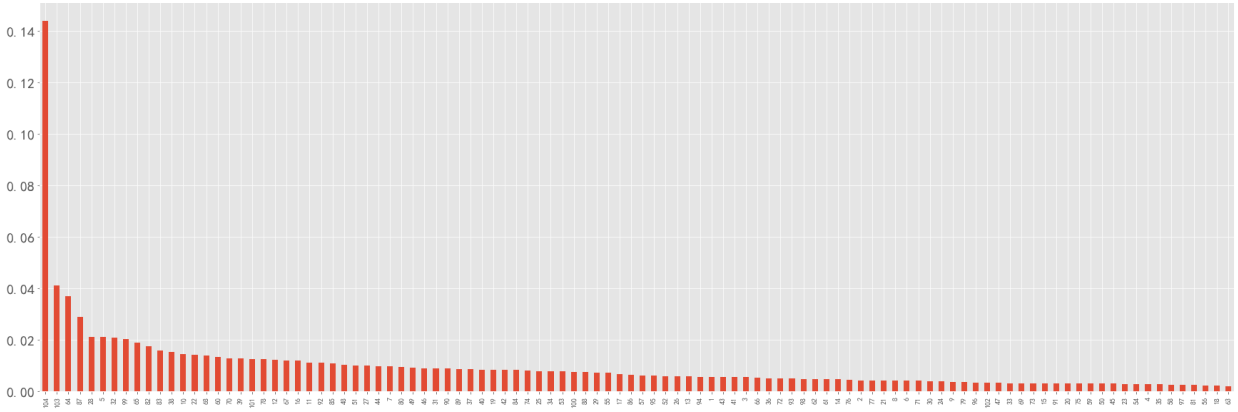
In [11]:
```
train = fullset.loc[train_idx]
test = fullset.loc[test_idx]
```

In [14]:
```
(fullset.ps_car_11_cat.value_counts()/fullset.shape[0]).plot(kind='bar',fig
plt.tick_params(axis='y', which='major', labelsize=20)
```



In [15]:
```
nominal_cols = metadata[(metadata.level == 'nominal') & (metadata.keep == T
nominal_cols
```

Out[15]:
```
['ps_ind_02_cat',
 'ps_ind_04_cat',
 'ps_ind_05_cat',
 'ps_car_01_cat',
 'ps_car_02_cat',
 'ps_car_04_cat',
 'ps_car_06_cat',
 'ps_car_07_cat',
 'ps_car_08_cat',
 'ps_car_09_cat',
 'ps_car_10_cat',
 'ps_car_11_cat']
```

In [16]:
```
from sklearn.preprocessing import OneHotEncoder

enc = OneHotEncoder(handle_unknown = "ignore",sparse=False)
trn_nominal_cols_enc = enc.fit_transform(train[nominal_cols])
tst_nominal_cols_enc = enc.transform(test[nominal_cols])
```

In [17]:
```
trn_nominal_cols_enc.shape
```

Out[17]:
```
(144626, 177)
```

In [18]:
```
tst_nominal_cols_enc.shape
```

Out[18]:
```
(892816, 177)
```

In [19]:
```
enc = OneHotEncoder(handle_unknown='ignore')
X = [['Male', 1], ['Female', 3], ['Female', 2]]
enc.fit(X)
```

Out[19]:
```
OneHotEncoder(handle_unknown='ignore')
```

In [20]:
```
enc.categories_
```

Out[20]:
```
[array(['Female', 'Male'], dtype=object), array([1, 2, 3], dtype=object)]
```

In [21]:
```
enc.transform([['Female', 1], ['Male', 4]]).toarray()
```

Out[21]:
```
array([[1., 0., 1., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

In [22]:
```
enc.inverse_transform([[0, 1, 1, 0, 0], [0, 0, 0, 1, 0]])
```

Out[22]:
```
array([['Male', 1],
       [None, 2]], dtype=object)
```

In [23]:
```
enc.get_feature_names_out(['gender', 'group'])
```

Out[23]:
```
array(['gender_Female', 'gender_Male', 'group_1', 'group_2', 'group_3'],
      dtype=object)
```

In [24]:
```
def add_noise(series, noise_level):
    return series * (1 + noise_level * np.random.randn(len(series)))

def target_encode(trn_series=None,
                  tst_series=None,
                  target=None,
                  min_samples_leaf=1,
                  smoothing=1,
                  noise_level=0):
    """
    Smoothing is computed like in the following paper by Daniele Micci-Barr
    https://kaggle2.blob.core.windows.net/forum-message-attachments/225952/
    trn_series : training categorical feature as a pd.Series
    tst_series : test categorical feature as a pd.Series
    target : target data as a pd.Series
    min_samples_leaf (int) : minimum samples to take category average into
    smoothing (int) : smoothing effect to balance categorical average vs pr
    """
    assert len(trn_series) == len(target)
    assert trn_series.name == tst_series.name
    temp = pd.concat([trn_series, target], axis=1)
    averages = temp.groupby(by=trn_series.name)[target.name].agg(["mean", "
    # 平滑
    smoothing = 1 / (1 + np.exp(-(averages["count"] - min_samples_leaf) / s
    prior = target.mean()
    averages[target.name] = prior * (1 - smoothing) + averages["mean"] * sm
    averages.drop(["mean", "count"], axis=1, inplace=True)

    ft_trn_series = pd.merge(
        trn_series.to_frame(trn_series.name),
        averages.reset_index().rename(columns={'index': target.name, target
        on=trn_series.name,
        how='left')['average'].rename(trn_series.name + '_mean').fillna(pri

    ft_trn_series.index = trn_series.index
    ft_tst_series = pd.merge(
        tst_series.to_frame(tst_series.name),
        averages.reset_index().rename(columns={'index': target.name, target
        on=tst_series.name,
        how='left')['average'].rename(trn_series.name + '_mean').fillna(pri

