Viewability study and prediction model

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Abstract

Using historical data from Centro campaigns, we developed an ad viewability prediction model. This model can be used to predict a viewability during campaign planning, and make a corresponding choice when maximization of the ad viewability is considered as one of campaign goals.

1 Introduction

The viewable impression is the key to making digital media measurement comparable to that of legacy media. In television, radio, and print, the consumer has the opportunity to see the ad. Television commercials are rendered on screens. Radio ads are broadcasted. This is not the case with digital media. Foundational industry technologies only measure if an ad has been served, not how fully it rendered on the screen or how long it was present. The viewable impression and the technological innovations that support it answer this need.

American Association of Advertising Agencies (4As), the Association of National Advertisers (ANA), and the Interactive Advertising Bureau (IAB) initiated five principles titled as "Making Measurement Make Sense" [1]. The first principle is move to a "viewable impressions" standard and count real exposures online. Traditionally, due to technology limitations, the industry was only able to measure "served impressions" as recorded by ad servers. Using this technique, ad units may not have been in a viewable space on the browser, or may have failed to fully load on the screen – potentially resulting in substantial over-counting of impressions that a user actually had an opportunity to see. Viewability addresses the issue of whether ads have the opportunity to be seen, and the viewable impression is the key to making digital media measurement comparable to that of other media types. Major digital advertising challenges are caused by a cross-domain iframe (what makes difficult measuring the position of the ad impression relative to the browser viewport), non-intentional, fraudulent impressions, etc [2]. Viewability metrics show how these major challenges have been solved, and, as a consequence, whether one can the audience of our interest by showing "in full" ordered impressions.

So, viewability of ads served during an advertising campaign is one of important components of a campaign planning stage, and also serves as an important indicator of a campaign performance. However, the problem here is twofold. First, viewability metrics are not available for all publishers since not all Centro campaigns go through corresponding vendors (typically, MOAT and Sizmek), and currently we have viewability data for just about 40% of sites. Second problem is more involved. Even for those sites, for which we have viewability measurements, the distributions are pretty broad. Figure 1 shows distribution for In-View-Rate (defined in the next section) for a few sites for a fixed ad size in different campaigns. One can see that in most cases the distributions are wide and make have a few 'bumps'. So, taking average In-View-Rate value for a given site would be a quite uncertain quantity.

It would be preferable to find out factors which affect viewability and be able to predict it provided a set of campaign specifications. *A priori*, it is also clear that in Centro's historical data + MOAT data, some potentially important components are missing, for instance, a location of ad on the web-page (e.g. below/above the fold) or an ad creative quality. So, here we try to explore other features which are in our hands.

To make the viewability predictions we develop a predictive tool based on a couple of machine learning techniques and using a set of variables (features) which might be potentially associated with viewabilities. Those variables are available through the Pentaho (MMS) data base and a user interface to MOAT data as discussed in Section 2.

