# Advertisement CTR Prediction

## Exploratory Data Analysis

DS5220 / Fall 2023 Semester

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# Updates on the source dataset

- As the original dataset contains over **40 million** observations, it could be expensive to run a **GridSearch** or complex modeling (e.g. **Random Forest**) in the afterward modeling phase.
- After communicating with the professor, we would only randomly resample **2.5%** of all observations (around **1 million**) from the original set for our project.
- Also, we have uploaded the resampled dataset on our **AWS S3**, which can be downloaded through ***download_data.ipynb*****,** and split into train and test set through ***train_test_split.ipynb*****.**
- We use GitHub for version control and collaborative development. Our repository: [https://github.com/LiyangSong/Advertisement-CTR-Prediction](https://github.com/LiyangSong/Advertisement-CTR-Prediction)

# Reproducibility

- Submitted files include Python module files (**.py** ), Jupyter Notebooks (**.jpynb** and **.html**), an environment file (**.yml**), and PowerPoints (**.pdf**).
- Run *download_data.ipynb* to download resampled dataset.
- Run *train_test_split.ipynb* to implement train and test set split.
- Run *eda.ipynb* to implement exploratory data analysis (EDA).
- Run *prep.ipynb* to try data transformation and EDA on the transformed dataset.

# EDA on Train Set: General information

df.head():

| | uid | task_id | adv_id | creat_type_cd | adv_prim_id | dev_id | inter_type_cd | slot_id | spread_app_id | tags | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1641431 | 5177 | 1998 | 7 | 191 | 60 | 5 | 21 | 82 | 14 | ... |
| **1** | 2021896 | 4628 | 4530 | 7 | 177 | 56 | 5 | 17 | 31 | 40 | ... |
| **2** | 1790795 | 2709 | 1413 | 7 | 134 | 55 | 4 | 17 | 65 | 18 | ... |
| **3** | 1216709 | 1949 | 6143 | 7 | 150 | 17 | 5 | 21 | 11 | 39 | ... |
| **4** | 1635521 | 4806 | 2176 | 7 | 206 | 64 | 5 | 15 | 22 | 39 | ... |

df.describe:

| | uid | task_id | adv_id | creat_type_cd | adv_prim_id | dev_id | inter_type_cd |
|---|---|---|---|---|---|---|---|
| **count** | 8.381420e+05 | 838142.000000 | 838142.000000 | 838142.000000 | 838142.000000 | 838142.000000 | 838142.000000 |
| **mean** | 1.618734e+06 | 3436.778738 | 3964.562067 | 6.491097 | 159.346748 | 41.596531 | 4.647426 |
| **std** | 3.574750e+05 | 1430.118430 | 1720.086656 | 1.230525 | 30.895882 | 17.418631 | 0.709892 |
| **min** | 1.000004e+06 | 1001.000000 | 1001.000000 | 2.000000 | 101.000000 | 11.000000 | 2.000000 |
| **25%** | 1.309340e+06 | 2229.000000 | 2504.000000 | 6.000000 | 134.000000 | 29.000000 | 5.000000 |
| **50%** | 1.618150e+06 | 3370.000000 | 4056.000000 | 7.000000 | 156.000000 | 37.000000 | 5.000000 |
| **75%** | 1.929031e+06 | 4595.000000 | 5461.000000 | 7.000000 | 180.000000 | 60.000000 | 5.000000 |
| **max** | 2.237671e+06 | 5992.000000 | 7020.000000 | 9.000000 | 214.000000 | 72.000000 | 5.000000 |

```
 24  emui_dev                     838142 non-null  int64
 25  list_time                    838142 non-null  int64
 26  device_price                 838142 non-null  int64
 27  up_life_duration             838142 non-null  int64
 28  up_membership_grade          838142 non-null  int64
 29  membership_life_duration     838142 non-null  int64
 30  consume_purchase             838142 non-null  int64
 31  communication_onlinerate     838142 non-null  object
 32  communication_avgonline_30d  838142 non-null  int64
 33  indu_name                    838142 non-null  int64
 34  pt_d                         838142 non-null  int64
 35  label                        838142 non-null  int64
dtypes: int64(35), object(1)
```

```
df.shape:
(838142, 36)
```

