In [1]:
```
import uproot
import numpy as np
import os
import random
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import altair as alt
from collections import Counter

%matplotlib inline
```

In [2]:
```
def path_generator(t:str, eda=True) -> list:
    '''
    Approximately (size of 50 QCD dataset) == (size of 14 Hbb dataset)
    '''
    lst = []

    if t.upper() == 'QCD':
        main = '/home/h8lee/teams/DSC180A_FA21_A00/a11/train_mass_qcd/\
QCD_HT{low}to{high}_TuneCP5_13TeV-madgraph-pythia8/'
        if eda:
            num_data = 10

        bounds = [
            [1000,1500],
            [1500,2000],
            [2000, 'Inf'],
            [500,700],
            [700,1000]
        ]

        for bound in bounds:
            low, high = bound
            fp = main.format(low=low, high=high)
            all_files = os.listdir(fp)
            all_files_fp = [fp + f for f in all_files]
            samples = random.sample(all_files_fp, k=num_data)

            # There's this one hidden file under (700-1000) bound
            while '.nano_mc2017_174_Skim.root.ViGCYO' in samples:
                samples = random.sample(all_files_fp, k=num_data) # Re-s
ample

            lst += samples # In total, randomly generate filepaths to 50
different QCD .root files
    elif t.upper() == 'HBB':
        main = '/home/h8lee/teams/DSC180A_FA21_A00/a11/train_mass_hbb/\
BulkGravitonToHHTo4Q_MX-600to6000_MH-15to250_part{}_TuneCP5_13TeV-madgra
ph_pythia8/'
        if eda:
            num_data = 4

        parts = [1,2]

        for part in parts:
            # Since files in Hbb directory1 are smaller than those in Hb
b directory2,
            # sample more from directory1 to balance size of samples gen
erating from
            # directory2
            # (11 .root files in dir1) == (3 .root files in dir2)

#             if part==1:
#                 num_data = 11
#             else:
#                 num_data = 3
```

```
            fp = main.format(part)
            all_files = os.listdir(fp)
            samples = random.sample(all_files, k=num_data)
            files = [os.path.join(fp, sample) for sample in samples]

            lst += files
    return lst
```

In [3]:
```
qcd_eda_sets = path_generator('QCD', eda=True)
hbb_eda_sets = path_generator('hbb', eda=True)
```

In [4]:
```
def load_jet_features(fps):
    '''
    For all files at defined filepaths,
    extract jet features from each of them as well as their type
    '''
    jet_features = []
    unnecesssary_attrs = [
        'fj_idx',
        'fj_genRes_mass',
        'fj_lsf3'
    ]
    df = pd.DataFrame()

    for i in range(len(fps)):
        path = fps[i]
        f = uproot.open(path)
        tree = f['Events']

        if i==0:
            attrs = [branch.name for branch in tree.branches]
            jet_features += list(filter(lambda x:x.startswith('fj'), att
rs))
            jet_features = [feat for feat in jet_features if feat not in
unnecesssary_attrs] # drop sterile attributes

        features = tree.arrays(jet_features, library='np')
        df = pd.concat([df, pd.DataFrame(features)], axis=0)

    df = df.reset_index(drop=True)

    return df
```

Validating the labels of QCD/signal jet samples

In [5]:
```
df_qcd = load_jet_features(qcd_eda_sets)
display(df_qcd.head())
print('\n', f'{df_qcd.shape[0]} randomly generated QCD jet samples')
```

	fj_pt	fj_eta	fj_phi	fj_mass	fj_msoftdrop	fj_deepTagMD_H4qvsQCD	fj_deepTag_Hvs
0	400.50	-1.977295	-3.072266	94.1250	84.562500	-1000.0	-1
1	305.50	-0.213806	-0.539429	68.4375	8.515625	-1000.0	-1
2	510.25	-1.650391	1.031006	214.6250	142.375000	-1000.0	-1
3	495.75	-1.653564	-2.175293	131.2500	0.609375	-1000.0	-1
4	685.00	-1.671387	1.073975	174.2500	80.562500	-1000.0	-1

