential of having values thatâĂŹs not in both validation and test datasets. This will cause problems in training and prediction flows.	To ensure consistency between training and predictions for the models, the training and validation sets were appended and the unique values of the affected columns collected and used for training and predictions.

3.1.2 Data pre-processing

With a better understanding of the datasets in Section 3.1.1, a series of sanity checks was performed on the dataset. Table 2 lists the problems found and the recommended solutions.

3.1.3 Class imbalance

Previously, it was noted that class imbalance were common occurrences in online advertisements. The dataset indeed showed a significant imbalance of non-clicks against clicks. Out of more than 2.5 million impressions, only 0.07% of impressions were clicked. The low empirical figure of 1986 clicks could also posed a problem in learning the effective clicks.

For most classification algorithms to perform, the number of samples of each class should preferably be around the same. As discussed in the literature review, there were several options to mitigate this issue. As class imbalance may pose more problems for some machine learning algorithms than others, this issue will be revisited in later sections.

3.1.4 Display advertising statistics

3.1.4.1 CTR, CPM, CPC.

This section will elaborate on metrics related to the display advertising as mentioned in section 2. The Click-Through-Rate (CTR) refers to the probability of clicks among all the impressions. The Cost-Per-Mile (CPM) refers to the approximate cost incurred for each 1000 impressions. The Cost-Per-Click (CPC) refers to the approximate incurred cost for each click. The computation draws from the dataset after the actions taken in Sections 3.1.1.

Table 3: : Display advertising statistics from training set

Advertiser	Clicks	Imp	Cost	CTR	CPM	CPC
1458	451	540293	37231239	0.0008	68909	82552
2259	45	146778	13649026	0.0003	92990	303311
2261	37	120619	10789152	0.0003	89448	291598
2821	144	231416	20625766	0.0006	89128	143234
2997	251	54487	3413227	0.004	62642	13598
3358	204	289982	24517382	0.0007	84547	120183
3386	358	498554	38341028	0.0007	76904	107097
3427	323	439787	33297891	0.0007	75713	103089
3476	173	342243	26328601	0.0005	76929	152188

From Table 3, it was obvious that advertiser 2997 has a leading edge in the CTR. To investigate further, advertiser 2997 was compared with an average performer 3476 in Figure 2.

Advertiser 2297 had focused entirely on android OS and safari browsers, it had also received its bids from an exchange different from 3476. Although anyone of these could have resulted in the high CTR but it would likely be the android OS since its touch based and may have contributed to unintentional clicks.

3.1.4.2 Bid, pay, reserved prices.

Table 4 was tabulated to analyse the bidding environment.

Figure 2: Comparison of advertiser 2997 and 3476 in terms of OS, browser and ad-exchange

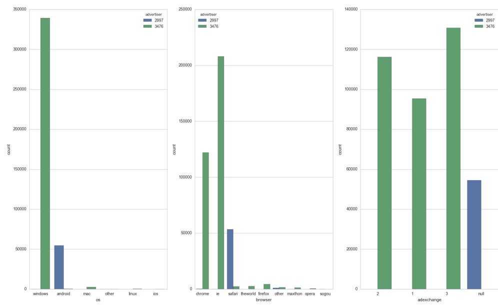


Figure 3: Correlation between attributes

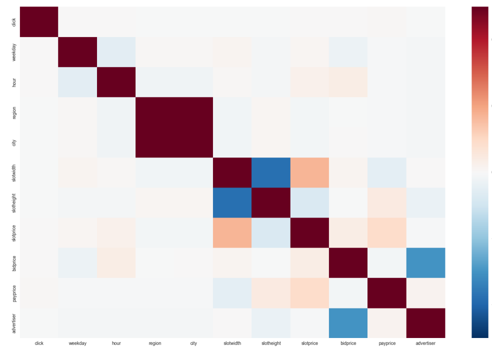


Table 4: Statistics of pay price, bid price and reserved prices

	Minimum	Mean	Maximum
Bid price	227	272.98	300
Pay price	0	78.14	300
Reserved price	0	26.73	300

It is worth noting that there are reserved prices at zero, this means that if one do not wish to bid for an impression, a bid value of less than zero has to be submitted. Another interesting finding was that there were winning bids that paid nothing for it (pay price is zero). Reserved price typically start at around 26.73 on average but the bid price starts at a minimum of 227. This was surprising as the minimum bid price is significantly higher than the average reserved price. Although the reason for this is unclear, this information could still prove to be very useful in the tuning of bid optimisation of the bidding strategy.