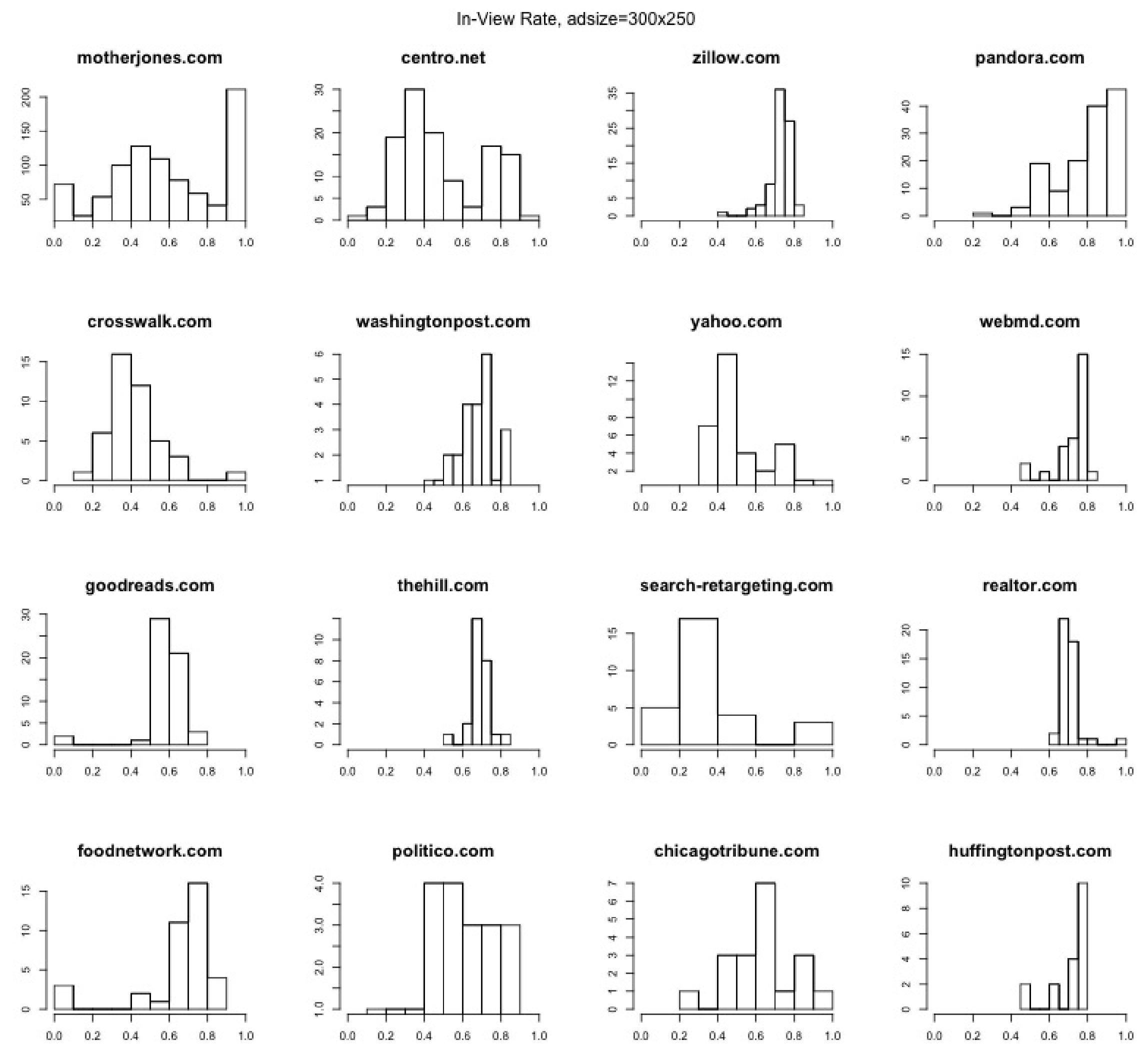


Figure 1: Measured In-View-Rate by MOAT for a few and a fixed ad size 300x250.

2 Data selection

To build a viewability model, we used MMS data collected since January 1, 2013 to reflect most recent advertising tendencies, on the one hand, and to have enough statistics to train/build the model, on the other hand. The Python script used for the data retrieval from a data base can be found by this link
`https://github.com/centro/Data-Science/blob/master/Recommendation-Engine/dev/Scores/MMS/mms_data_pull.py`

We use data from monthly fact tables, so all the metrics (e.g. the number of impressions, clicks) for a given campaign are calculated per month.

The extracted data have to satisfy the following selection criteria:

- 5000 < delivered_impressions < 10^7 ;
- delivered_clicks > 1;
- 0 < CTR < 1;
- delivered_gross_revenue / ordered_gross_revenue > 0.1;
- cost_type != 'Added Value' & cost_type != 'Flat Rate'.

We also use all MOAT data, collected by Centro for a period of April 1, 2013 till March 1, 2016.

From MMS, we explored a relevance of following variables to the viewability: Platform, Ad class, Cost type, Cost subtype, Ad size, (Google) Vertical, CPM, Number of flight days, Ordered gross revenue. There is a number of metrics that may characterize the viewability. In this note we limit our scope to In-View-Rate and Total Rate, and extract from MOAT Impressions Analyzed, In-View Measurable Impressions, In-View Impressions, Browser, Ad Size.

3 Data Analysis

Let us first introduce a few useful viewability definitions commongly used in digital advertising:
Analyzed Impressions: impressions tracked by MOAT.
In-View Measurable Impressions: impressions where viewability was measurable.
In-View Impressions: impressions where >50% of ad was in-view for >1 continuous second.

In terms of the extracted variables, In-View-Rate is defined as

$$\text{In-View-Rate} = \text{In-View Impressions}/\text{In-View Measurable Impressions} \tag{1}$$