5 rows × 57 columns

```
 375774 randomly generated QCD jet samples
```

In [6]:
```
df_signal = load_jet_features(hbb_eda_sets)
display(df_signal.head())
print('\n', f'{df_signal.shape[0]} randomly generated signal jet sample
s')
```

	fj_pt	fj_eta	fj_phi	fj_mass	fj_msoftdrop	fj_deepTagMD_H4qvsQCD	fj_deepTag_Hvs(
0	1472.0	0.506348	-1.967285	149.750	10.703125	-1000.0	-10
1	1303.0	-0.658936	1.231445	219.500	159.375000	-1000.0	-10
2	1750.0	-0.059731	0.198761	321.000	2.937500	-1000.0	-10
3	1644.0	-0.657715	-2.906250	493.500	420.500000	-1000.0	-10
4	1338.0	-0.167816	-3.049805	239.125	12.265625	-1000.0	-10

5 rows × 57 columns

```
 488716 randomly generated signal jet samples
```

Data validation

Validate the type of jets in our samples; each jet should only be associated to one unique type of QCD/signal

In [7]:
```
# QCD
# For this checkup, we only need label attribute

IS_QCDb = 'fj_isQCDb'
IS_QCDothers = 'fj_isQCDothers'
all_attrs = df_qcd.columns.tolist()
start_idx = all_attrs.index(IS_QCDb)
end_idx = all_attrs.index(IS_QCDothers)+1

qcd_labels = all_attrs[start_idx:end_idx]
```

In [8]:
```
df_qcd_labels = df_qcd[qcd_labels]
display(df_qcd_labels.head())
```

	fj_isQCDb	fj_isQCDbb	fj_isQCDc	fj_isQCDcc	fj_isQCDlep	fj_isQCDothers
0	0	0	0	0	0	1
1	0	0	1	0	0	0
2	0	0	0	0	0	1
3	0	0	0	0	0	1
4	0	0	1	0	0	0

In [9]:
```
# We want each jet corresponding to exactly one type

print(f'Each jet corresponds to exactly one type:\
 {len(df_qcd_labels.sum(axis=1).unique()) == 1}')
```

```
Each jet corresponds to exactly one type: True
```

In [10]:
```
# How many jets are there for different QCD types?

display(df_qcd_labels.sum(axis=0).sort_values(ascending=False).to_frame(
name='Count'))
```

	Count
fj_isQCDothers	229069
fj_isQCDlep	81626
fj_isQCDcc	26146
fj_isQCDc	26124
fj_isQCDb	6552
fj_isQCDbb	6257

In [11]:
```
# Signal jets
# For this checkup, we only need label attribute

IS_HBB = 'fj_H_bb'
IS_HQQ = 'fj_H_qq'
all_attrs = df_signal.columns.tolist()
start_idx = all_attrs.index(IS_HBB)
end_idx = all_attrs.index(IS_HQQ)+1

signal_labels = all_attrs[start_idx:end_idx]
```

In [12]:
```
df_signal_labels = df_signal[signal_labels]

# We're only going to include signal jets
# of types H_bb, H_cc, H_qq for performing EDA
df_signal_labels = df_signal_labels[
    (df_signal_labels['fj_H_bb'] == 1) |
    (df_signal_labels['fj_H_cc'] == 1) |
    (df_signal_labels['fj_H_qq'] == 1)
]

# Drop observations that are associated to more than single type
df_signal_labels['temp'] = df_signal_labels['fj_H_bb'] + df_signal_label
s['fj_H_cc'] + df_signal_labels['fj_H_qq']
print(f'Before filtering: {df_signal_labels.shape[0]} rows', '\n')

df_signal_labels = df_signal_labels[df_signal_labels['temp'] == 1].drop(
columns='temp')
print(f'After filtering: {df_signal_labels.shape[0]} rows')
```

```
Before filtering: 462597 rows

After filtering: 462555 rows
```

In [13]:
```
# We want each jet corresponding to exactly one type

print(f'Each jet corresponds to exactly one type:\
 {len(df_signal_labels.sum(axis=1).unique()) == 1}')
```

```
Each jet corresponds to exactly one type: True
```

In [14]:
```
# How many jets are there for each signal type?

display(df_signal_labels.sum(axis=0).sort_values(ascending=False).to_fra
me(name='Count'))
```

	Count
fj_H_cc	159807
fj_H_bb	159789
fj_H_qq	159476

EDA #1

Plot distribution of our target attribute(`fj_genjetmsd`), generator-level soft drop mass, of QCD jets according to their type

