[1]:
```
import h5py
import matplotlib.pyplot as plt
import numpy as np
import tensorflow.keras as K
import pandas as pd
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs
import pandas as pd
```

```
Intel MKL WARNING: Support of Intel(R) Streaming SIMD Extensions 4.2 (Intel(R)
SSE4.2) enabled only processors has been deprecated. Intel oneAPI Math Kernel
Library 2025.0 will require Intel(R) Advanced Vector Extensions (Intel(R) AVX)
instructions.
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instructions.
```

```
2024-04-14 01:18:28.522266: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: SSE4.1 SSE4.2, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

1 Loading The Data

[2]:
```
with h5py.File("info/data/output_signal.h5", "r") as file:
    signal_data = file["events"][:]

with h5py.File("info/data/output_bg.h5", "r") as file:
    bg_data = file["events"][:]
```

2 Subset of the Data

[3]:
```
# storing signal and background data in panda DataFrame
signal = pd.DataFrame(signal_data)
background = pd.DataFrame(bg_data)

# concatenating the data frames to be part of one big set
df = pd.concat([signal, background])

# reseting the indicies
df = df.reset_index()

# creating the labels for the data sets i.e; signal = 1, background = 0 for␣
↪classification
labels = np.concatenate([np.ones(signal.shape[0]), np.zeros(background.shape[0])])
labels = pd.DataFrame({'ttZ': labels})

# adding labels as a column at the end of the DataFrame
df = df.join(labels)
```

```
# shuffling the DataFrame
df_shuffled = df.sample(frac=1, random_state=42)  # 'random_state' for reproducibility
df_shuffled.head()
```

[3]:

	index	jet_1_pt	jet_2_pt	jet_3_pt	jet_1_eta	jet_2_eta
469349	469349	110.017174	89.244843	42.692078	-1.638234	-1.114363
8248	8248	183.934067	125.170509	93.043922	0.185653	-1.264277
699594	190559	195.334396	155.822617	39.977455	-0.860027	1.231296
149760	149760	165.566879	136.009689	124.258598	0.903266	-0.343321
72006	72006	128.334076	54.510422	45.616039	-0.975434	-2.489865

	jet_3_eta	jet_1_twb	jet_2_twb	jet_3_twb	bjet_1_pt	lep_1_pt
469349	0.334825	3	1	1	110.017174	165.685593
8248	1.190622	1	4	1	125.170509	68.110207
699594	2.197089	1	1	1	35.366051	184.187210
149760	0.041760	5	5	1	165.566879	113.711166
72006	-1.147104	1	1	1	32.256153	109.551361

	lep_2_pt	lep_3_pt	n_jets	n_bjets	n_leptons	met_met
469349	81.492973	32.393501	3	1	3	64.430573
8248	35.741417	12.237628	4	1	3	104.903961
699594	82.709946	36.546856	5	1	3	48.988052
149760	112.550560	34.406342	6	2	3	172.116821
72006	100.125435	48.681091	6	2	3	29.693062

	H_T	ttZ
469349	585.956726	1.0
8248	654.210388	1.0
699594	807.437683	0.0
149760	1007.604309	1.0
72006	606.260437	1.0

[4]:
```
# taking the first 30 000 rows from the shuffled DataFrame
subset_df = df_shuffled.iloc[:30000]

# splitting the labels from the rest of the dataset
X_sub = subset_df[['jet_1_pt', 'jet_2_pt', 'jet_3_pt', 'jet_1_eta', 'jet_2_eta',
       'jet_3_eta', 'jet_1_twb', 'jet_2_twb', 'jet_3_twb', 'bjet_1_pt',
       'lep_1_pt', 'lep_2_pt', 'lep_3_pt', 'n_jets', 'n_bjets', 'n_leptons',
       'met_met', 'H_T']]
y_sub = subset_df['ttZ']

# we can check the class distribution in the subset
print('ttZ events: {:.2f}%'.format(np.sum(y_sub)/len(y_sub) * 100))
print('WZ events: {:.2f}%'.format((1 - np.sum(y_sub)/len(y_sub)) * 100))
```

```
ttZ events: 68.69%
WZ events: 31.31%
```

3 Sequential Feature Selector

https://rasbt.github.io/mlxtend/user_guide/feature_selection/SequentialFeatureSelector/#example-9-selecting-the-best-feature-combination-in-a-k-range

[5]:
```
# model for classification
def build_model(input_dim=None):
    model = K.Sequential([
        K.layers.Normalization(),
        K.layers.Dense(50, activation="relu", input_dim=input_dim),
        K.layers.Dense(25, activation="relu"),
        K.layers.Dense(10, activation="relu"),
        K.layers.Dense(1, activation="sigmoid")
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