# EDA on Train Set: Duplication and missingness

```
eda_utils.check_out_duplicate_obs(train_df_eda)

Check out duplicate observations:
df.shape:  (838142, 36)
drop_dup_df.shape:  (833795, 36)
Caution: data set contains duplicate observations!!!
```

```
eda_utils.check_out_missing_target(train_df_eda, target)

Check out observations with missing target:
df.shape:  (838142, 36)
drop_miss_tar_df.shape:  (838142, 36)
No missing-target observations observed in data set.
```

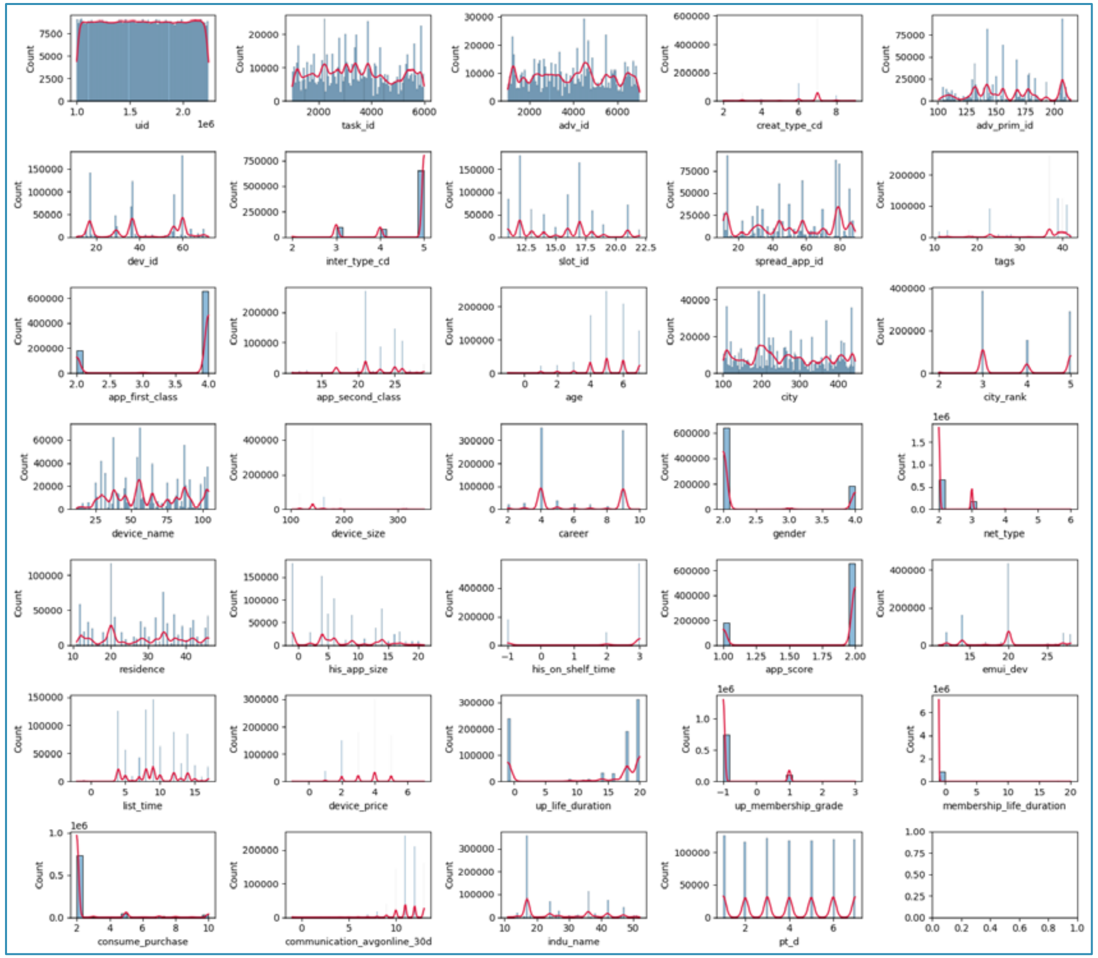
```
eda_utils.check_out_missingness(train_df_eda)

Check out missingness:
No missing values in data set.
```

- There are **duplicate observations** in the set, which should be dropped at the beginning of the data transformation.
- **No missing value** in both attributes and the target variable.