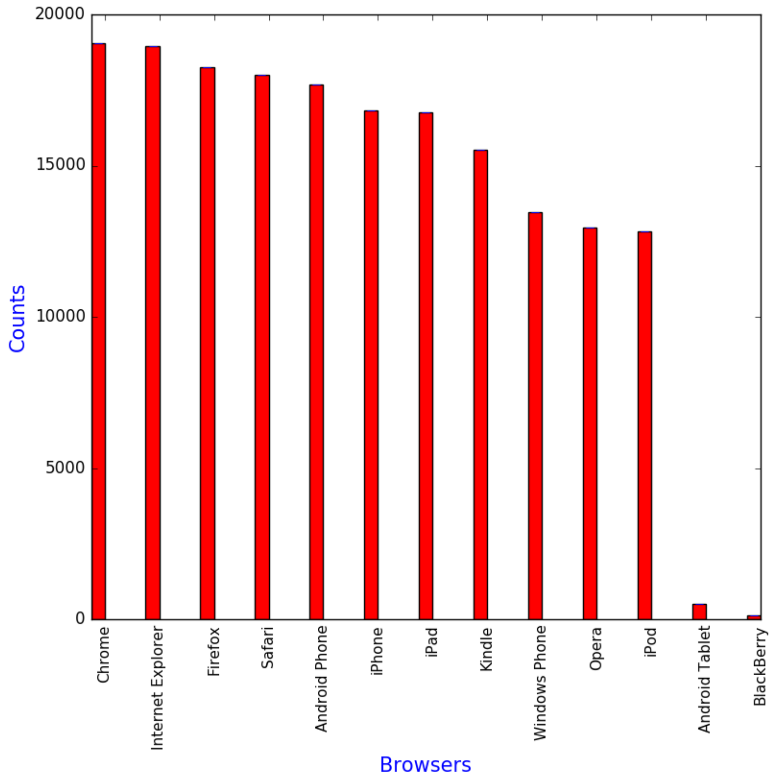
One needs to distinguish also Measure Rate, defined as

$$\text{Measure Rate} = \text{In-View Measurable Impressions}/\text{Impressions Analyzed} \tag{2}$$

Finally, Total Rate is a product of the two, or just

$$\text{Total Rate} = \text{In-ViewImpressions}/\text{ImpressionsAnalyzed} \tag{3}$$

Fig. 2 shows a distribution of a number of MOAT measurements over different browsers, and over different ad sizes. One can see that Chrome and Internet Explorer browsers dominate, but Android Phone and iPhone are pretty close in popularity as well. Among ad sizes, 300x250, 728x90, 160x600, 300x600 and 320x50 dominate (in this order) with 1-2 orders of magnitude more events than with any other size.



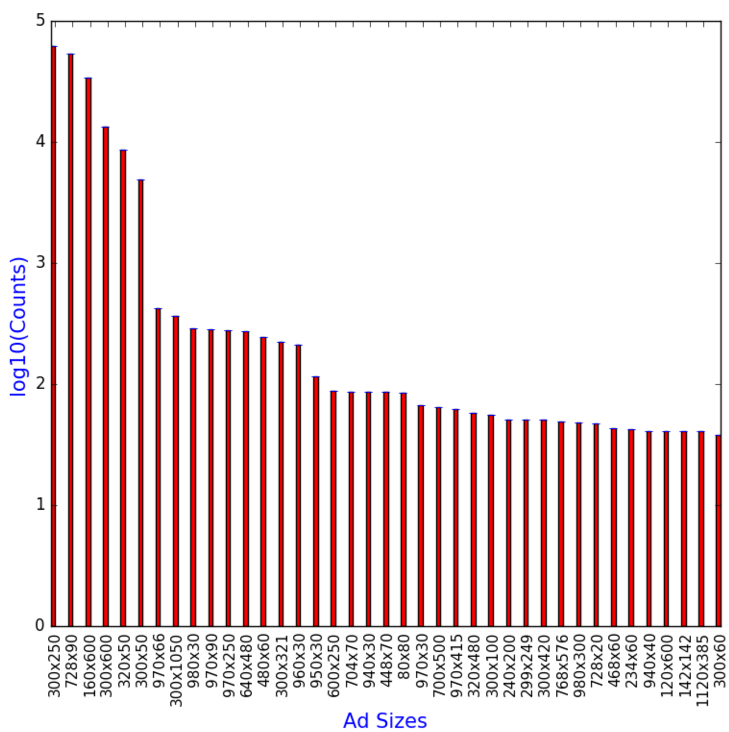


Figure 2: Distribution of a number of MOAT measurements over different browsers (top) and ad sizes (bottom).

Table 1: Viewability metics (in %) vs Browsers (MOAT, 4/2013 - 3/2016).

	Impressions Analyzed (K)	Measure Rate	In-View-Rate	Total Rate
Browser				
iPod	34647.1	80	62	49
Firefox	857100.7	98	39	39
Chrome	2585251.3	87	43	37
iPad	945226.1	77	48	37
Android Phone	1188588.9	76	47	35
Internet Explorer	2870670.0	86	41	35
iPhone	1035717.9	78	41	32
Kindle	38890.0	68	42	29
Safari	741043.0	61	44	27
Opera	9280.2	60	42	25
Windows Phone	17145.4	68	34	23
Android Tablet	1976.5	51	39	20

In Table 1 we show the three main viewability metrics, ordered by Total Rate for different Browsers. Note that here Impressions Analyzed are in thousands. Table 2 shows similar information for Ad Sizes, ordered by Total Rate. However, since different Ad Sizes may have different compatibilies (optimal fits) with different browsers, and may make sense to estimate Total Rate for their combination, (Browser, Size). That is done in Table 3 for the *most viewable* combinations having Total Rate $> 75\%$, and in Table 4 for the *least viewable* combinations having Total Rate $< 25\%$.