# wrapper function
model = KerasClassifier(build_fn=lambda: build_model(input_dim=X_sub.shape[1]),␣
 ↪epochs=10, batch_size=32, verbose=0)
```

```
/var/folders/3x/lv7sddxn2gg8mq0dwdcn1wg40000gn/T/ipykernel_29259/2265007354.py:1
3: DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras
(https://github.com/adriangb/scikeras) instead. See
https://www.adriangb.com/scikeras/stable/migration.html for help migrating.
  model = KerasClassifier(build_fn=lambda:
build_model(input_dim=X_sub.shape[1]), epochs=10, batch_size=32, verbose=0)
```

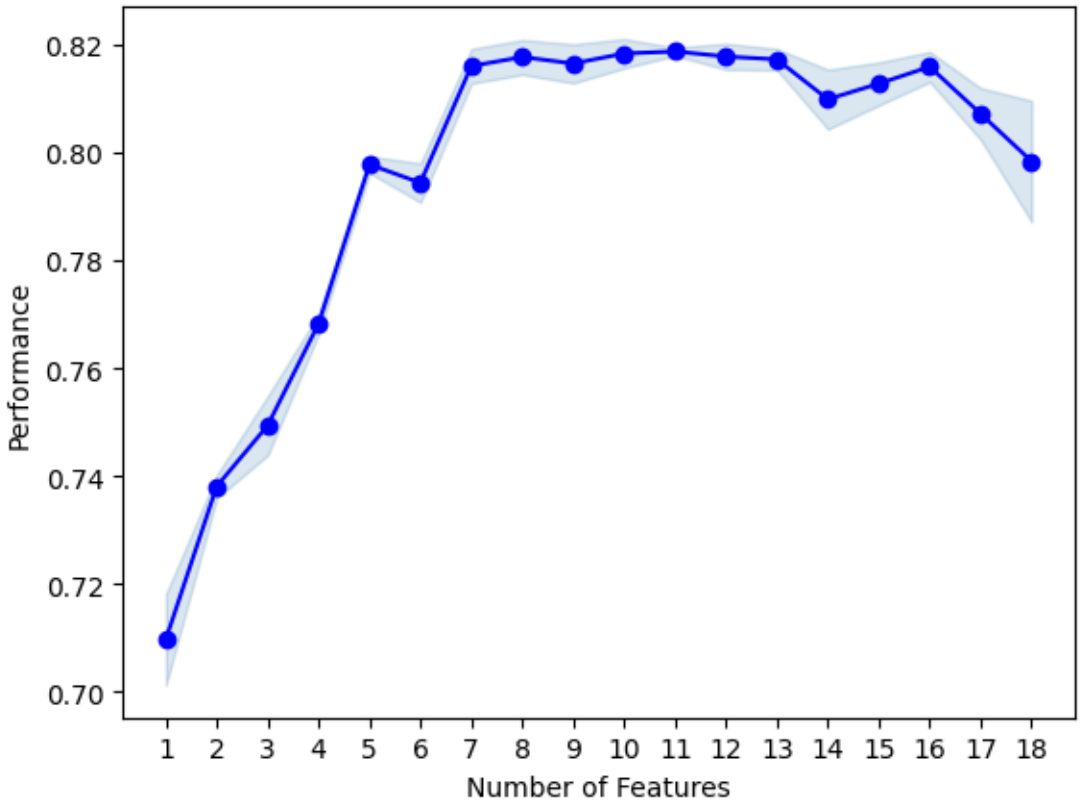
[6]:
```
# SFS model, will check performance from 1 feature to all 18
sfs = SFS(model,
          k_features = (1,18),
          forward=True,
          floating=False,
          scoring='accuracy',
          cv=5,
          verbose=0)

sfs = sfs.fit(X_sub, y_sub)
```

[7]:
```
# plotting performance improvement with each additional feature

print('best combination (ACC: %.3f): %s\n' % (sfs.k_score_, sfs.k_feature_idx_))
plot_sfs(sfs.get_metric_dict(), kind='std_err');
plt.savefig('feature_num_performance_30k.pdf')
```