# EDA on Train Set: Identify numerical and categorical attributes

- Based on the data type of attribute columns, there is only one categorical attribute *communication_onlinerate*. However, some 'numerical' attributes seem to be categorical from the field explanation (see *data_fields.json* in repo) and domain knowledge.
- After checking the original dataset, it seems the data has been **label-encoded**, which means categories in categorical attributes are replaced with numbers.
- These pre-encoded categorical attributes have no statistical meaning with their number. These numbers can be actually seen as another type of 'label'.
- In addition, directly label-encoding categorical attributes may be not suitable sometimes. It could be suitable if the attribute is ordinal, yet label-encoding nominal attributes is meaningless, as there is no actual numerical relationship between them.
- Thus, we will look at the distribution of all 'numerical' attributes and **find actually categorical ones** within them.

# EDA on Train Set: Identify numerical and categorical attributes




- The histogram plots reveal some **possible pre-encoded attributes**.
- Some are clearly nominal: IDs(***uid***, ***task_id***, etc), city, career, gender, etc.
- Some are like ordinal: ***age***, ***city_rank***, etc. However, they may also be pre-aggregated. For instance, there are only 8 unique values of ***age***, which is not realistic.
- After communicating with the professor, we would treat all categorical attributes as the same type rather than splitting into nominal and ordinal ones.
- After looking into the original dataset, **all attributes are pre-encoded and no one can be defined as numerical**. It may be for the consideration of privacy.

# EDA on Train Set: Target encode categorical attributes

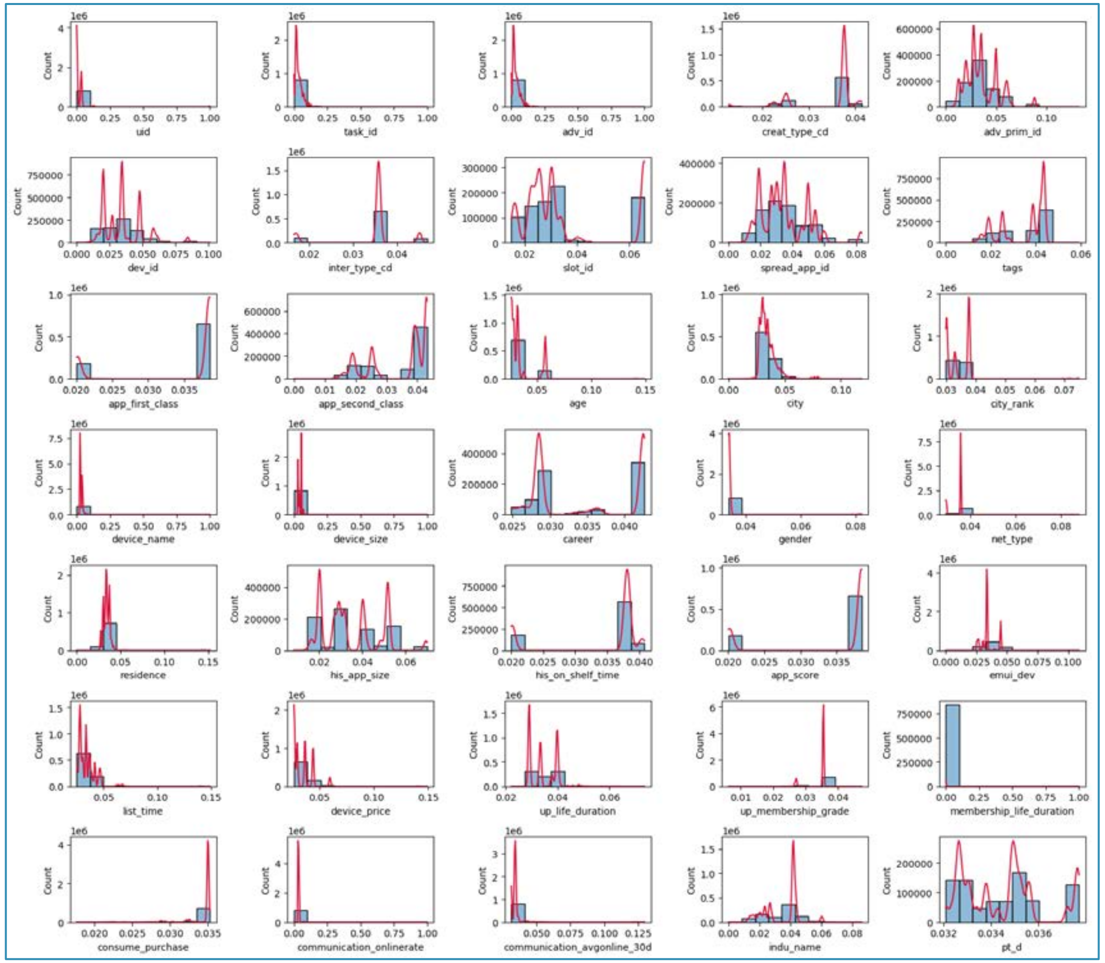
- As the high number of unique values in some attributes, **Target-Encoding** rather than OneHot-Encoding should be applied.

```
train_df_eda_encoded = data_prepare_utils.target_encode_categorical(train_df_eda, categorical_attr_list, target)
```

```
Target encode categorical attributes:
encoded_df.head():
```