Table 5 shows viewability results versus major Google verticals with Shopping at the top and Jobs & Education at the end of the list. Table 6 shows viewability results versus site types, direct and network. One can see that direct sites have, on average, about 20% higher viewability.

For a few technical reasons we cannot join MMS and MOAT data sets at the ad placement level. Instead, we merge them using a pair of (Campaign ID, Ad size). In case of a few placements with same Ad size, we get average value of a continous variable. Also, for the same reason, and to know for sure what Ad size we use in a given campaign listed in MMS, we chose just campaign with a single Ad size. Luckily, it is a majority (about 65%) of cases.

After such a merging (MMS+MOAT) we have got a data set extended in the number of variables. After a few trials. we have decided to use this list all the variables used as an input to the viewability model:

$$\mathsf{features} = \{\mathsf{CPM}, \mathsf{flight\ days}, \mathsf{Browser}, \mathsf{Ad\ size}, \mathsf{Google\ vertical}, \mathsf{platform}, \mathsf{sitetype}\}. \tag{4}$$

Adding of other variables listed above does not improve performance. Please note that first two variables are continuous, and the last four are categorical (non-numerical).

Table 2: Viewability metics (in %) vs Ad Sizes (MOAT, 4/2013 - 3/2016).

Size	Impressions Analyzed (K)	Measure Rate	In-View-Rate	Total Rate
448x70	2265.5	100	99	99
704x70	5200.5	100	99	99
480x60	66.5	100	86	86
980x30	3362.7	100	76	76
960x30	1213.9	100	75	75
700x500	2975.9	100	72	72
980x300	261.6	100	72	72
300x1050	20538.4	100	73	72
320x480	4010.7	100	70	69
970x66	9052.8	98	67	66
950x30	2012.4	100	66	66
640x480	7023.2	98	65	64
940x30	1284.4	100	64	64
240x200	7026.9	92	68	62
320x50	629716.5	84	71	60
300x50	31104.3	83	72	60
970x415	1056.6	100	59	59
300x600	352439.2	95	54	52
970x250	14505.0	99	50	49
768x576	544.9	82	59	48
300x321	5551.5	95	48	46
299x249	1886.9	100	46	46
970x90	10874.3	100	37	37
80x80	831.1	97	33	33
300x250	4546535.5	83	40	33
728x90	3538156.7	81	39	32
160x600	1120796.7	79	41	32
600x250	4506.6	91	33	30
970x30	736.0	100	28	28

Table 3: Viewability metics (in %) vs Browsers and Ad Sizes (MOAT, 4/2013 - 3/2016), Total Rate> 75%.

Browser	Size	Impressions Analyzed (K)	Meas_Rate	In_View_Rate	Total_Rate
iPad	704x70	5200.5	100	99	99
	448x70	2265.5	100	99	99
Kindle	980x30	2.0	100	95	95
iPad	320x480	38.5	100	91	91
Kindle	320x480	12.5	100	90	90
iPad	480x60	55.3	100	89	89
Kindle	960x30	1.2	100	87	87
Internet Explorer	960x30	503.9	100	86	86
Windows Phone	970x66	1.1	100	86	86
Opera	300x1050	1.5	98	84	83
Internet Explorer	940x30	397.2	100	81	81
	700x500	1067.6	100	81	81
Android Phone	700x500	1.8	100	80	80
iPad	980x30	168.0	100	80	80
	940x30	110.0	100	79	79
Internet Explorer	980x30	1749.4	100	79	79
Safari	300x1050	2233.3	98	81	79
Windows Phone	970x30	1.0	100	79	79
iPod	320x50	16056.1	92	85	78
Safari	980x30	192.3	100	78	78
Kindle	970x66	12.7	100	78	78
Internet Explorer	980x300	138.0	100	77	77
Android Phone	320x480	1655.9	100	77	77
Internet Explorer	320x480	1.6	100	76	76

Table 4: Viewability metics (in %) vs Browsers and Ad Sizes (MOAT, 4/2013 - 3/2016), Total Rate< 25%.