    ft_tst_series.index = tst_series.index
    return add_noise(ft_trn_series, noise_level), add_noise(ft_tst_series,
```

In [25]:
```
train_encoded, test_encoded = target_encode(train["ps_car_11_cat"],
                              test["ps_car_11_cat"],
                              target=train.target,
                              min_samples_leaf=100,
                              smoothing=10,
                              noise_level=0.01)
```

In [26]:
```
train["ps_car_11_cat_tar_enc"] = train_encoded.astype('float64')
test['ps_car_11_cat_tar_enc'] = test_encoded.astype('float64')
```

In [27]:
```
cols_to_drop = metadata[metadata['imputation'] == 'remove'].index.tolist()
```

In [28]:
```
cols_to_drop.append('ps_car_11_cat')
```

In [29]:
```
train_clean = train.drop(cols_to_drop,axis=1)
```

In [30]:
```
test_clean = test.drop(cols_to_drop,axis=1)
```

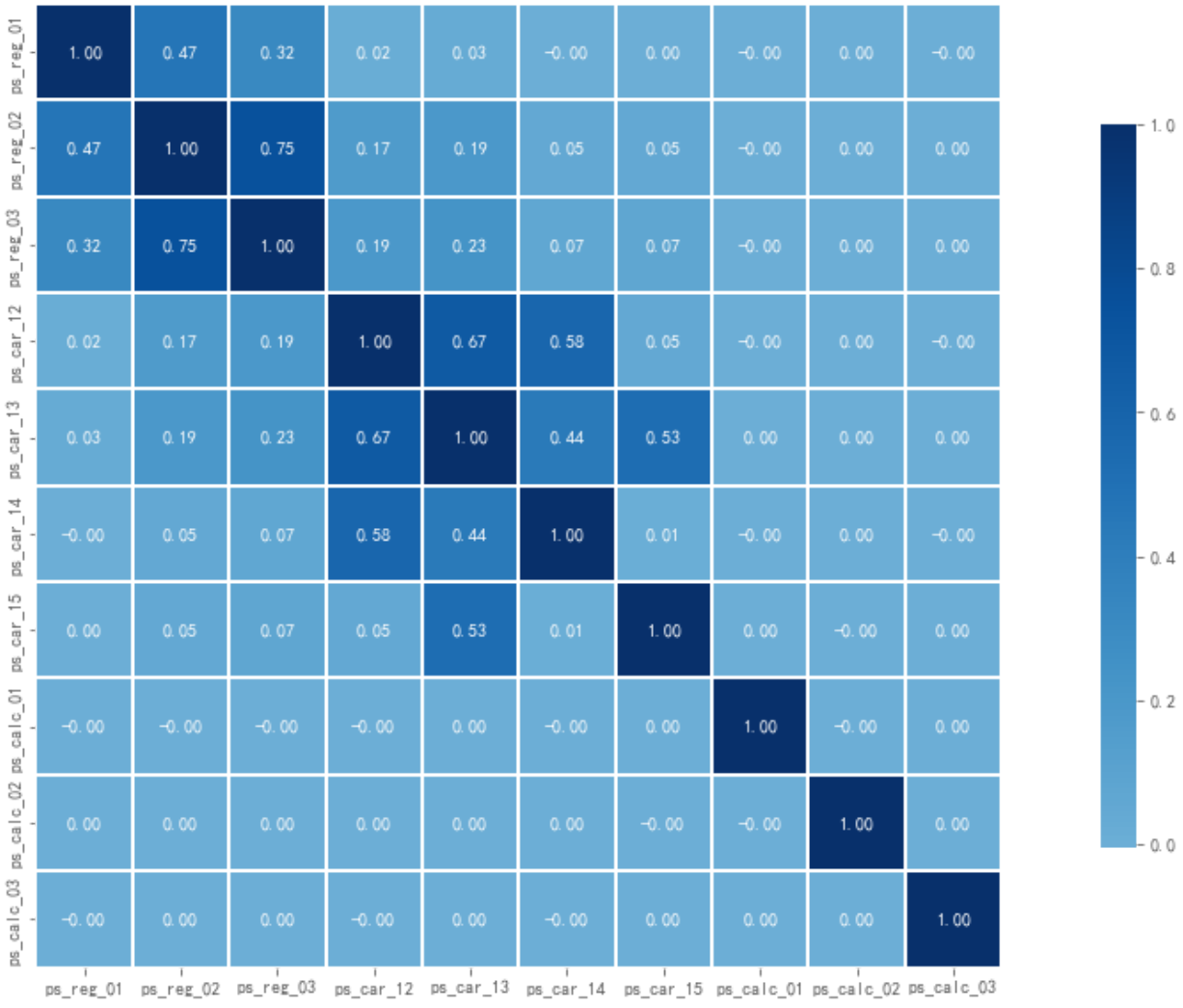
In [ ]:
```
train_clean.to_csv('train_clean.csv')
test_clean.to_csv('test_clean.csv')
```

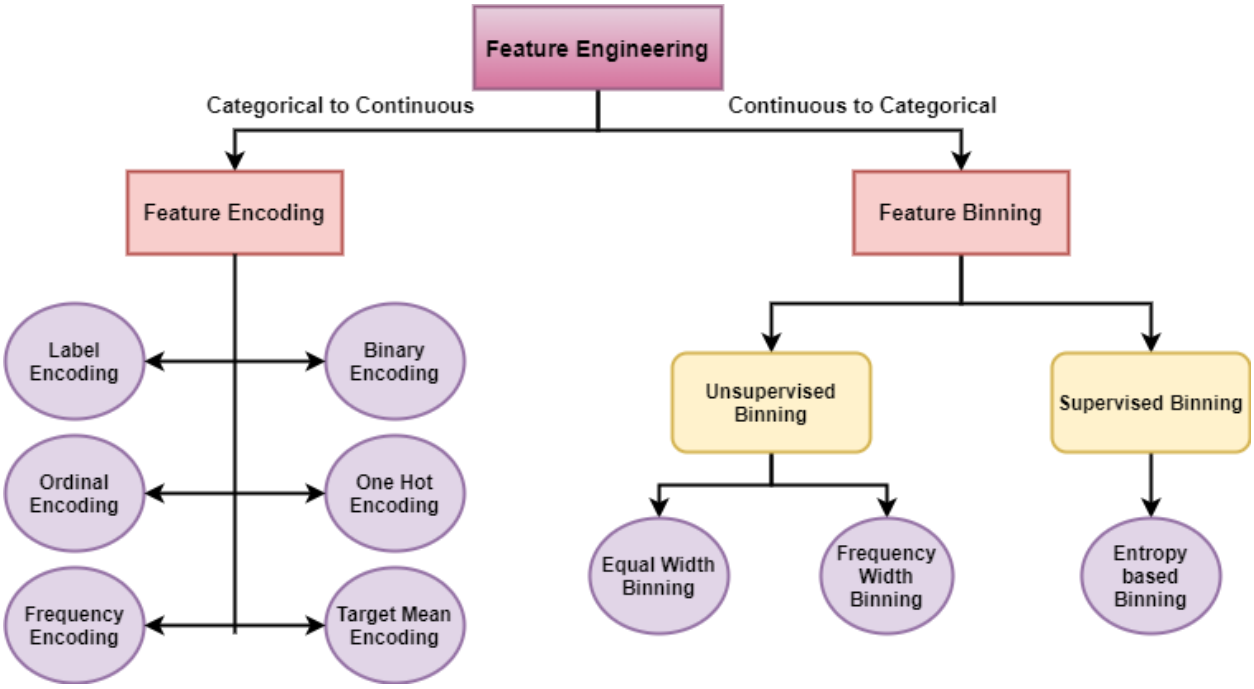
In [31]:
```
fullset = pd.concat([train_clean,test_clean],ignore_index=True)
```

In [32]:
```
continuous_cols = metadata[(metadata.level == 'interval')|(metadata.level =
```

In [33]:
```
plt.figure(figsize = [20,10])
sns.heatmap(data = fullset[continuous_cols].corr(),
            vmax=1,
            center=0,
            square=True,
           annot = True,
          fmt='.2f',
           cmap = 'Blues',
           linewidths = .3,
           cbar_kws={"shrink": .75})
```

Out[33]: <AxesSubplot:>

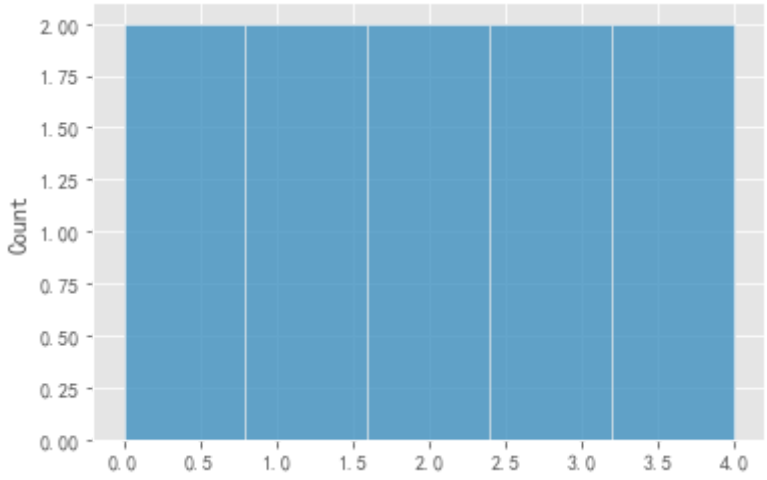




In [34]:
```
import pandas as pd
value_list = [0, 10, 20, 59, 61, 79, 80, 90, 99, 100]