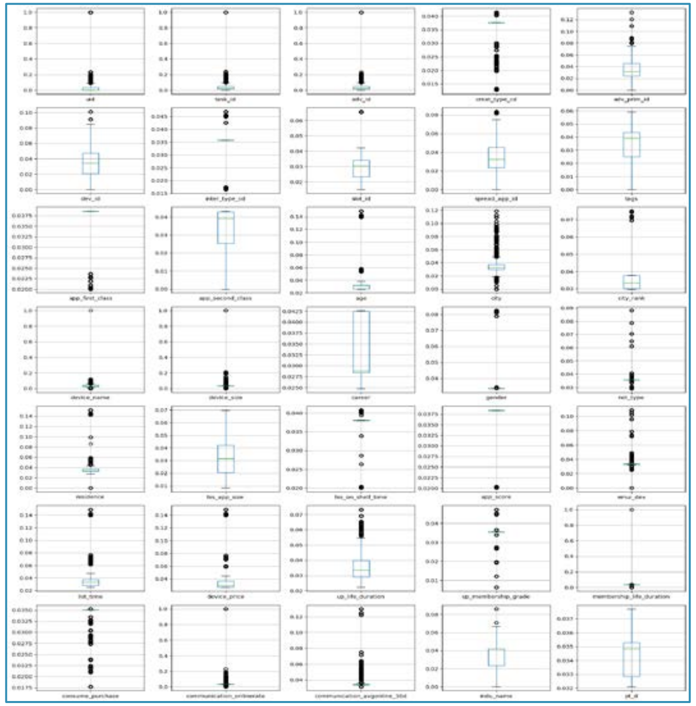
| | uid | task_id | adv_id | creat_type_cd | adv_prim_id | dev_id | inter_type_cd | slot_id | spread_app_id | tags | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.000000 | 0.038679 | 0.038679 | 0.037668 | 0.029137 | 0.020065 | 0.035876 | 0.025592 | 0.029137 | 0.029137 | ... |
| **1** | 0.034493 | 0.012218 | 0.012218 | 0.037681 | 0.032378 | 0.034536 | 0.035878 | 0.030219 | 0.030939 | 0.038545 | ... |
| **2** | 0.034493 | 0.033665 | 0.033665 | 0.037665 | 0.033763 | 0.033763 | 0.045227 | 0.030463 | 0.033763 | 0.028481 | ... |
| **3** | 0.000000 | 0.008956 | 0.008956 | 0.037665 | 0.035366 | 0.047814 | 0.035886 | 0.025305 | 0.035366 | 0.042652 | ... |
| **4** | 0.000000 | 0.053058 | 0.053058 | 0.037665 | 0.038609 | 0.039587 | 0.035886 | 0.016242 | 0.038609 | 0.042652 | ... |

# EDA on Train Set: EDA on encoded attributes (distribution)




- The distribution of encoded attributes becomes **consecutive and smoother** than before, as target encoding is less sensitive to extreme values.