Browser	Size	Impressions Analyzed (K)	Meas_Rate	In_View_Rate	Total_Rate
Firefox	970x30	114.9	100	24	24
Windows Phone	300x600	491.0	89	27	24
Android Phone	80x80	46.1	98	25	24
Opera	728x90	3759.9	57	43	24
	300x250	4147.0	62	39	24
Windows Phone	160x600	1182.9	65	36	24
iPhone	300x600	20966.6	91	26	23
Safari	728x90	275629.9	58	39	23
Android Phone	300x250	531227.5	73	32	23
Opera	600x250	10.8	76	29	22
iPhone	970x90	295.8	100	21	21
	300x250	521090.3	78	27	21
iPod	300x321	7.1	86	24	21
Android Phone	640x480	203.6	84	25	21
iPhone	160x600	57338.7	66	31	20
Windows Phone	300x321	4.8	88	23	20
iPod	728x90	4649.1	55	37	20
Android Phone	160x600	70351.7	63	31	20
iPod	300x600	180.0	92	21	19
Safari	970x30	91.5	100	19	19
Chrome	970x30	239.0	100	19	19
Safari	160x600	96540.6	45	43	19
Windows Phone	970x90	8.4	100	18	18
Android Tablet	728x90	626.1	53	35	18
Windows Phone	300x250	8819.1	69	25	17
iPod	160x600	1169.3	57	30	17
iPhone	80x80	49.2	96	17	17
Safari	320x50	489.0	49	32	16
Android Tablet	300x250	699.9	55	27	15
	160x600	110.4	45	33	15
iPhone	970x30	9.6	99	14	14
Android Phone	600x250	227.8	71	18	13
iPod	970x90	23.1	100	11	11
iPhone	600x250	189.7	97	10	10
Kindle	80x80	1.7	99	10	10
	640x480	2.3	5	66	4
iPod	600x250	2.6	97	4	4

Table 5: Viewability metics (in %) vs Browsers and Ad Sizes (MOAT, 4/2013 - 3/2016), Total Rate> 75%.

	Impressions Analyzed (K)	Meas_Rate	In_View_Rate	Total_Rate
Google Vertical				
Shopping	59677.0	99	64	63
Arts & Entertainment	34150.0	97	63	61
Sports	87482.8	95	54	51
Home & Garden	88464.7	90	53	48
Beauty & Fitness	67059.6	91	52	47
Business & Industrial	338404.0	92	51	47
Real Estate	151709.3	92	48	44
Health	145603.5	89	49	43
Computers & Electronics	56404.2	86	47	40
Internet & Telecom	116684.2	90	43	39
Finance	244121.5	84	43	36
Autos & Vehicles	133854.1	88	40	35
Food & Drink	435589.3	79	42	33
Law & Government	367941.1	82	40	33
Travel	113585.5	79	42	33
Jobs & Education	89651.1	83	39	32

Table 6: Viewability metics (in %) vs site type (MOAT, 4/2013 - 3/2016).

	Impressions Analyzed (K)	Meas_Rate	In_View_Rate	Total_Rate
site type				
direct	768393.1	95	57	54
network	99976.9	89	48	43

4 Viewability model

To build a predictive model, we used the set of feature variables listed in Eq. (4). We decided to use machine learning predictive tools based on ensemble methods which are less sensitive to noise and outliers in data, less prone to overfitting and also able to classify for us importance of input variables for precise predictions. Specifically, we have chosen Random Forest (RF) [3] and Gradient Boosted Trees (GBT) [4] methods to build our model.

4.1 Validation

We randomly split our initial sample into training (85%) and test (15%) samples, and use the first to train a model to predict either In-View-Rate or Total Rate. Then we use the test sample, which the model has not seen before, to estimate accuracy of predictions. Left plot in Fig. 4 shows predicted In-View-Rate versus true In-View-Rate for the RF model. In right plot of Fig. 4 we estimate an average true In-View-Rate with standard deviation in ten bins of predicted In-View-Rate for RF model. Fig. 5 shows similar results for GBT model. We see that relative prediction accuracy (ratio of the standard deviation to the true value) is worse for small In-View-Rate values. We also see the predicted values are linear, on average, with respect to true values, with a negligibly small off-diagonal bias of average values.