3.1.5 Features correlation

Finally, an analysis was performed on the attributes to discover relationships between the attributes. From Figure 3, it was noted that the following pairs of attributes were inversely correlated at varying strengths, bid price and advertiser, slot height and slot price, slot width and pay price. The following pairs of attributes displayed at positive correlation at varying strength, slot width and slot height, slot width and slot price. This corresponds to the literature review that second order interaction features could be used together to produce better CTR prediction models.

3.2 Bidding Strategy

The bidding strategy is built on two components. The first is the CTR estimation to predict the probability of click for each impression in the test set. The second is optimal bidding to derive a bid price based on the probability of click and other bid related parameters. Sections 3.2.1 to 3.2.3 would discuss the approach on CTR estimation while sections 3.2.4 would discuss on the optimal bidding strategy.

3.2.1 Model: Factorisation Machine

The Factorisation Machine model was explored as a non-linear model for CTR estimation. A second-order Factorisation Machine model was used, in other words, only second-order interactions between variables will be modelled.

To explain the intuition of Factorisation Machines, it must first begin by understanding Matrix Factorisation. In normal real number factorisation, it means decomposing the number into several numbers such that the product of these numbers would be the same as the original number. In matrix factorisation, the same intuition applies. Take for example, a matrix of shape UxI can be decomposed into a UxK and a IxK matrix where $K << U$ and $K << I$. The interaction between the row and the column of the original matrix can be approximated by the dot product of a pair of vectors $row_i.col_j$.

The equation for a multivariate linear regression is stated as follows.

$$y = w_0 + \sum_{i=1}^{n} w_i x_i \quad (1)$$

where y is the label, x_i are the features, w_0 and w_i are the weights to be trained. Now consider the polynomial situation where pairwise feature interactions are captured, the equation would be as follows.

$$y = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{ij} x_i x_j \quad (2)$$

where $x_i x_j$ refers to the interaction between features x_i and x_i, and w_0, w_i and w_{ij} refers to the weights to be trained respectively. The problem is now effectively a non-linear problem and would be computationally too expensive for a sparse set of features. To solve the problem, Factorisation Machines imitate the workings of matrix factorisation and use the dot product of features interactions in modelling the feature interactions. The equation would be as follows.

$$y = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} < v_i, v_j > x_i x_j \quad (3)$$

where $< v_i, v_j >$ is a vector that model the feature interaction. The above equation model a two-way interaction but can be extended to higher order interactions. Recall the K parameter in Matrix Factorisation, this would capture K latent features for each feature interaction vector.

There were several available implementations of Factorisation Machines. Polylearn follows scikit-learn conventions closely and thus offered a wide range of tools from scikit-learn to be used without problems, it was however plagued with long training times on the training set. FastFM on the other hand, claimed to follow scikit-learn interfaces but proved not to be so. It was however optimally implemented and clearly documented which allowed custom overriding of methods to fit into scikit-learn tools.

FastFM is a Python implementation of RendleâĂŹs Factorisation Machine and it supports regression, classification and ranking requirements. FastFM support a variety of optimisers such as Alternating Least Squares (ALS), MCMC and Stochastic Gradient Descent (SGD) to solve for the optimal values of $< v_i, v_j >$ vectors for each pair of features x_i and x_j. For this model, FastFM is chosen to be used.

3.2.2 Data

3.2.2.1 Features.

Inherently, Factorisation Machines do not have the capability to compute importance of each attribute as would Boosted Tree algorithms. Yet, learning interactions between features is the main draw of the algorithm, which means there is no need to define custom features that measures the relationship between features. Unfortunately, this also implied that the successful performance of Factorisation Machine depended heavily on careful feature selection (Or non-selection). As an example, it can probably learn that the probability of click will be very high when the impression came from a bid request where region is 276 and city is 282. But if one of these features were not considered initially in the training, the opportunity to bank on this information would be lost. With the above considerations, only the following features were removed from the datasets.