value_freq_bins = pd.qcut(value_list, q=5)

value_dis_bins = pd.cut(value_list, bins=5)
```

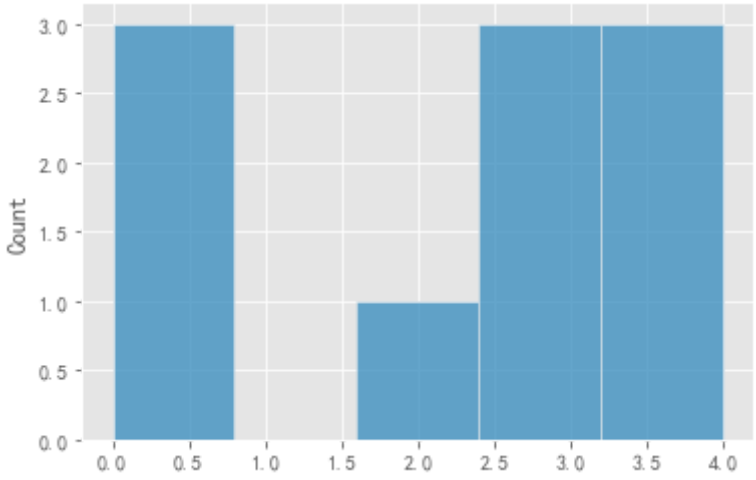
In [36]:
```
sns.histplot(value_freq_bins.codes)
```

Out[36]: <AxesSubplot:ylabel='Count'>

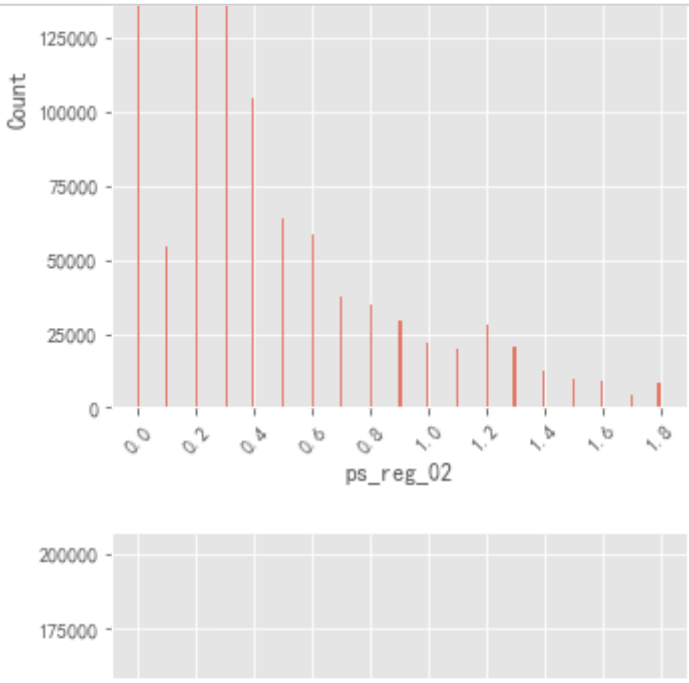


In [37]:
```
sns.histplot(value_dis_bins.codes)
```

Out[37]: <AxesSubplot:ylabel='Count'>



In [38]:
```
for col in continuous_cols:
    sns.displot(fullset[col])
    plt.xticks(ticks = np.linspace(start = fullset[col].min(),
                                   stop = fullset[col].max(),
                                   num = 10),rotation = 45)
```



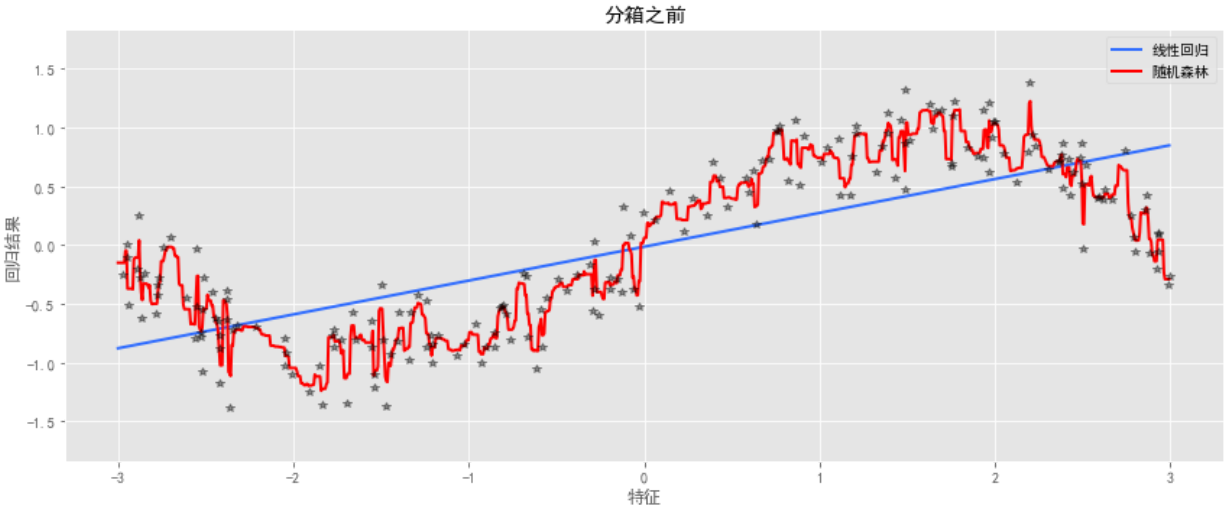
In [39]:
```
def woe_iv_encoding(data, feat, target, max_intervals, verbose = False):

    feat_bins = pd.qcut(x = data[feat], q = max_intervals, duplicates='drop
    gi = pd.crosstab(feat_bins,data[target])
    gb = pd.Series(data=data[target]).value_counts()

    bad =
    good =

    # 计算woe
    woe =

    # 计算iv
    iv =
    # 计算整个特征的iv
    f_iv = iv.sum()  # 5.2958917587905745
    if verbose == True:
        print(f"根据当前的间隔数{max_intervals}，特征{feat}所计算的总information
        print('='*80)