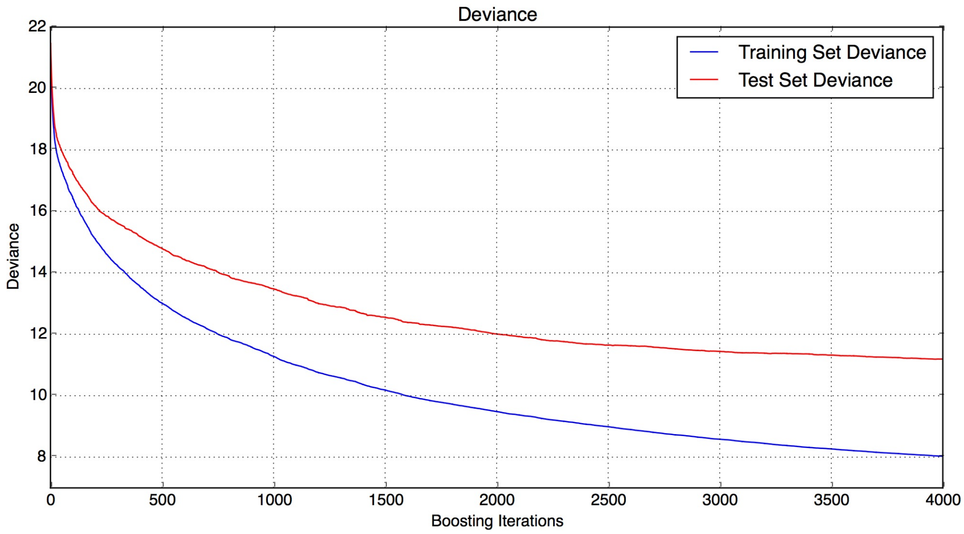
Fig. 3 shows behaviour of a deviance of a predicted value from true one versus a number of iterations used in the GBT model training with 'least-square' loss function. One can see that while the deviance continues decreasing versus interations, it saturates at about 3000–4000 iterations for the test sample.

Table 7 shows two accuracy metrics, root-mean-squared error (RMSE) and R^2 measured on the test samples for In-View-Rate prediction. We see that GBT model shows a better result for the both metrics. We will be using it as a default model.

Left plot of Fig. 6 shows predicted versus true Total Rate for the GBT model. In right plot of Fig. 6 we estimate an average true Total Rate with standard deviation in ten bins of predicted Total Rate for GBT model. Table 8 shows two accuracy metrics, RMSE and R^2 measured on the test samples for Total Rate prediction.

4.2 Variable importance

Figure 7 shows variable/feature importance listed above to predict In-View-Rate. All the variable importances are normalized to maximum importance corresponding to CPM. Distribution for features importance to predict Total Rates almost identical (differs by $< 2\%$ from Figure 7).



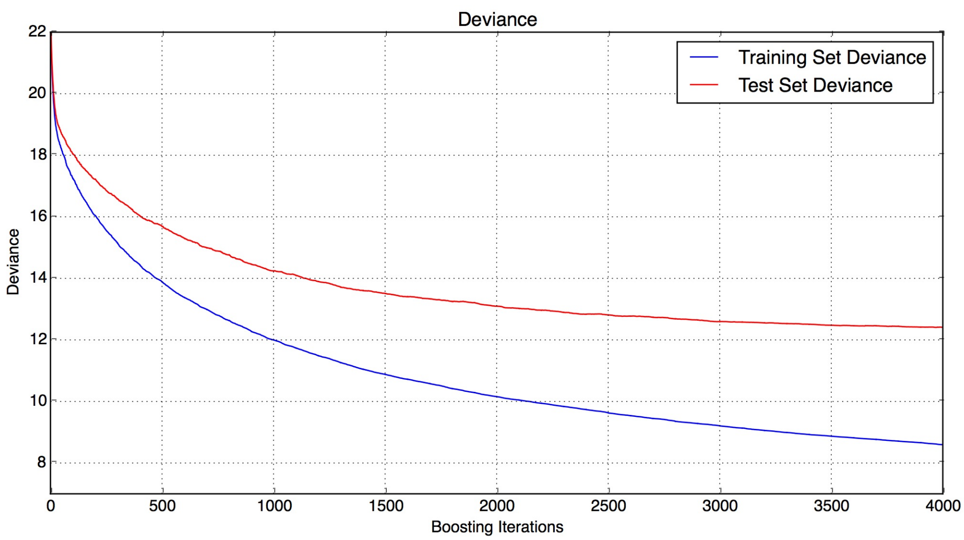


Figure 3: A deviance of predicted from true value versus boosting iterations in training and test samples used in GBT model for prediction of In-View-Rate (top) and Total Rate (bottom).

Table 7: Accuracy metrics for RF and GBT models obtained on the test samples for In-View-Rate prediction.

Measure	RF	GBT
RMSE	11.17	9.73
R^2	0.62	0.71

Table 8: Accuracy metrics for RF and GBT models obtained on the test samples for Total Rate prediction.