# EDA on Train Set: EDA on encoded attributes (outlier detection)

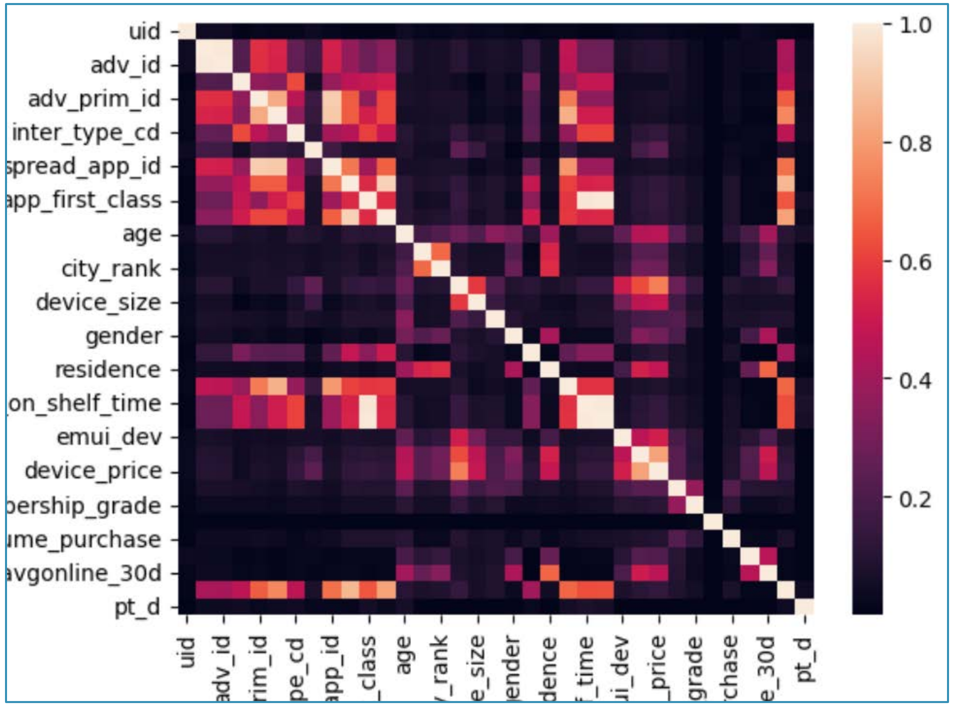


Implement Tukey's fences to identify outliers based on the Inter Quartile Range (IQR) method:

| | Attribute | Outliers Prob Count | Outliers Prob Fraction | Outliers Poss Count | Outliers Poss Fraction |
|---|---|---|---|---|---|
| 16 | device_size | 364305 | 0.434658 | 364845 | 0.435302 |
| 24 | emui_dev | 296287 | 0.353505 | 360704 | 0.430361 |
| 22 | his_on_shelf_time | 267541 | 0.319207 | 267541 | 0.319207 |
| 3 | creat_type_cd | 261764 | 0.312315 | 261764 | 0.312315 |
| 6 | inter_type_cd | 184833 | 0.220527 | 184833 | 0.220527 |
| 10 | app_first_class | 184675 | 0.220339 | 184675 | 0.220339 |
| 23 | app_score | 180435 | 0.215280 | 180435 | 0.215280 |
| 19 | net_type | 171692 | 0.204848 | 171692 | 0.204848 |
| 18 | gender | 158172 | 0.188717 | 195166 | 0.232856 |
| 12 | age | 151191 | 0.180388 | 151191 | 0.180388 |
| 30 | consume_purchase | 104001 | 0.124085 | 104001 | 0.124085 |
| 28 | up_membership_grade | 101984 | 0.121679 | 101984 | 0.121679 |
| 32 | communication_avgonline_30d | 39365 | 0.046967 | 225254 | 0.268754 |
| 31 | communication_onlinerate | 24121 | 0.028779 | 70296 | 0.083871 |

- Outlier fraction in all attributes decreased after target encoding. This is reasonable as target encoding can kind of smooth extreme values and make the feature less "outliery".
- However, there are still some attributes with a significantly high outlier fraction (>20%). We will not decide to drop them simply in this step. Some of them seem like useful predictors.