    # 进行映射操作
    dic = iv.to_dict()

    iv_bins = feat_bins.map(dic)

    return iv_bins.astype('float64')
```

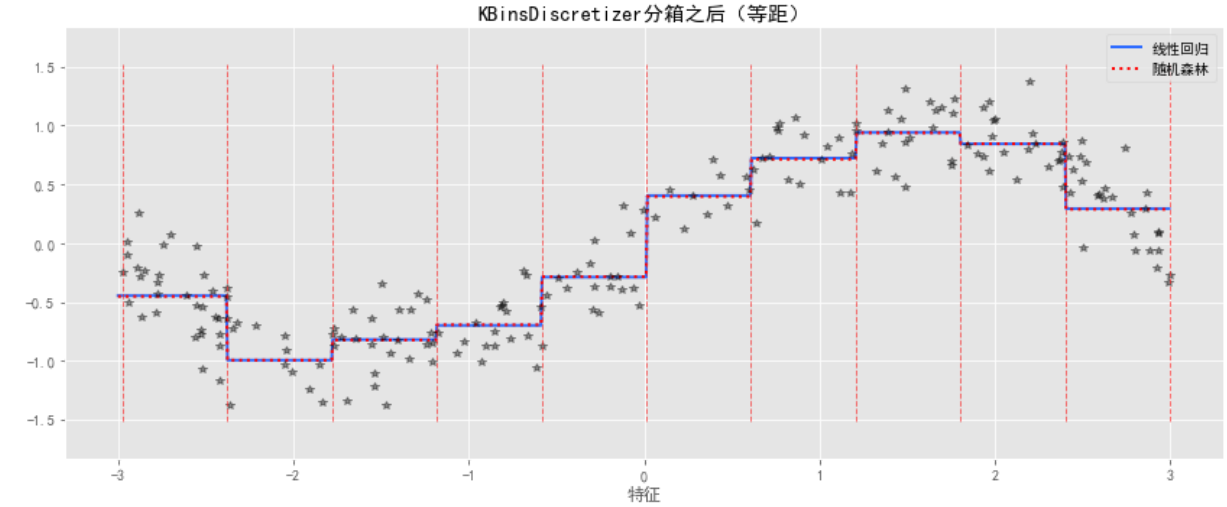
Information Value (IV)	Predictive Power
< 0.02	useless for prediction
0.02 to 0.1	weak predictor
0.1 to 0.3	medium predictor
0.3 to 0.5	strong predictor
> 0.5	suspicious or too good to be true

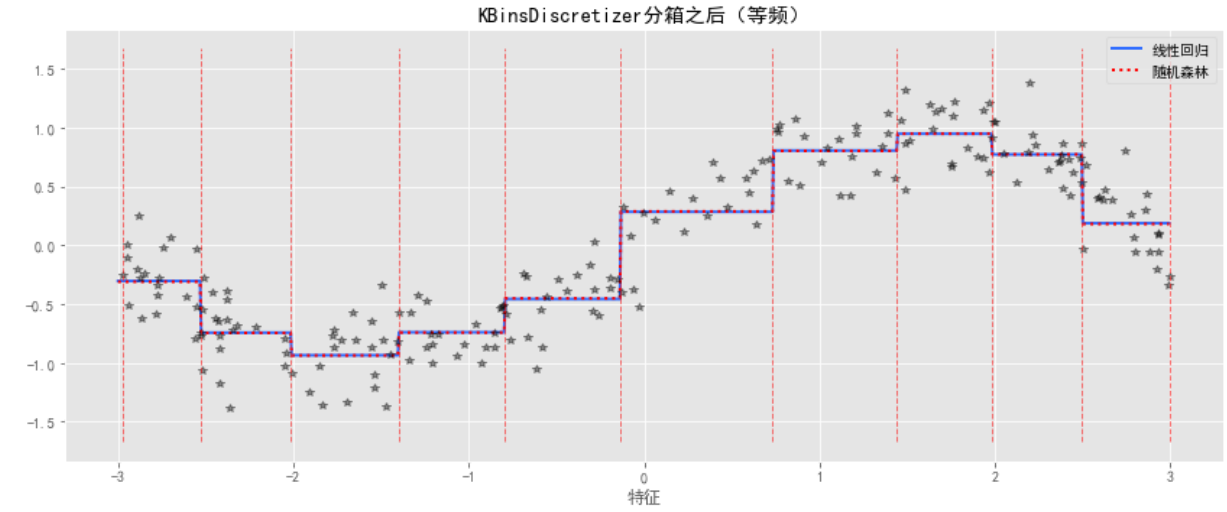
In [40]:
```
for col in continuous_cols:
    fullset[f"{col}_woe"] = woe_iv_encoding(data = fullset, feat = col, tar
    #sns.displot(fullset_copy[f"{col}_woe"])
```

In [41]:
```
import numpy as np
import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.ensemble import RandomForestRegressor

# construct the dataset
rnd = np.random.RandomState(2022)
X = rnd.uniform(-3, 3, size=200)
y = np.sin(X) + rnd.normal(size=len(X)) / 4
X = X.reshape(-1, 1)

# transform the dataset with KBinsDiscretizer
enc1 = KBinsDiscretizer(n_bins=10, encode="onehot", strategy = 'uniform')
enc2 = KBinsDiscretizer(n_bins=10, encode="onehot", strategy = 'quantile')
X_binned_unif = enc1.fit_transform(X)
X_binned_quan = enc2.fit_transform(X)

# predict with original dataset
fig, (ax1, ax2, ax3) = plt.subplots(ncols=1,nrows = 3, sharey=True, figsize
line = np.linspace(-3, 3, 1000, endpoint=False).reshape(-1, 1)
reg = LinearRegression().fit(X, y)


ax1.plot(line, reg.predict(line), linewidth=2, color="#306dff", label="线性回
reg = RandomForestRegressor(random_state=0).fit(X, y)
ax1.plot(line, reg.predict(line), linewidth=2, color="red", label="随机森林"
ax1.plot(X[:, 0], y, "*", c="k",alpha = .4)
ax1.legend(loc="best")
ax1.set_ylabel("回归结果")
ax1.set_xlabel("特征")
ax1.set_title("分箱之前")

# predict with transformed dataset
line_binned_unif = enc1.transform(line)
reg = LinearRegression().fit(X_binned_unif, y)
ax2.plot(
    line,
    reg.predict(line_binned_unif),
    linewidth=2,
    color="#306dff",
    linestyle="-",
    label="线性回归",
)

reg = RandomForestRegressor(random_state=0).fit(X_binned_unif, y)
ax2.plot(
    line,
    reg.predict(line_binned_unif),
    linewidth=2,
    color="red",
    linestyle=":",
    label="随机森林",
)
ax2.plot(X[:, 0], y, "*", c="k", alpha = .4)
```

```
ax2.vlines(enc1.bin_edges_[0], *plt.gca().get_ylim(), linewidth=1,alpha= .6
ax2.legend(loc="best")
ax2.set_xlabel("特征")
ax2.set_title("KBinsDiscretizer分箱之后（等距）")