Table 5: Features removed from training

Feature unused	Reason
logtype	This feature only consists of 1s, which makes it redundant as a feature.
bidprice	This feature would not be available in the test set
payprice	This feature would not be available in the test set
click	This would be the label that we seek to predict

3.2.2.2 Class Imbalance.

As discussed, data sets from online advertising tends to be class imbalanced. In our dataset, it was shown that the percentage of clicks to the total number of impression is 0.07%. There were several approaches including selecting evaluation metrics that are less impacted by class imbalance, or by under-sampling or over-sampling data. With over two million impressions, simply down-sampling would have been a perfect choice for its simplicity if not for the extreme class imbalance of only 1986 impressions with clicks. To mitigate the issue, the non-clicks in the dataset was first randomly down-sampled to a ratio of 8:2 to the all clicks impression. Thereafter an oversampling SMOTE algorithm was applied to generate synthetic impressions such that the ratio between clicks and non-clicks are balanced out.

3.2.3 Training

3.2.3.1 Metrics.

Accuracy, precision, recall and F1 could be considered, but their values varies across thresholds and metrics such as accuracy do not hold well in class imbalance scenarios. For example, if 99.9% of impressions are non-clicks, and the model predict non-clicks even for actual clicks, the accuracy level would still extremely high. As discussed in section 4.2.2.3, class imbalance inherent in computational advertising was one of the factors in deciding the metrics to apply. One class imbalance in-sensitive metric is Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC). The AUC of ROC metric is also independent of the threshold that decides if a prediction is a positive or negative. Finally, AUC works for any binary classification models that can produce the relevant probabilities. In this assignment, the unique requirements of computational advertising may mean that different thresholds may be set for different models. With above in mind, the AUC of ROC would be used as the main metric for CTR estimation evaluation.

3.2.3.2 Training parameters.

In training the model, there are a few hyper parameters that needs to be set. These parameters were evaluated against the AUC discussed in section 4.2.3.1.

Table 6: Training parameters

Type	Hyper-parameter	Remarks
Model	Rank	The K in the matrix factorisation
	L2 regularisation for linear components	A regularisation for the weight of wi
	L2 regularisation for pairwise components	A regularisation for the weight of <Vi,Vj>
SGD*	Iterations	Set according to step size.
	Step size	Step size of the SGD optimiser.

* Other solvers not indicated in report.

3.2.3.3 Thresholding.

The problem of computational advertising adds a domain specific consideration in that clicks could be considered as one of the contributing factors to the Return Of Investment (ROI) of the bidding process. In computational advertising, the goal was to be able to bid for a lucrative slot and from there generate profits in the form of follow up purchases of some form by the user, which would in turn be generated into revenue for the slot bidder. This means that it may be necessary to capture all the clicks and bid for it than to miss it. As such, the threshold for determining a potential click could be shifted. This understanding would be useful in determining the optimal bidding later.

3.2.4 Optimal Bidding

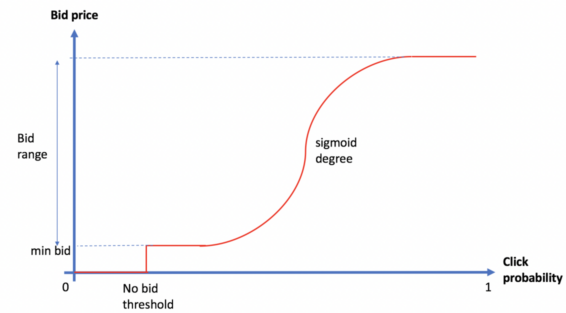
For a successful bidding, a bid must be calculated such that it would be above the market price (2nd price). A linear bidding strategy was proposed in the assignment,

$$bid = basebid * (pCTR/avgCTR) \quad (4)$$

where the tuning parameter *basebid* is the bidprice for the average CTR cases. With the $pCTR$ computed in the CTR estimation model, the next step would be to find the optimal base bid that would generate a bid for every impression that would optimise the metrics given the limited budget.