In [15]:
```
# Filtering using the validation results

signal_idx = df_signal_labels.index.tolist()
df_signal = df_signal.filter(items=signal_idx, axis=0)
```

In [16]:
```
# Create temporary `class` label to differentiate QCD jets from signal j
ets
# Then concatenate QCD dataset to signal dataset

df_qcd['Type'] = 'QCD'
df_signal['Type'] = 'Signal'

df_qcd_and_signal = pd.concat([df_qcd, df_signal], axis=0)
display(df_qcd_and_signal.head())
```

	fj_pt	fj_eta	fj_phi	fj_mass	fj_msoftdrop	fj_deepTagMD_H4qvsQCD	fj_deepTag_HvsQ(
0	542.0	0.640747	1.734131	219.625	3.312500	-1000.0	-100(
1	406.5	-0.386230	-1.934814	204.000	185.750000	-1000.0	-100(
2	754.5	1.823486	-1.008789	270.000	1.124023	-1000.0	-100(
3	655.0	-0.609375	2.122559	142.750	0.982422	-1000.0	-100(
4	608.5	-1.126221	0.986084	481.250	484.500000	-1000.0	-100(

5 rows × 58 columns

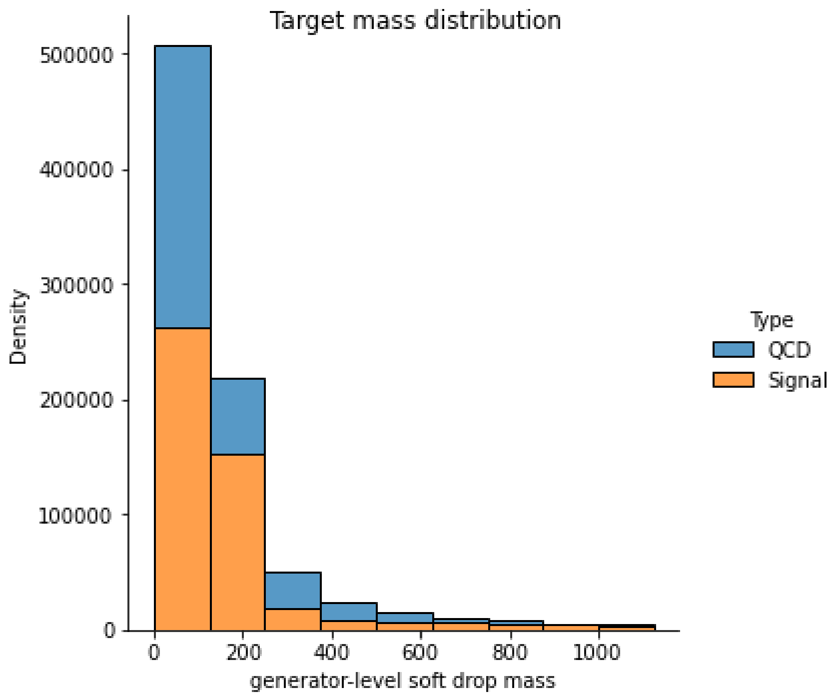
In [17]:
```
df_qcd_and_signal['Type'].value_counts()
```

Out[17]:
```
Signal    479072
QCD       375355
Name: Type, dtype: int64
```

In [18]:
```
# Used `.displot()` from seaborn for visualization

ax = sns.displot(x='fj_genjetmsd', data=df_qcd_and_signal, hue='Type',
                 bins=range(0, 1250, 125), multiple='stack')

ax.set_axis_labels('generator-level soft drop mass', 'Density');
ax.fig.suptitle('Target mass distribution');
```



In [25]:
```
# BELOW COULD BE USED FOR VALIDATION OF signal jets DATASET

# Hbb jets are known to be the most common type of
# jet that contains Higgs boson
# This is because Higgs boson is more likely to decay into
# *exactly* two b-quarks in a single proton-proton event
# These b quarks are known for their relatively heavier weights
# compared to other elementary particles
# which gives them longer lifespan
# One conspicuous characteristic of Hbb jets
# is hence their long lifespan
# which is enabled by heavy weights of Higgs boson and its decay produc
t, b quarks
# Let's now explore if this finding holds in our datset
# using `fj_genjetmsd` attribute

# Does above trend hold for QCD jets also?
# i.e. Do certain types of QCD jet tend to be heavier than otehr types?
```

EDA #2

Does presence of secondary vertices in a jet have any effect on jet mass?