# predict with transformed dataset
line_binned_quan = enc2.transform(line)
reg = LinearRegression().fit(X_binned_quan, y)
ax3.plot(
    line,
    reg.predict(line_binned_quan),
    linewidth=2,
    color="#306dff",
    linestyle="-",
    label="线性回归",
)

reg = RandomForestRegressor(random_state=0).fit(X_binned_quan, y)
ax3.plot(
    line,
    reg.predict(line_binned_quan),
    linewidth=2,
    color="red",
    linestyle=":",
    label="随机森林",
)
ax3.plot(X[:, 0], y, "*", c="k", alpha = .4)
ax3.vlines(enc2.bin_edges_[0], *plt.gca().get_ylim(), linewidth=1, alpha= .
ax3.legend(loc="best")
ax3.set_xlabel("特征")
ax3.set_title("KBinsDiscretizer分箱之后（等频）")

plt.tight_layout()
plt.show()
```


分箱之前
线性回归
随机森林
回归结果
特征


KBinsDiscretizer分箱之后（等距）
线性回归
随机森林
特征


KBinsDiscretizer分箱之后（等频）
线性回归
随机森林
特征

In [42]:
```
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2, interaction_only=True, include_bias=Fal

interactions = pd.DataFrame(data=poly.fit_transform(fullset[continuous_cols
                            columns=poly.get_feature_names_out(continuous_c


interactions.drop(continuous_cols, axis=1, inplace=True)  # Remove the orig
# Concat the interaction variables to the train data
print('特征交互前，训练集有 {}个变量 '.format(fullset.shape[1]))
fullset = pd.concat([fullset, interactions], axis=1)
print('特征交互后，训练集有 {}个变量'.format(fullset.shape[1]))
```

```
特征交互前，训练集有 67个变量
特征交互后，训练集有 112个变量
```

Step 6:

- 简述【特征交互】的意义和原理
- 请叙述 PolynomialFeatures 的 degree、interaction_only、include_bias的含义

In [45]:
```
train
```

Out[45]:

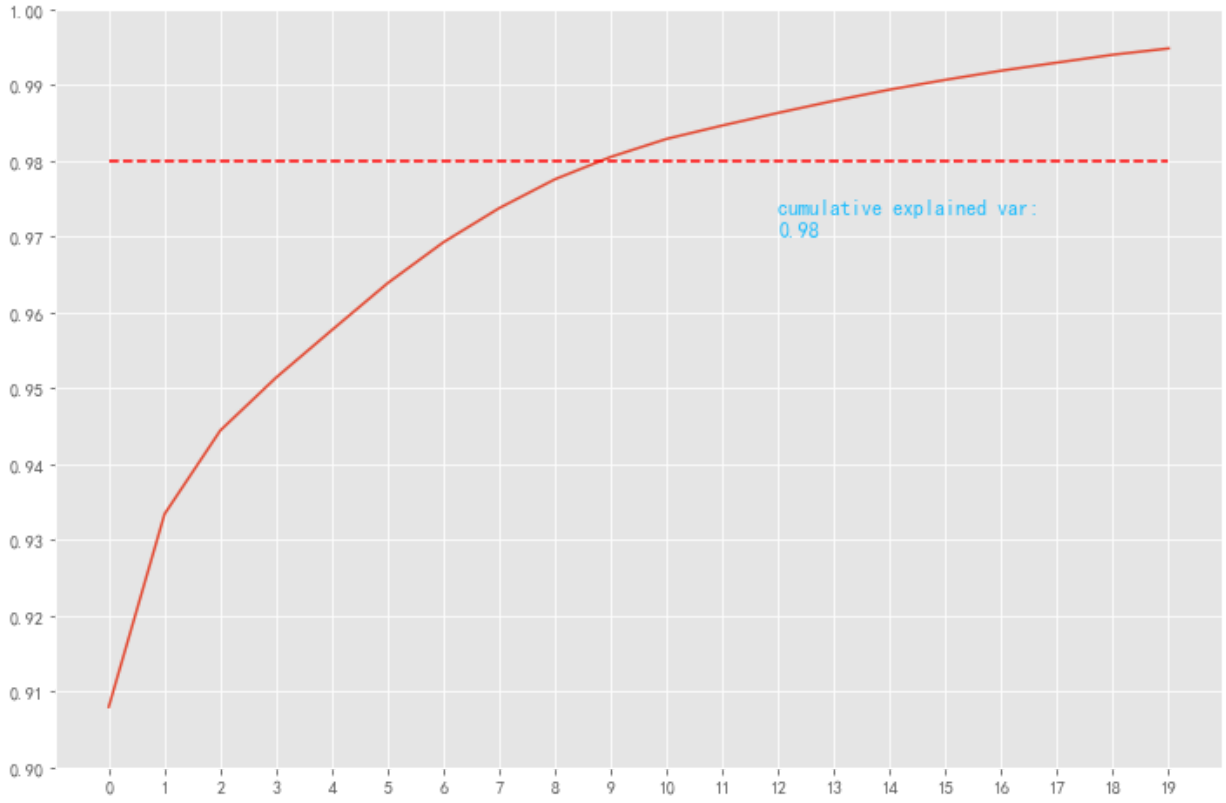
	id	target	ps_ind_01	ps_ind_02_cat	ps_ind_03	ps_ind_04_cat	ps_ind_05_cat	ps_ind_
0	744529	0.0	2	1	9	1	0	
1	673907	0.0	1	1	2	1	0	
2	730796	0.0	7	1	6	0	4	
3	306142	0.0	1	1	3	0	0	
4	1102701	0.0	6	2	7	1	0	
...	...	...	...	...	...	...	...	
144621	1487473	1.0	5	1	7	0	3	
144622	1487566	1.0	1	1	5	0	0	
144623	1487716	1.0	0	1	6	1	0	
144624	1487748	1.0	0	2	2	0	0	
144625	1487866	1.0	1	2	1	0	0	

144626 rows × 60 columns

In [46]:
```
from sklearn.decomposition import PCA

X = train.drop(['id', 'target'], axis=1)
y = train.target

n_comp = 20
print('\nPCA执行中...')
pca = PCA(n_components=n_comp, svd_solver='full', random_state=1001)
X_pca = pca.fit_transform(X)
print('Total Explained variance: %.4f' % pca.explained_variance_ratio_.sum(


plt.figure(figsize = [12,8])

pd.Series(pca.explained_variance_ratio_).cumsum().plot()

plt.plot(range(n_comp),[0.98]*20, 'r--')
plt.xticks(ticks = range(n_comp))
plt.yticks(ticks = np.linspace(0.9,1,11))
plt.text(12,0.97,'cumulative explained var: \n0.98',fontsize = 12, color =

plt.figure(figsize=(10,10))
plt.scatter(X_pca[:,0],X_pca[:,1],c=y,cmap='Set1',alpha = .7)
plt.xlabel('pc1')
plt.ylabel('pc2')
plt.title(
        "第一第二主成分散点分布图")
plt.xlabel("第一主成分解释 %.1f %% 方差" % (
        pca.explained_variance_ratio_[0] * 100.0))
plt.ylabel("第二主成分解释 %.1f %% 方差" % (
        pca.explained_variance_ratio_[1] * 100.0))
```