It was noted in the data exploration that the minimum bid for all the impressions was 227. Although the analysis did not capture the reason, this information was strongly considered for the bidding strategy. A variation of linear bidding would be to capture the essence of limited budget, capitalising on higher chances of clicks (Thresholding), bidding from a base and scaling the bid along the probabilities of clicks in a non-linear manner. This means that lower confidence bid requests would not be bid, and there would be a cap on the highest bid per bid request to ensure high confidence bids are treated similarly and does not exhaust the budget quickly. Once the budget is exhausted, no more bidding will be made for subsequent bid requests. Figure 4 below exhibits the idea, which will be termed as Threshold-Sigmoid bid price in this report.

Figure 4: Visualisation of Sigmoid-Threshold bidding strategy



The bid function would look like

$$Bid = (1/(1 + e^{(\theta*(Pr(click=1))+(-0.2-T))})) * R + m \quad (5)$$

where, θ is a hyper-parameter, $Pr(click = 1)$ is the probability of a click, T is the threshold of $Pr(click = 1)$ to start bidding, R is the maximum bidding range and m is the minimum bid. Note that the equation doesn't consider a zero bid for below T. This would be handled in the software implementation. During implementation, θ, R, T and m were optimised by iteratively running the algorithm with different combinations of the parameters (Grid Search). The target of optimisation was to score against number of clicks and CTR.

3.2.5 Evaluation

The Factorisation Machine CTR and Logistic Regression estimation models are trained on the individually corrected training set and then evaluated based on the individually corrected validation set. The two models are then compared. The main metric for comparison is AUC. As can be seen from the AUC curves, Factorisation Machines performed better in terms of accuracy. Moreover, an analysis of predicted probabilities for click and non-clicks of each model showed that Factorisation Machines showed a better probability distinction between a click and a non-click. This would also offer stronger outcomes if thresholding is performed.

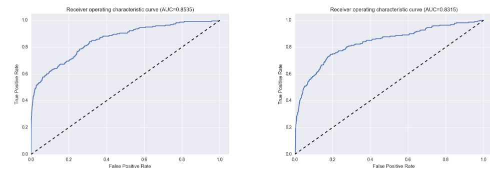


Figure 5: Left: AUC for Factorisation Machine, Right AUC for Logistic Regression

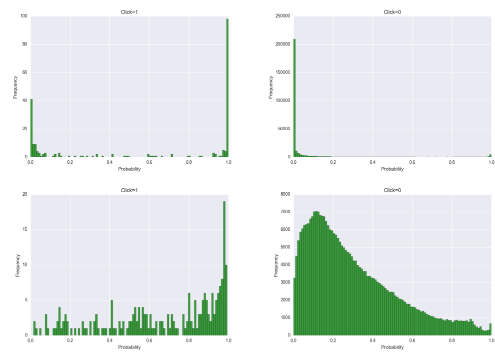


Figure 6: Upper left: FM predicted probabilities for clicks. Lower left: LR predicted probabilities for clicks. Upper right: FM predicted probabilities for non-clicks. Lower right: LR predicted probabilities for non-clicks

Both the Linear (based on average CTR of 0.07% on validation set) and Threshold-Sigmoid strategies were optimised for their parameters for best CTR and number of clicks on the Factorisation Machine estimator on the validation and then compared.

Table 7: Comparing advertising metrics between Sigmoid-Threshold (ST) and Linear (L) bidding strategies.

Model	CTR	Spend	Clicks	CPM	CPC
ST	0.0036	3088940	140	79458.26	22063.86
L	0.0015	6249815	138	66192.34	45288.51

As seen in Table 7, the Threshold-Sigmoid bidding achieved a higher CTR rate, with a significantly lower spend. In terms of number of clicks, there wasn't much difference. The lower cost could be attributed to the Threshold-Sigmoid bidding function which places a limit on the maximum confident bid on each bid request, and making all high confident bids to bid the same price. The linear model exhausted its budget before the campaign ends, in contrast the Sigmoid-Threshold bidding sustained throughout the campaign. This is important when budget is constrained and the model is to be used online (Without knowing how many impressions will arrive).

3.3 Conclusion

In this assignment, the Factorisation Machine model was compared to the baseline logistic regression and it has been shown that Factorisation Machine models can be a very effective solution to binary classification problems despite it being less easy to interpret. A bid price estimator was also proposed to accommodate the budget and findings based on the data analysis.