Measure	RF	GBT
RMSE	12.0	10.7
R^2	0.66	0.73

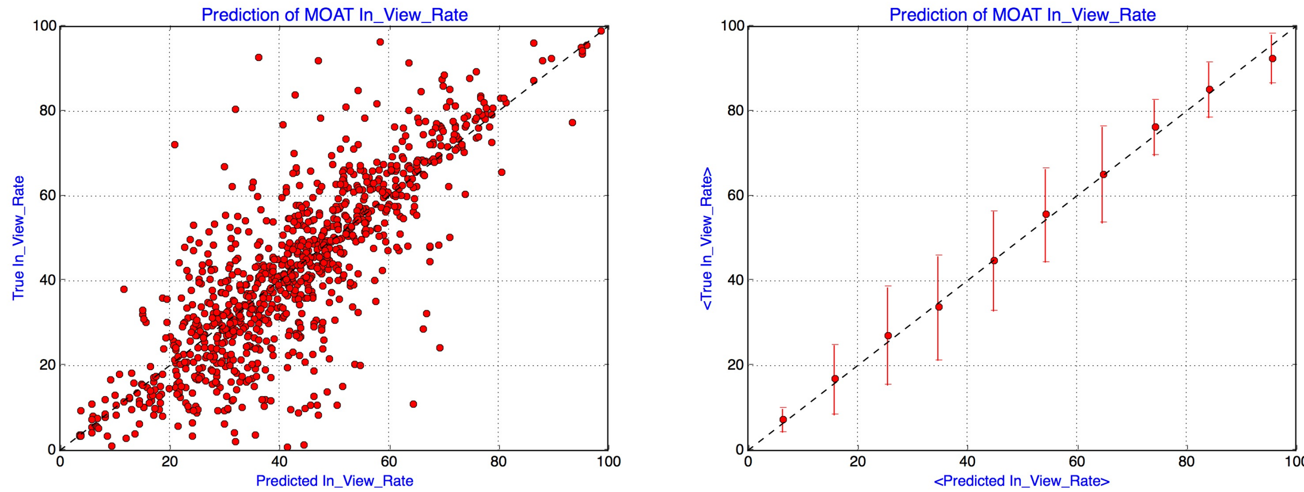


Figure 4: Left: true versus predicted In-View-Rate versus for RF model. Right: average true In-View-Rate with standard deviation in bins of predicted In-View-Rate for RF model.

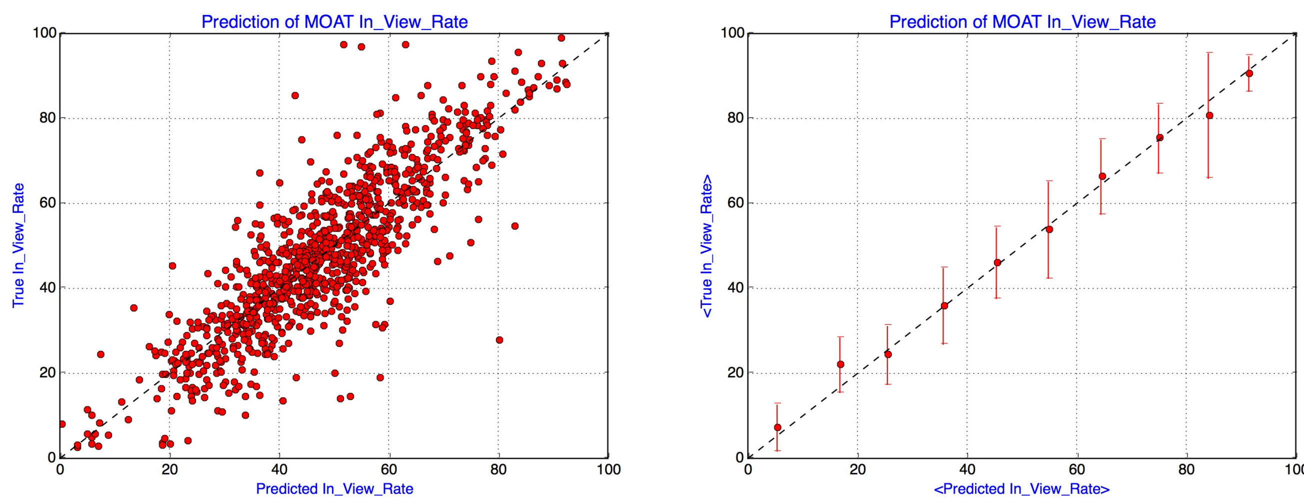


Figure 5: Left: true versus predicted In-View-Rate versus for GBT model. Right: average true In-View-Rate with standard deviation in bins of predicted In-View-Rate for GBT model.