```
PCA执行中...
Total Explained variance: 0.9948
```

Out[46]:
```
Text(0, 0.5, '第二主成分解释 2.5 % 方差')
```


1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0.90
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
cumulative explained var:
0.98

第一第二主成分散点分布图

Step 6:

- 对上面代码每一行进行comment
- 上面的方法有问题吗？如果有问题，出在哪里，怎么处理？

Step 7:

- GBDT+LR的优势有哪些？解决什么问题？

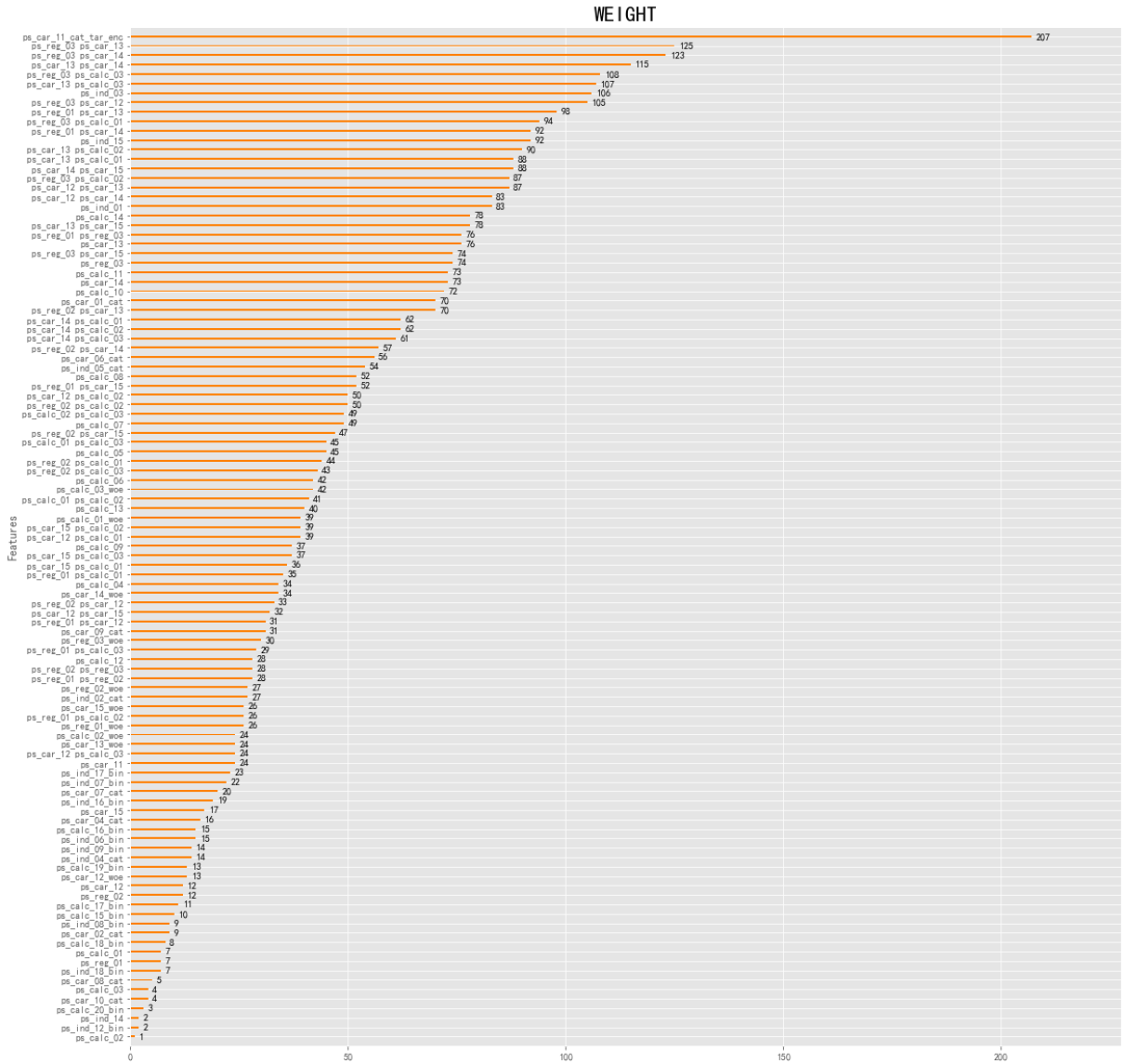
In [47]:
```
from sklearn.feature_selection import VarianceThreshold

selector = VarianceThreshold(threshold=.01)
selector.fit(fullset.drop(['id', 'target'], axis=1)) # Fit to train without

f = np.vectorize(lambda x : not x) # Function to toggle boolean array eleme

v = fullset.drop(['id', 'target'], axis=1).columns[f(selector.get_support()
print('{} variables have too low variance.'.format(len(v)))
```

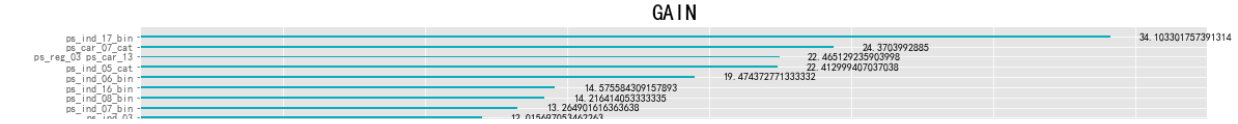
```
19 variables have too low variance.
```

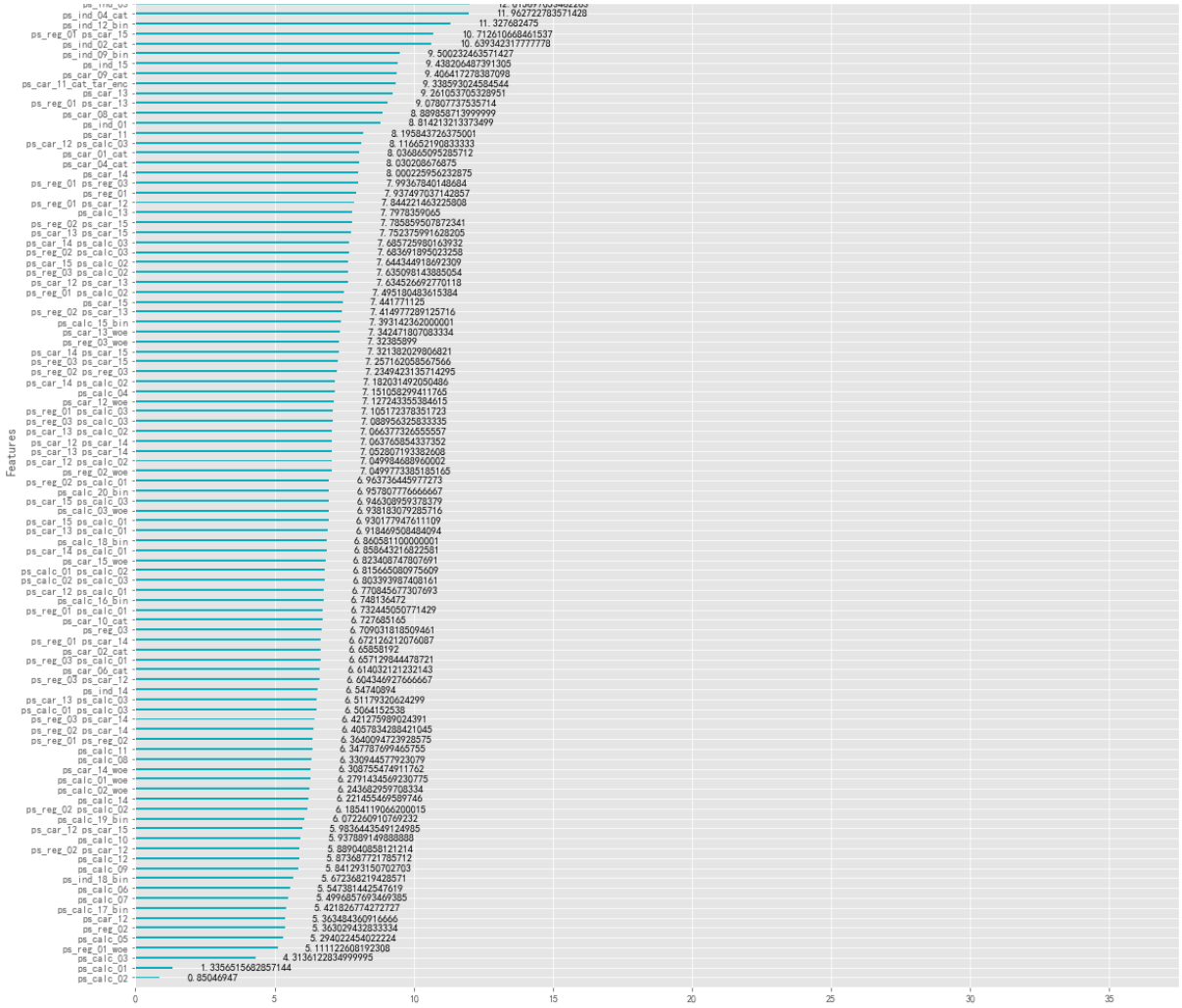
In [48]:
```
from xgboost import XGBClassifier
from xgboost import plot_importance