In [19]:
```
def load_num_sv(fps):
    '''
    For all files at defined filepaths,
    extract secondary vertex features from
    each of the file
    '''
    NUMPY = 'np'
    SV_PT_LOG = 'sv_pt_log'
    FJ_GENJETMSD = 'fj_genjetmsd'
    num_svs = []
    jet_mass = []

    for i in range(len(fps)):
        path = fps[i]
        f = uproot.open(path)
        tree = f['Events']
        sv_pt_logs = tree.arrays(SV_PT_LOG, library=NUMPY)[SV_PT_LOG]
        num_sv = list(map(lambda sublst: len(list(filter(lambda x: x !=
0, sublst))), sv_pt_logs))
        num_svs += num_sv

        # Jet masses(target)
        masses = tree.arrays(FJ_GENJETMSD, library=NUMPY)[FJ_GENJETMSD].
tolist()
        jet_mass += masses

#     df = df.reset_index(drop=True)

    return num_svs, jet_mass
```

In [59]:
```
# QCD

qcd_num_svs, qcd_jet_mass = load_num_sv(qcd_eda_sets)

avg_qcd_num_svs = np.mean(qcd_num_svs)
avg_qcd_jet_mass = np.mean(qcd_jet_mass)

med_qcd_num_svs = np.median(qcd_num_svs)
med_qcd_jet_mass = np.median(qcd_jet_mass)

qcd_num_svs_counter = Counter(qcd_num_svs)
temp = qcd_num_svs_counter.items()
qcd_num_svs_counts = sorted(temp, reverse=True, key=lambda x:x[1])
# Later create 2 x 2 dataframe; indexing QCD and Signal, columns of mea
n, median
```

In [68]:
```
df_qcd_num_svs_counts = pd.DataFrame(qcd_num_svs_counts,
                                     columns=['# of SVs in a jet', 'coun
ts'],
                                    ).set_index('# of SVs in a jet')

display(df_qcd_num_svs_counts)
print(f'Majority of QCD jets in our data has no to only few secondary ve
rtex\
 recorded', '\n')
```

	counts
# of SVs in a jet	
0	136230
1	121613
2	66522
3	30217
4	12459
5	4997
6	1995
7	1322

```
Majority of QCD jets in our data has no to only few secondary vertex re
corded
```

In [70]:
```
qcd_dict = {
    '# of SVs recorded':qcd_num_svs,
    'generator-level soft drop mass':qcd_jet_mass
}

qcd_df = pd.DataFrame(qcd_dict)
display(qcd_df.head())
```

