某电商平台针对优化落地页设计的A/B测试

1. 确定实验样本量

In [1]:
```
# 使用Python完成最小样本量计算
import numpy as np
import pandas as pd
import scipy.stats as stats
import statsmodels.stats.api as sms
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# 根据我们的预期比率计算效果量
effect_size = sms.proportion_effectsize(0.13, 0.15)
```

In [3]:
```
effect_size
```

Out[3]: -0.0576728617308947

In [4]:
```
# 计算所需的样本量
required_n = sms.NormalIndPower().solve_power(
    effect_size,
    power=0.8,
    alpha=0.05,
    ratio=1 ,
    )
```

In [5]:
```
required_n
```

Out[5]: 4719.4740575998185

In [6]:
```
# 向上取整
np.ceil(required_n)
```

Out[6]: 4720.0

In [7]:
```
# 此次AB测试至少需要9440个用户参与测试
np.ceil(required_n)*2
```

Out[7]: 9440.0

2. 数据导入

In [8]:
```
df = pd.read_csv("ab_data.csv")
df.head()
```

Out[8]:

	user_id	timestamp	group	landing_page	converted
0	851104	11:48.6	control	old_page	0
1	804228	01:45.2	control	old_page	0
2	661590	55:06.2	treatment	new_page	0
3	853541	28:03.1	treatment	new_page	0
4	864975	52:26.2	control	old_page	1

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294478 entries, 0 to 294477
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   user_id       294478 non-null  int64 
 1   timestamp     294478 non-null  object
 2   group         294478 non-null  object
 3   landing_page  294478 non-null  object
 4   converted     294478 non-null  int64 
dtypes: int64(2), object(3)
memory usage: 11.2+ MB
```

- 字段名称含义：
  - user_id：用户ID
  - timestamp：用户访问页面的时间
  - group：用户分组情况（新落地页为treatment组，旧版落地页为control组）
  - landing_page：每位用户看到的落地页（分为新旧两版落地页）
  - converted：是否成功转化（1代表成功转化，0代表未转化）

In [10]:
```
df["group"].value_counts()
```

Out[10]:
```
treatment    147276
control      147202
Name: group, dtype: int64
```

In [11]:
```
df["landing_page"].value_counts()
```

Out[11]:
```
old_page    147239
new_page    147239
Name: landing_page, dtype: int64
```

3. 数据清洗

- 检查缺失值、重复值

In [12]:
```
# 检查缺失值并处理
df.isnull().sum()
```

Out[12]:
```
user_id         0
timestamp       0
group           0
landing_page    0
converted       0
dtype: int64
```

In [13]:
```
# 检查重复值并处理
df.duplicated().sum() #对于整体数据集没有重复值
```

Out[13]:
```
0
```

In [14]:
```
# 检查用户是否有重复值
df["user_id"].duplicated().sum()
```

Out[14]:
```
3894
```

In [15]:
```
df[df["user_id"].duplicated()]["user_id"]
```

Out[15]:
```
2656      698120
2893      773192
7500      899953
8036      790934
10218     633793
           ...
294308    905197
294309    787083
294328    641570
294331    689637
294355    744456
Name: user_id, Length: 3894, dtype: int64
```

In [16]:
```
# 查看其中一位重复用户
df[df["user_id"]==698120]
```

Out[16]:

	user_id	timestamp	group	landing_page	converted
988	698120	09:37.5	control	new_page	0
2656	698120	13:42.6	control	old_page	0

In [17]:
```
# 储存所有的重复用户ID，准备删除
del_id = df[df["user_id"].duplicated()]["user_id"].values
```

In [18]:
```
# 需要删除的重复样本量
df["user_id"].isin(del_id).sum()
```

Out[18]:
```
7788
```

In [19]:
```
~df["user_id"].isin(del_id)
```

Out[19]:
```
0         True
1         True
2         True
3         True
4         True
          ...
294473    True
294474    True
294475    True
294476    True
294477    True
Name: user_id, Length: 294478, dtype: bool
```

In [20]:
```
# 删除后生成新的df
df_new = df[~df["user_id"].isin(del_id)]
df_new
```

Out[20]:

	user_id	timestamp	group	landing_page	converted
0	851104	11:48.6	control	old_page	0
1	804228	01:45.2	control	old_page	0
2	661590	55:06.2	treatment	new_page	0
3	853541	28:03.1	treatment	new_page	0
4	864975	52:26.2	control	old_page	1
...	...	...	...	...	...
294473	751197	28:38.6	control	old_page	0
294474	945152	51:57.1	control	old_page	0
294475	734608	45:03.4	control	old_page	0
294476	697314	20:29.0	control	old_page	0
294477	715931	40:24.5	treatment	new_page	0

286690 rows × 5 columns

- 接下来，要保证control组对应old_page,treatment组对应new_page

In [21]:
```
(((df_new['group']=='treatment')&(df_new['landing_page']=='new_page'))|((df_new['group']=='contr
```

Out[21]: 286690

In [22]:
```
# 确保contorl组每个用户看到的是旧页面，treatment组看到的是新页面
pd.crosstab(df_new['group'], df_new['landing_page'])
```

Out[22]:

landing_page	new_page	old_page
group		
control	0	143293
treatment	143397	0

- 至此，所有的数据清洗工作已完成

4. 抽样

思考：

1. 根据前面最小样本量的计算，我们至少需要每组4720个样本，这里我们选择每组抽样5000个（**实际工作中不需要抽样这一步**）

In [23]:
```
required_n = 5000
control_sample = df_new[df_new['group'] == 'control'].sample(n=required_n, random_state=0)
treatment_sample = df_new[df_new['group'] == 'treatment'].sample(n=required_n, random_state=0)