plt.figure(figsize = [100,20])

X = fullset.loc[train.index].drop(['id', 'target'], axis=1)
y = fullset.loc[train.index].target

model = XGBClassifier()

model.fit(X, y)
# plot feature importance
```

Out[48]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_sta
te=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)

<Figure size 7200x1440 with 0 Axes>
```

In [49]:
```
# define subplot grid
fig, axs = plt.subplots(nrows=5, ncols=1, figsize=(15, 80))
plt.tight_layout()
plt.subplots_adjust(hspace=0.1)

types = ['weight', 'gain', 'cover', 'total_gain', 'total_cover']
# loop through tickers and axes
colors = ['#ff7f01','#08aebd','#fc5531','#139948','#8950fe']
for ty, ax, color in zip(types, axs.ravel(), colors):
    # filter df for ticker and plot on specified axes
    plot_importance(ax = ax, booster = model,importance_type=ty, color = co

    # chart formatting
    ax.set_title(ty.upper(),fontsize = 22)
    ax.set_xlabel("")

plt.show()
```






Features
ps_ind_04_cat
ps_ind_12_bin
ps_reg_01 ps_car_15
ps_ind_02_cat
ps_ind_09_bin
ps_ind_15
ps_car_09_cat
ps_car_11_cat_tar_enc
ps_car_13
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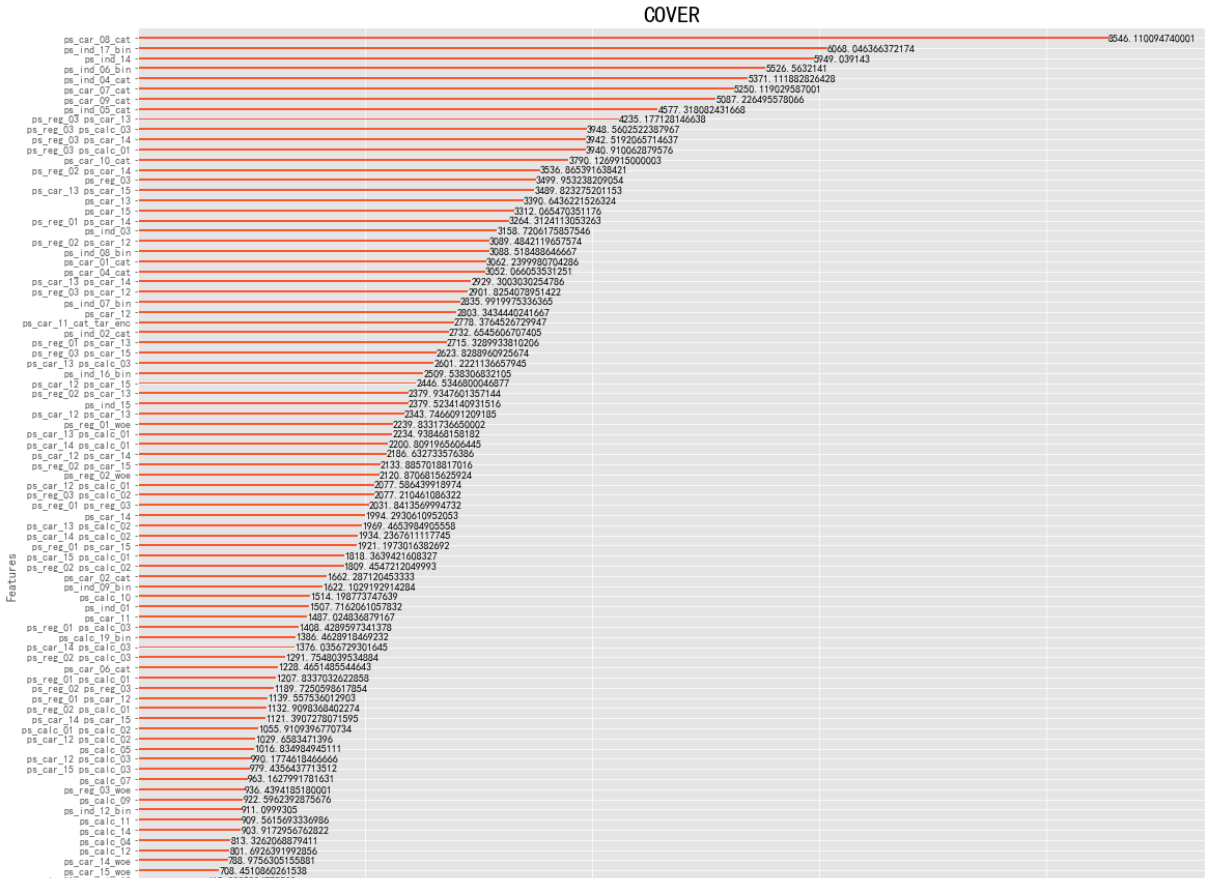
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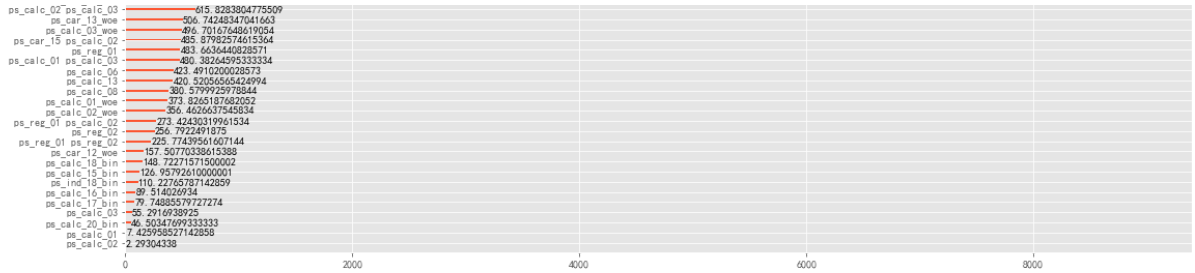

