

**Avazu Click-Through Rate Prediction** 

Late submission solution by Pavel Troshenkov Moscow, Russia, 2018

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### **Task**

In this competition we are asked for CTR problem. We need to predict the probability of user's click on advertisement

#### Metrics

Logloss

#### <u>Dataset</u>

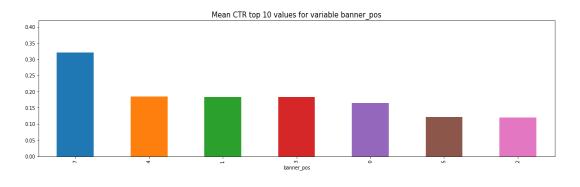
- 40 kk samples for train and 1 kk for test
- 22 categorical features

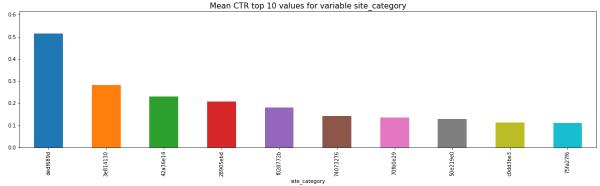
#### Feature space

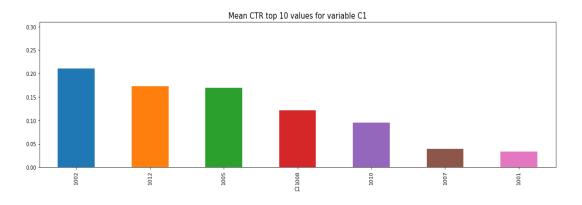
We are given with only categorical features with thousands of unique values

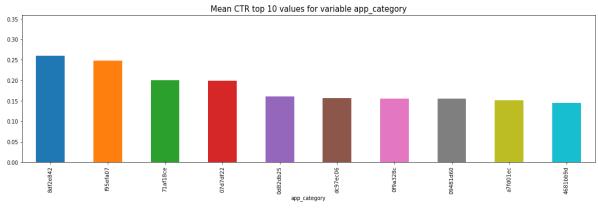
## Data observation (1/3)

#### CTR average values differ by different categorical features



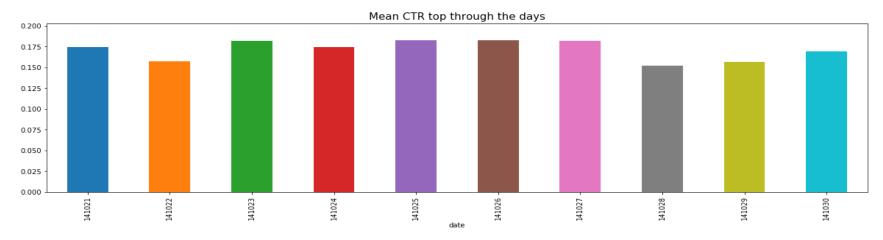




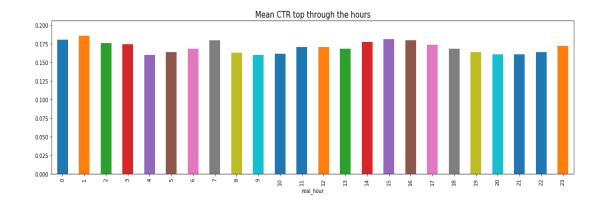


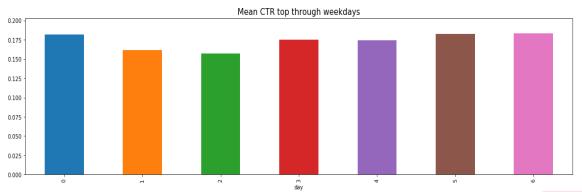
## Data observation (2/3)

#### CTR average values through dates in train file



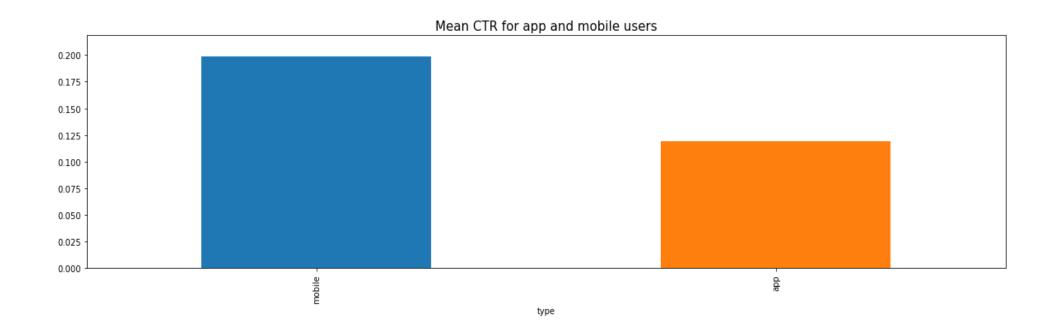
CTR seasonality by weekdays and hours





## Data observation (3/3)

- 'site\_id' == 85f751fd stands for app users
- Mobile and app users have a huge difference in average CTR