3.4 Roles

The team composed of Kah Siong (KS), Chun Siong (CS) and Min Ying (Min). We worked by picking up items to work on based on our progress and workload. The following table is based on member ownership in specific aspects of the listed items, however other members do enhance existing codes to add new features or or enhance performance.

Table 8: Member mainly involved in item.

	KS	CS	Min
Data Read Write		X	
Feature extraction	X	X	X
Imbalance Resampling	X	X	
Constant Bidding		X	
Random Bidding (Gaussian)		X	
Random Bidding (Uniform)			X
Logistic Regression	X	X	X
XGBoost		X	
CNN			X
Factorisation Machine variants	X		
Bidding Strategies	X	X	X
Ensemble (CTR models)	X	X	X
Evaluator class for Bids	X	X	
Evaluator class for Clicks		X	X

References

[1] Josh Attenberg and Foster Provost. 2010. Why Label when you can Search? Alternatives to Active Learning for Applying Human Resources to Build Classification Models Under Extreme Class Imbalance. In *KDD '10 Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, Vol. 17. 1–5.

[2] Immanuel Bayer. 2016. fastFM: A Library for Factorization Machines. In *Journal of Machine Learning Research*, Vol. 17. 1–5.

[3] O. Chapelle, E. Manavoglu, and R. Rosales. 2014. Simple and scalable response prediction for display advertising. In *ACM Trans. Intell. Syst. Technol*, Vol. 5. 61–1–61–34.

[4] Nitesh V. Chawla, Kevin W. Bowyer, Lawrence O. Hall, and W. Philip Kegelmeyer. 2002. SMOTE: Synthetic Minority Over-sampling Technique. In *Journal of Artificial Intelligence Research*, Vol. 16. 321–357.

[5] Qiao-Hong Chen, Shi-Min Yu, Zi-Xuan Guo, and Yu-Bo Jia. 2016. Estimating AdsâĂŹ Click through Rate with Recurrent Neural Network. In *ITM Web of Conferences*, Vol. 17. 1–5.

[6] Xinjian Guo, Yilong Yin, Cailing Dong, Gongping Yang, and Guangtong Zhou. 2008. On the Class Imbalance Problem. In *Fourth International Conference on Natural Computation.*

[7] Haibo He, Yang Bai, Edwardo A. Garcia, and Shutao Li. 2008. ADASYN: Adaptive synthetic sampling approach for imbalanced learning. In *Neural Networks, 2008. IJCNN 2008. (IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on*, Vol. 17. 1–5.

[8] Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. 2016. Field-aware Factorization Machines for CTR Prediction. In *RecSys '16 Proceedings of the 10th ACM Conference on Recommender Systems.* 43–50.

[9] Min Ying Ong Kah Siong Tan, Chun Siong Poh. 2017. Web Economics assignment Group 5. (Apr 2017). https://github.com/jax79sg/webecon2017

[10] Bartosz Krawczyk. 2016. Learning from imbalanced data: open challenges and future directions. *Springer Link* 5, 4 (Nov 2016).

[11] Vlad Niculae. 2016. A library for factorization machines and polynomial networks for classification and regression in Python. (2016). Retrieved March 6, 2017 from https://github.com/scikit-learn-contrib/polylearn/

[12] Zhen Pan, Enhong Chen, Qi Liu, Tong Xu, Haiping Ma, and Hongjie Lin. 2016. Sparse Factorization Machines for Click-through Rate Prediction. In *2016 IEEE 16th International Conference on Data Mining.*

[13] Steffen Rendle. 2010. Factorization Machines. In *Data Mining (ICDM), 2010 IEEE 10th International Conference.* 995–1000.

[14] STEFFEN RENDLE. 2012. Factorization Machines with libFM. In *ACM Trans. Intell. Syst. Technol*, Vol. 3.

[15] Anh-Phuong TA. 2015. Factorization Machines with Follow-The-Regularized-Leader for CTR prediction in Display Advertising. In *Big Data (Big Data), 2015 IEEE International Conference on.*

[16] Ilya Trofimov, Anna Kornetova, and Valery Topinskiy. 17. *Using boosted trees for click-through rate prediction for sponsored search.* Technical Report. Yandex.