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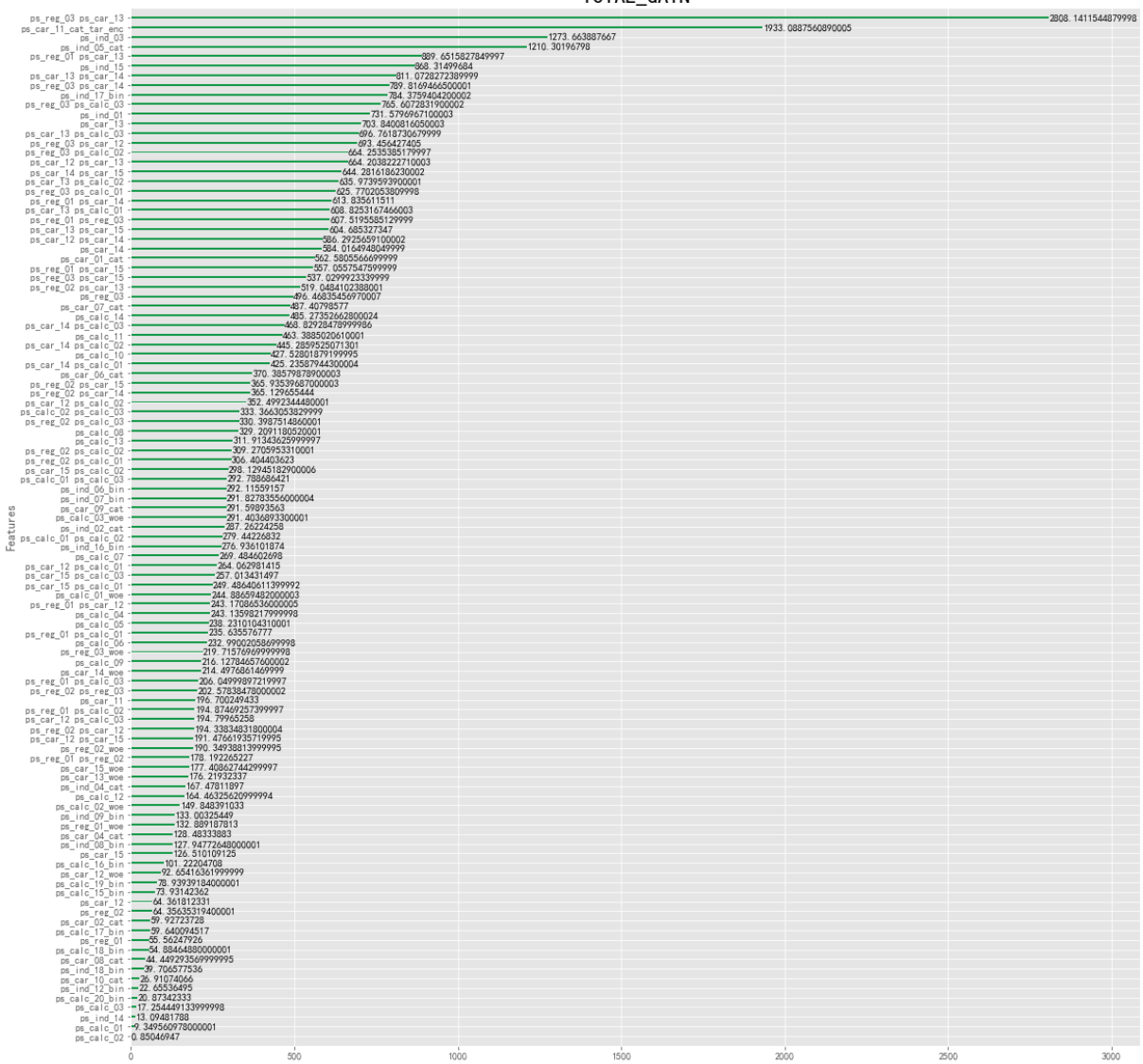
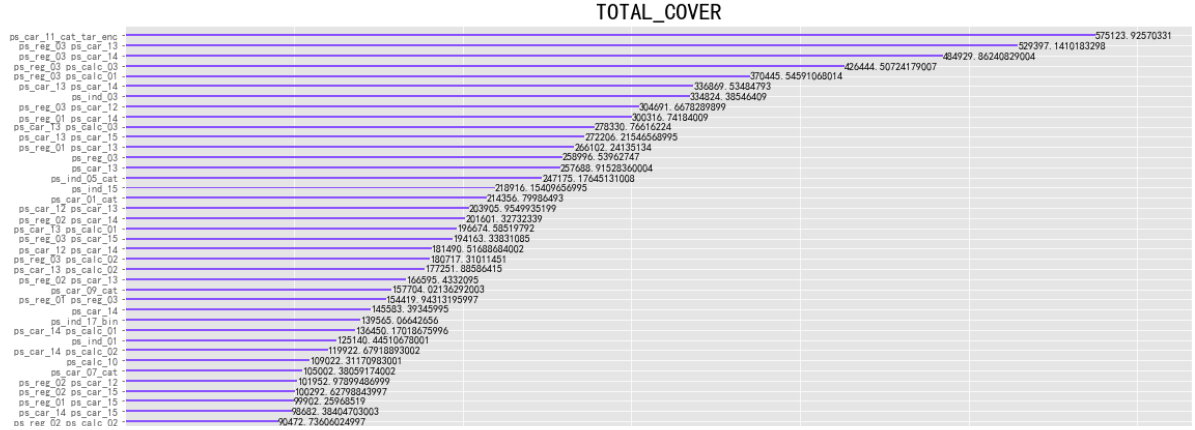


TOTAL_COVER



In [51]:
```
# 特征工程的strategy作为key，对应的变量名组成的list作为value
from sklearn.feature_selection import SelectFromModel
feat_dict = {}
for thres in ['median','mean','1.25*mean']:
    model_select = SelectFromModel(model, threshold=thres, prefit=True)
    print(f'筛选前总计：{X.shape[1]}个特征')
    n_features = model_select.transform(X.values).shape[1]
    print(f'筛选后总计：  {n_features}个特征【{thres}】 ')
    print('#'*60)
    selected_vars = list(X.columns[model_select.get_support()])
    feat_dict[thres] = selected_vars
```

```
筛选前总计：110个特征
筛选后总计：  55个特征【median】
############################################################
筛选前总计：110个特征
筛选后总计：  28个特征【mean】
############################################################
筛选前总计：110个特征
筛选后总计：  13个特征【1.25*mean】
############################################################
```

In [52]:
```
for ty in types:
    feat_dict[ty] = list(model.get_booster().get_score(importance_type=ty).
```

In [54]:
```
final_train = fullset.loc[train.index][feat_dict['mean']+['target']]
final_test = fullset.loc[test.index][feat_dict['mean']]
```

In [55]:
```
final_train.to_csv("final_train.csv")
final_test.to_csv("final_test.csv")
```