Exploratory data analysis

PREDICTING CTR WITH MACHINE LEARNING IN PYTHON



Kevin HuoInstructor



A closer look at features

```
print(df.columns)
['id', 'click', 'hour', 'C1', ....]
print(df.dtypes)
id
                    object
click
                     int64
```

```
int: an integer: 1, 2, etc.
  float : decimals: 3.02 , 4.56 , etc.
  object :string: "hello", "world", etc.
  datetime: datetime: 2018-01-01, etc.
df.select_dtypes(
  include=['int', 'float'])
click
                     int64
```

Missing data

```
df.info()
Data columns (total 24 columns):
id
             50000 non-null object
df['id'].isnull()
[False, False, False, ...]
```

```
df.isnull().sum(axis = 0)
dtype: object
id
df.isnull().sum(axis = 0).sum()
```

Looking at distributions

```
search_engine_type click
1002 0 940
1 240
...
```

```
click 0 1
search_engine_type
1002 940 240
...
```

Breakdown by CTR

```
df.reset_index()
```

```
click search_engine_type 0 1
1002 940 240
```

```
df.rename(columns = {0: 'non_clicks'}, inplace = True)
```

```
click search_engine_type non_clicks clicks
1002 940 240
```



Let's practice!

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Feature engineering

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Dealing with dates

```
print(df.hour.head(1))
```

14102101

```
df['hour'] = pd.to_datetime(
    df['hour'], format = '%y%m%d%H')
df['hour_of_day'] = df['hour'].dt.hour
print(df.hour.head(1))
```

```
2014-10-21 01:00:0
```

```
print(df.groupby('hour_of_day')
    ['click'].sum())
```

```
click
hour_of_day
1 1092
2 6546
```

Converting categorical variables via hashing

- Categorical features must be converted into a numerical format
- Hash function: maps arbitrary input to an integer output, returning exact same output for a given input
- Lambda function: lambda x: f(x)
- Apply hash function via f(x) = hash(x) as follows:

```
df['site_id'] = df['site_id'].apply(lambda x: hash(x), axis = 0)
```

```
83a0ad1a -> -9161053084583616050
85f751fd-> 818242008494177460
```

A closer look at features

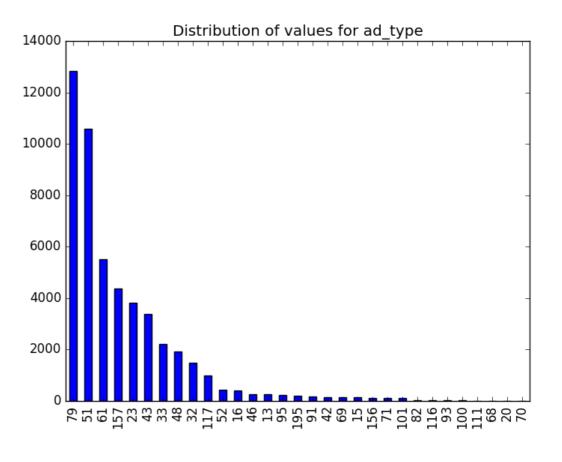
Examples of count() and nunique():

```
df['ad_type'].count()
```

50000

```
df['ad_type'].nunique()
```

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Creating features

- Most of variables are categorical
- Adding more features is better for predictive power
- Example of new feature: impressions by device_id (user) and search_engine_type :

```
df['device_id_count'] = df.groupby('device_id')['click'].transform("count")

df['search_engine_type_count'] = df.groupby('search_engine_type')['click'].transform("count")

print(df.head(1))
```

```
... device_id_count search_engine_type_count
... 40862 47710
```

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Standardizing features

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Why standardization is important

- Standardization: ensuring your data fits assumptions that models have
- Certain features may have too high variance, which might unfairly dominate models
- Example: certain count have too large of a range of values due to one spam user
- Does not apply to categorical variables such as site_id , app_id , device_id , etc.

Log normalization

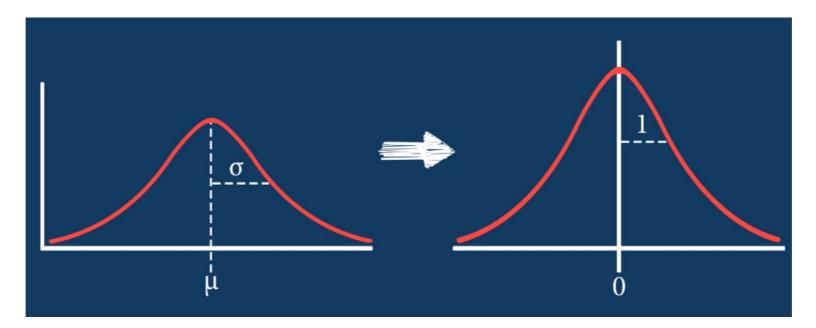
```
df.var()
click
                         1.294270e-01
                         1.123316e-01
hour
df.var().median()
0.7108583771671939
```

```
print(df['click'].var())
df['device_id_count'] = df[
  'device_id_count'].apply(
  lambda x: np.log(x))
print(df['click'].var())
```

```
249362570.1013482515.628476003312514
```

Scaling data

• Standard scaling converts all features to have mean of 0 and standard deviation of 1



• Generally a good practice for machine learning models

How to standard scale data

• Scaling can be done using StandardScaler() as follows:

```
scaler = StandardScaler()
X[numeric_cols] = scaler.fit_transform(X[numeric_cols])
```

```
dtype: float64
1  10.5 -> 0.85
2  32.3 -> 1.54
```

Let's practice!

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