ab_test = pd.concat([control_sample, treatment_sample], axis=0)
ab_test.reset_index(drop=True, inplace=True)
ab_test
```

Out[23]:

	user_id	timestamp	group	landing_page	converted
0	740761	06:22.2	control	old_page	0
1	685906	37:19.4	control	old_page	0
2	803229	46:36.5	control	old_page	0
3	771051	49:52.4	control	old_page	0
4	726377	18:54.6	control	old_page	0
...	...	...	...	...	...
9995	721371	27:27.0	treatment	new_page	0
9996	795324	53:31.9	treatment	new_page	0
9997	895599	04:03.6	treatment	new_page	0
9998	760897	24:15.8	treatment	new_page	0
9999	768726	23:28.8	treatment	new_page	0

10000 rows × 5 columns

In [24]:
```
pd.crosstab(ab_test['group'], ab_test['landing_page'])
```

Out[24]:

landing_page	**new_page**	**old_page**
group		
control	0	5000
treatment	5000	0

5. 转化率计算

In [25]:
```
conversion_rates = ab_test.groupby('group')['converted'].agg([np.mean, np.std])
conversion_rates
```

Out[25]:

	mean	**std**
group		
control	0.1122	0.315644
treatment	0.1202	0.325228

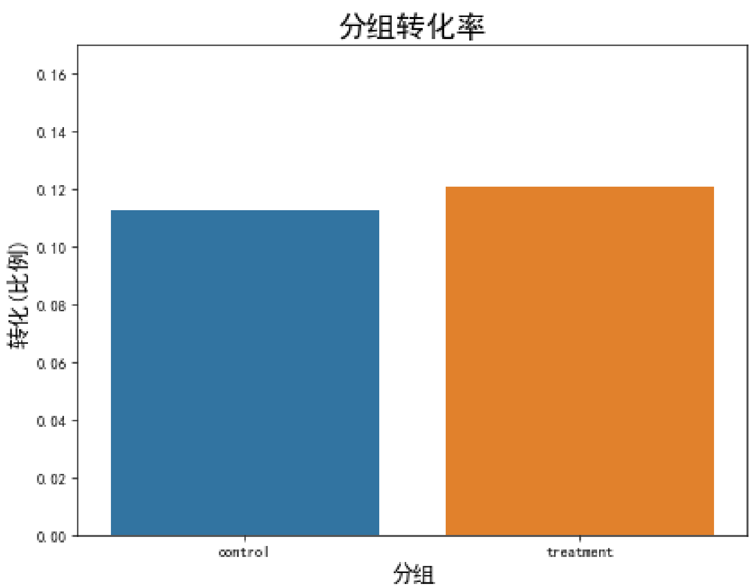
In [26]:
```
# 更换列名
conversion_rates.columns = ['conversion_rate', 'std_deviation']
conversion_rates
```

Out[26]:

	conversion_rate	std_deviation
group		
control	0.1122	0.315644
treatment	0.1202	0.325228

In [27]:
```
plt.rcParams['font.family'] = 'SimHei'
plt.rcParams['axes.unicode_minus'] = False