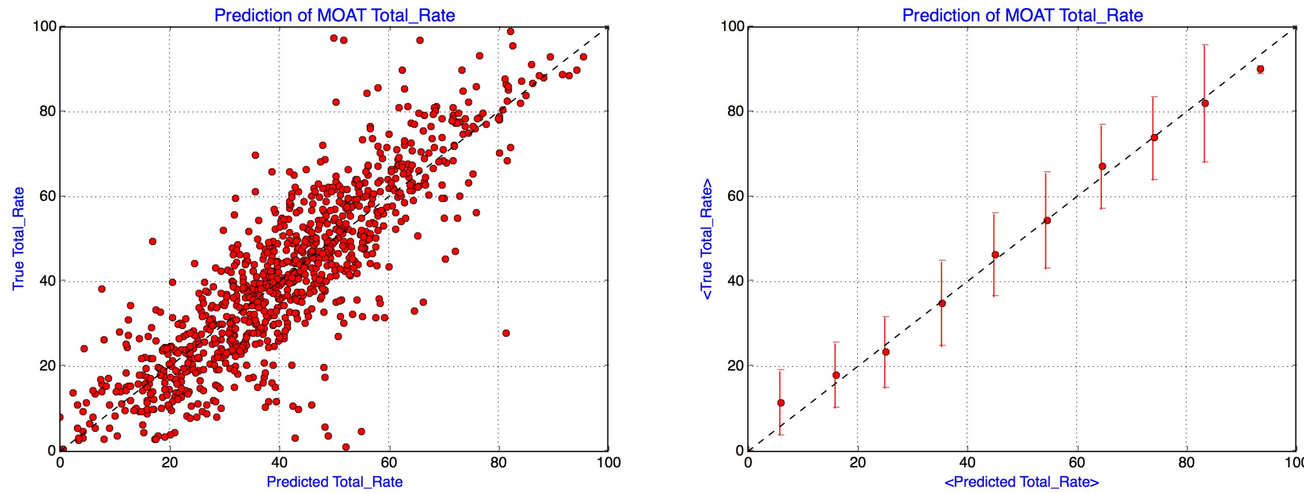


Figure 6: Left: true versus predicted Total Rate versus for GBT model. Right: average true Total Rate with standard deviation in bins of predicted Total Rate for GBT model.

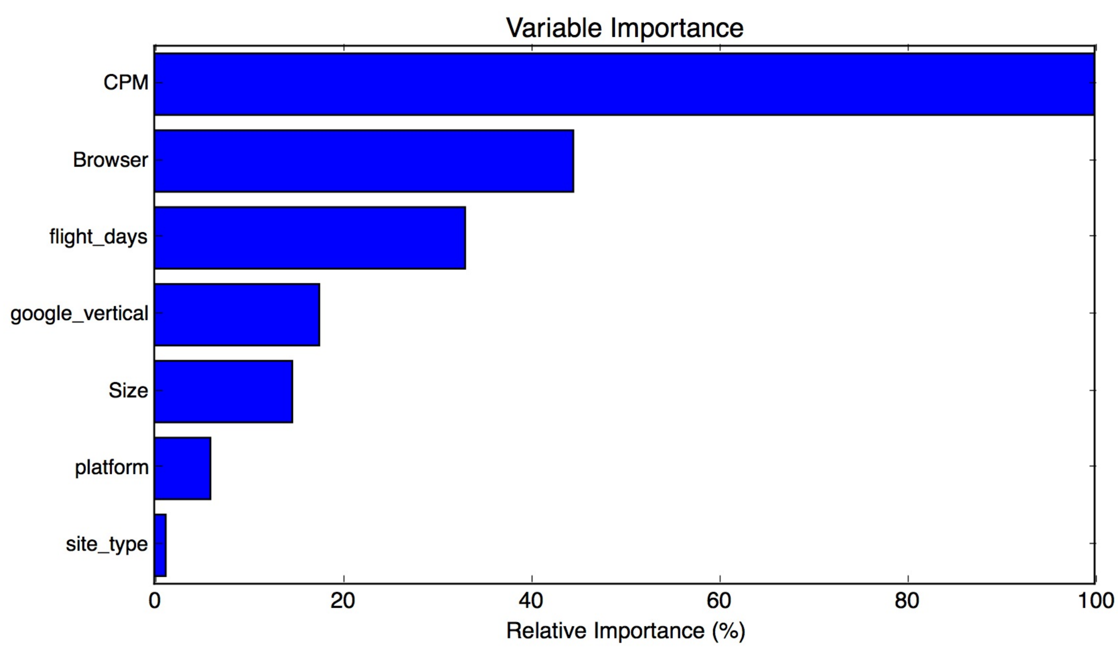


Figure 7: Importance of variables for the In-View-Rate and Total Rate predictions.

5 Discussion

[To be extended later.]

The prediction model is implemented in Python codes and available via Git at `https://github.com/centro/Data-Science/tree/master/MOAT`.

Two input data files ("Moat Export 20130401-20160302.csv", "mms_platform_reduced_gv.csv") as well as current version of analysis note ("view.pdf") can be found at p-drive:/DataScience/DmitryBandurin.

References

[1] Making Measurement Make Sense (Five guiding principles of digital measurement): http://measurementnow.net/faqs/

[2] Major challenges in measuring ad viewability: https://www.quora.com/What-are-the-major-challenges-in-measuring-ad-viewability

[3] `https://en.wikipedia.org/wiki/Random_forest`.

[4] `https://en.wikipedia.org/wiki/Gradient_boosting`.