### Data observation: Conclusion

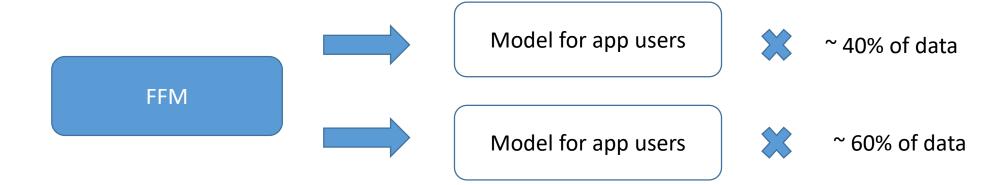
- Use factorization machines model as we have only categorical features with a lot of ( > 2kk) unique values
- Since mobile and app users have a huge difference in average CTR, I will set up different models for them

## Feature engineering

Feature	Comment
day	extracted from hour as a weekday number
time	extracted from hour
user	device_id + device_model + device_ip
user_count_hour	how many times times user appeared per hour
user_count_date	how many times times user appeared per date
user_nunique_hour_site_category	how many times site_category user visited per hour
user_nunique_hour_app_domain	how many times app_domain user visited per hour
user_nunique_hour_C15	how many times C15 user visited per hour
user_nunique_hour_C16	how many times C16 user visited per hour
user_nunique_hour_C17	how many times C17 user visited per hour
user_nunique_hour_C19	how many times C19 user visited per hour
user_nunique_hour_C21	how many times C21 user visited per hour
user_nunique_date_site_category	how many times site_category user visited per day
user_nunique_date_app_domain	how many times app_domain user visited per day
user_nunique_date_C15	how many times C15 user visited per day
user_nunique_date_C16	how many times C16 user visited per day
user_nunique_date_C17	how many times C17 user visited per day
user_nunique_date_C19	how many times C19 user visited per day
user_nunique_date_C21	how many times C21 user visited per day
place_id	site_id + app_id
place_genre_id	site_id + app_id + site_category + app_category
tech_position	banner_pos + device_conn_type
add_position	place_id + banner_pos
union_category	site_category + app_category
ultra_C_type	C1 + C14 + + C21
user_history	cumulative sum of visits of user per day
place_history	cumulative sum of visits of place per day

### Models structure

!!! Both models were trained only on 40% of data due to technical reasons



### Models based on LibFFM<sup>1</sup>

Model for app users where train with 10 latent features and gave local CV around 0.372 logloss

```
C:\Users\user>"D:\Downloads\avazu_feedzai\libffm-ftrl-master\libffm-ftrl-master\ffm-train.exe" -p "D:\Downloads\avazu_f
eedzai\ffm_txt\val_app_ffm.txt" -s 4 -k 10 -t 200 --no-rand --on-disk --auto-stop "D:\Downloads\avazu_feedzai\ffm_txt\
train_app_ffm.txt"
iter tr_logloss va_logloss
1 0.29883 0.37209
2 0.27931 0.38885
Auto-stop. Use model at 1th iteration.
```

Model for mob users where train with 6 latent features and gave local CV around 0.412 logloss

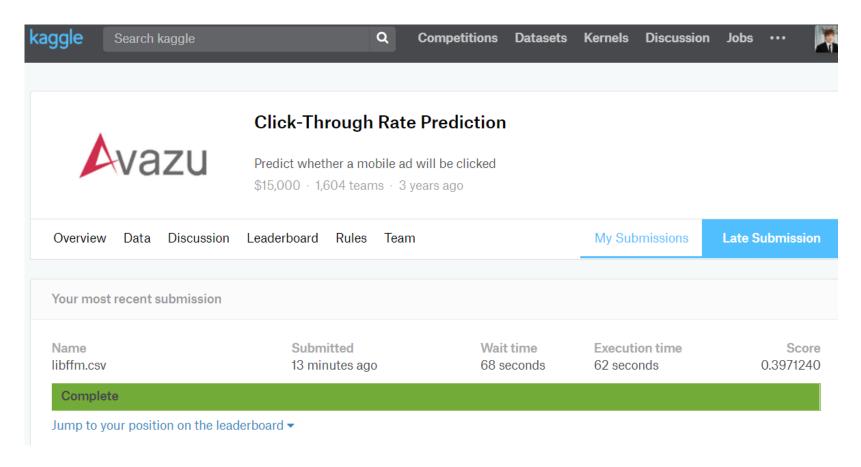
#### **CV** validation

- Same features were generated separately for mobile and app users
- Test size was set as 20%

<sup>&</sup>lt;sup>1</sup> Library can be found at <a href="https://github.com/CNevd/libffm-ftrl">https://github.com/CNevd/libffm-ftrl</a>

## Results<sup>1</sup>

#### Private LB 0.397 Logloss (~990 place)



<sup>&</sup>lt;sup>1</sup>This result was obtained on 40% of training data. Using full set should improve accuracy

### Area for improvement

- Parameter tuning (latent features and regularization)
- More feature engineering
- More data
- More models (additional splits by other categorical features besides site\_id)

# Thank you

- Code <a href="https://github.com/paveltr/avazu late submission">https://github.com/paveltr/avazu late submission</a>
- My profile <a href="https://www.linkedin.com/in/paveltr">https://www.linkedin.com/in/paveltr</a>