plt.figure(figsize=(8,6),dpi=60)
sns.barplot(x=ab_test['group'], y=ab_test['converted'], ci=False)
plt.ylim(0, 0.17)
plt.title( '分组转化率', fontsize=20)
plt.xlabel('分组', fontsize=15)
plt.ylabel('转化(比例)', fontsize=15);
```



- 从上面的统计数据来看，新旧两版落地页的表现结果非常相近，相比于旧版落地页，新版落地页的转化率略微好一点点，高了0.8%

思考:

1. 那么，这种差异在统计学上显著么？我们可以直接说，新版落地页更好么？

- 需要通过假设检验进行验证

6. 假设检验

- 在统计学中，当样本容量较大时（一般是大于30），我们可以使用Z检验或者t检验。
- 在这个案例中，由于我们的样本非常大，所以我们使用Z检验。Python中的statsmodels.stats.proportion模块可以来计算P值和置信区间：

In [28]:
```
from statsmodels.stats.proportion import proportions_ztest, proportion_confint

control_results = ab_test[ab_test['group'] == 'control']['converted']
treatment_results = ab_test[ab_test['group'] == 'treatment']['converted']
```

In [29]:
```
# 1的个数
control_results.sum()
```

Out[29]: 561

In [30]:
```
# 1的个数
treatment_results.sum()
```

Out[30]: 601

In [31]:
```
n_con = control_results.count()
n_treat = treatment_results.count()
successes = [control_results.sum(), treatment_results.sum()]
nobs = [n_con, n_treat]
```

In [32]:
```
nobs
```

Out[32]: [5000, 5000]

In [33]:
```
successes
```

Out[33]: [561, 601]

In [34]:
```
z_stat, pval = proportions_ztest(successes, nobs=nobs)
```

In [35]:
```
z_stat
```

Out[35]: -1.2481877864638855

In [36]:
```
# p值
pval
```

Out[36]: 0.21196229562845081

In [37]:
```
(lower_con, lower_treat), (upper_con, upper_treat) = proportion_confint(successes,
                                                                       nobs=nobs,
                                                                       alpha=0.05)

print(f'z statistic: {z_stat:.2f}')
print(f'p-value: {pval:.3f}')
print(f'ci 95% for control group: [{lower_con:.3f}, {upper_con:.3f}]')
print(f'ci 95% for treatment group: [{lower_treat:.3f}, {upper_treat:.3f}]')
```

```
z statistic: -1.25
p-value: 0.212
ci 95% for control group: [0.103, 0.121]
ci 95% for treatment group: [0.111, 0.129]
```

6. 结果分析与建议

- 由于我们计算出来的P值=0.212远高于显著水平 α=0.05 ，所以我们不能拒绝原假设H0.这意味着新版落地页与旧版落地页没有明显不同（更不用说更好了）
- 此外，我们继续看置信区间，treatment组的置信区间为 [0.111, 0.129]，可以看出：
  - 它包括我们的转化率基准线13%
  - 但它不包括我们的转化率目标值15%
  - 这就说明，新版落地页的真实转化率更有可能与我们的基线相似，而没有办法达到我们期望的15%。进一步证明了，新版设计并不是一个很好的改进。