# EDA on Train Set: EDA on encoded attributes (feature correlation)




Matrix visualizing correlation (>0.7) between n

| | correlation |
|---|---|
| his_on_shelf_time with app_score | 0.994035 |
| task_id with adv_id | 0.990200 |
| app_first_class with app_score | 0.988605 |
| app_first_class with his_on_shelf_time | 0.982526 |
| tags with app_second_class | 0.929792 |
| adv_prim_id with spread_app_id | 0.921037 |
| dev_id with spread_app_id | 0.907717 |
| tags with indu_name | 0.863911 |
| dev_id with his_app_size | 0.846389 |
| adv_prim_id with dev_id | 0.833137 |
| list_time with device_price | 0.815580 |
| app_second_class with indu_name | 0.814459 |
| spread_app_id with his_app_size | 0.791584 |
| dev_id with indu_name | 0.753021 |

| | attribute | vif |
|---|---|---|
| 24 | app_score | 133.794539 |
| 23 | his_on_shelf_time | 87.679437 |
| 2 | task_id | 51.808286 |
| 3 | adv_id | 51.275208 |
| 11 | app_first_class | 47.327007 |
| 9 | spread_app_id | 15.577611 |
| 10 | tags | 11.949464 |
| 6 | dev_id | 11.120764 |
| 12 | app_second_class | 8.287784 |
| 5 | adv_prim_id | 7.862803 |
| 34 | indu_name | 6.486875 |
| 27 | device_price | 5.075470 |
| 22 | his_app_size | 4.207545 |

- There are a remarkable number of attribute pairs with a **high correlation** (>0.7). We will consider dropping one from the pair of them.
- There are some very **high VIFs** (>5), which reveals the existence of multi co-linearity.

# EDA on Train Set: EDA on encoded attributes (feature usefulness)

Calculate the correlation between each attribute and the target:

| | correlation |
|---|---|
| membership_life_duration | 0.000068 |
| pt_d | 0.008201 |
| consume_purchase | 0.008991 |
| net_type | 0.014096 |
| up_membership_grade | 0.014871 |
| communication_onlinerate | 0.018961 |
| city | 0.025930 |
| city_rank | 0.026971 |
| up_life_duration | 0.028191 |
| gender | 0.028615 |
| communication_avgonline_30d | 0.031160 |
| emui_dev | 0.033253 |

Calculate the variance of each attribute:

| | variance |
|---|---|
| membership_life_duration | 0.000002 |
| pt_d | 0.000003 |
| consume_purchase | 0.000003 |
| net_type | 0.000007 |
| up_membership_grade | 0.000008 |
| city_rank | 0.000025 |
| gender | 0.000027 |
| up_life_duration | 0.000029 |
| communication_avgonline_30d | 0.000034 |
| emui_dev | 0.000038 |
| creat_type_cd | 0.000041 |

- The correlation of each attribute with the target is **not high** enough. This is reasonable for a large-number attributes model.
- The variance for all attributes is **quite tiny** with the biggest one < 0.01. This may due to the highly unbalanced target variable, or the high cardinality of attributes.
- Low-variance attributes do not represent useless as they may still carry useful information.

# Identify the promising transformations

- Deal with duplicate observations.
- No missingness in data set.
- Targe encode categorical attributes.
- Drop highly correlated attributes.
  - *app_score*. A very high VIF, very high correlations, and a high outlier fraction.
  - *his_on_shelf_time*. A very high VIF, very high correlations, and a high outlier fraction.
  - *task_id*. A very high VIF and a very high correlation.
  - *spread_app_id*. A high VIF and very high correlations.
  - *tags*. A high VIF and very high correlations.
  - *dev_id*. A high VIF and very high correlations.
  - *app_second_class*. A high VIF and very high correlations.
  - *adv_prim_id*. A high VIF and very high correlations.
  - *device_price*. A high VIF and very high correlations.

```
attrs_to_drop

['app_score',
 'his_on_shelf_time',
 'task_id',
 'spread_app_id',
 'tags',
 'dev_id',
 'app_second_class',
 'adv_prim_id',
 'device_price']
```