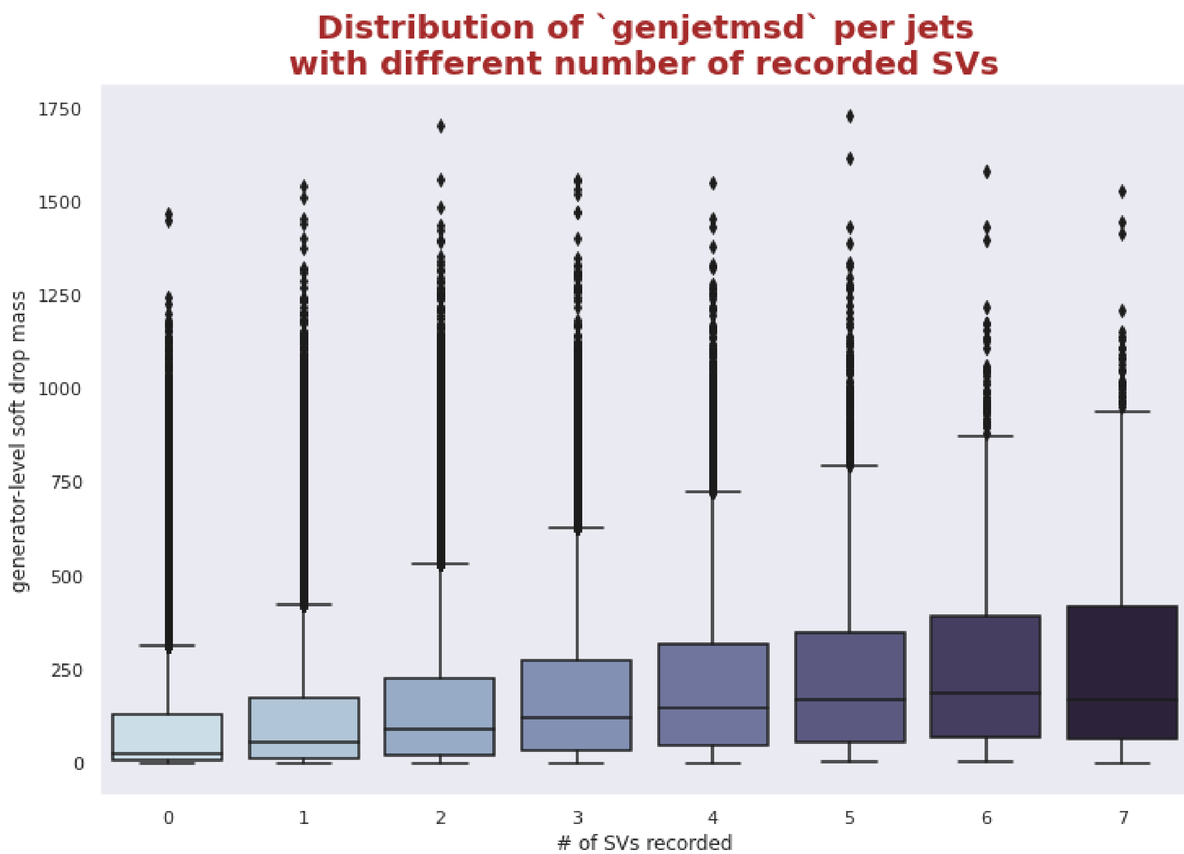
	# of SVs recorded	generator-level soft drop mass
0	1	262.750000
1	2	186.125000
2	0	4.648438
3	0	1.876953
4	2	453.250000

In [92]:
```
# Boxplot to show relationship between them

_ = sns.set(rc={'figure.figsize':(12,8)})

qcd_box = sns.boxplot(x='# of SVs recorded',
            y='generator-level soft drop mass',
            data=qcd_df, palette='ch:s=.25,rot=-.25')

_ = qcd_box.grid(False)
TITLE = 'Distribution of `genjetmsd` per jets\nwith different number of
 recorded SVs'
_ = qcd_box.set_title(TITLE, fontdict={'size':20, 'weight':'bold', 'colo
r':'brown'})
```



In [20]:
```
# Only need subset of attributes for this part of EDA
# Maximize memory(space) efficiency

eda1_attrs = [
    'fj_pt',
    'fj_msoftdrop',
    'fj_genRes_mass',
    'fj_eta',
    'fj_genjetmsd'
]

df_qcd_eda1 = df_qcd[eda1_attrs]
print(f'Before filterting: {df_qcd_eda1.shape[0]} observations', '\n')

# Data filtering
# df_qcd_eda1 = df_qcd_eda1.apply(filter_jet, axis=1)
# df_qcd_eda1 = df_qcd_eda1[df_qcd_eda1['filter'] == 1]
# print(f'After filterting: {df_qcd_eda1.shape[0]} observations')
```

```
Before filterting: 375479 observations
```

In [21]:
```
ax = sns.displot(df_qcd_eda1[TARGET], kde=False, bins=20);
    sns.displot(df_signal[TARGET], bins=20)
```

```
  File "<ipython-input-21-166f582302a7>", line 2
    sns.displot(df_signal[TARGET], bins=20)
    ^
IndentationError: unexpected indent
```

In [15]:
```
df_hbb = load_jet_features(hbb_eda_sets)
```

In [18]:
```
# Check if the size of samples we have for QCD and Hbb
# are apporoximately equivalent to minimize bias factors

epoch = 10
qcd_size = []
hbb_size = []

for _ in range(epoch):
    df_qcd = load_jet_features(qcd_eda_sets)
    df_hbb = load_jet_features(hbb_eda_sets)

    qcd_size.append(df_qcd.size)
    hbb_size.append(df_hbb.size)
```

In [21]:
```
np.average(qcd_size), np.average(hbb_size)
```

Out[21]:
```
(22530780.0, 34830540.0)
```