```
best combination (ACC: 0.819): (0, 2, 3, 5, 6, 7, 8, 9, 13, 14, 15)
```



[8]:
```
# saving performance of all feature sets

feature_performance_df = pd.DataFrame.from_dict(sfs.get_metric_dict()).T
feature_performance_df.to_csv('performance_30k.csv', index=False)
feature_performance_df
```

[8]:

	feature_idx	\
1	(9,)	
2	(9, 13)	
3	(9, 13, 14)	
4	(6, 9, 13, 14)	
5	(6, 7, 9, 13, 14)	
6	(2, 6, 7, 9, 13, 14)	
7	(2, 6, 7, 8, 9, 13, 14)	
8	(2, 5, 6, 7, 8, 9, 13, 14)	
9	(2, 3, 5, 6, 7, 8, 9, 13, 14)	
10	(2, 3, 5, 6, 7, 8, 9, 13, 14, 15)	
11	(0, 2, 3, 5, 6, 7, 8, 9, 13, 14, 15)	
12	(0, 2, 3, 5, 6, 7, 8, 9, 10, 13, 14, 15)	
13	(0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15)	
14	(0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15, 17)	
15	(0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15, 16...	
16	(0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15...	
17	(0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14...	

```
18  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...

                                              cv_scores avg_score  \
1   [0.7248333333333333, 0.6886666666666666, 0.721...  0.709633
2   [0.7351666666666666, 0.7353333333333333, 0.735...  0.738067
3   [0.7548333333333334, 0.765, 0.7485, 0.747, 0.7...  0.749367
4   [0.765, 0.7721666666666667, 0.7733333333333333...  0.768233
5   [0.7918333333333333, 0.8003333333333333, 0.8, ...    0.7978
6   [0.7828333333333334, 0.8046666666666666, 0.794...    0.7944
7   [0.8116666666666666, 0.8283333333333334, 0.810...  0.816067
8   [0.8115, 0.8275, 0.8211666666666667, 0.81, 0.8...  0.817733
9   [0.815, 0.8263333333333334, 0.812, 0.8065, 0.8...  0.816533
10  [0.8146666666666667, 0.8246666666666667, 0.811...    0.8184
11  [0.8196666666666667, 0.8185, 0.817, 0.8175, 0...  0.818767
12  [0.8168333333333333, 0.8203333333333334, 0.816...  0.817833
13  [0.8201666666666667, 0.8226666666666667, 0.811...    0.8173
14  [0.8206666666666667, 0.8223333333333334, 0.810...    0.8099
15             [0.8215, 0.82, 0.8055, 0.8155, 0.8015]    0.8128
16  [0.817, 0.8243333333333334, 0.811, 0.808666666...  0.815933
17  [0.8131666666666667, 0.789, 0.806, 0.815333333...    0.8072
18  [0.7715, 0.8163333333333334, 0.8115, 0.8218333...    0.7984

                                       feature_names  ci_bound   std_dev  \
1                                        (bjet_1_pt,)  0.021713  0.016894
2                                  (bjet_1_pt, n_jets)  0.005534  0.004306
3                            (bjet_1_pt, n_jets, n_bjets)  0.014078  0.010953
4                 (jet_1_twb, bjet_1_pt, n_jets, n_bjets)  0.004797  0.003732
5   (jet_1_twb, jet_2_twb, bjet_1_pt, n_jets, n_bj...  0.003981  0.003097
6   (jet_3_pt, jet_1_twb, jet_2_twb, bjet_1_pt, n_...  0.009342  0.007268
7   (jet_3_pt, jet_1_twb, jet_2_twb, jet_3_twb, bj...  0.008231  0.006404
8   (jet_3_pt, jet_3_eta, jet_1_twb, jet_2_twb, je...  0.008258  0.006425
9   (jet_3_pt, jet_1_eta, jet_3_eta, jet_1_twb, je...  0.009256  0.007201
10  (jet_3_pt, jet_1_eta, jet_3_eta, jet_1_twb, je...  0.006957  0.005413
11  (jet_1_pt, jet_3_pt, jet_1_eta, jet_3_eta, jet...  0.001938  0.001508
12  (jet_1_pt, jet_3_pt, jet_1_eta, jet_3_eta, jet...  0.006169  0.004799
13  (jet_1_pt, jet_3_pt, jet_1_eta, jet_2_eta, jet...  0.005066  0.003942
14  (jet_1_pt, jet_3_pt, jet_1_eta, jet_2_eta, jet...  0.014196  0.011045
15  (jet_1_pt, jet_3_pt, jet_1_eta, jet_2_eta, jet...  0.010215  0.007947
16  (jet_1_pt, jet_3_pt, jet_1_eta, jet_2_eta, jet...  0.007186  0.005591
17  (jet_1_pt, jet_3_pt, jet_1_eta, jet_2_eta, jet...  0.012362  0.009618
18  (jet_1_pt, jet_2_pt, jet_3_pt, jet_1_eta, jet_...  0.028888  0.022476

     std_err
1   0.008447
2   0.002153
3   0.005477
4   0.001866
5   0.001549
6   0.003634
7   0.003202
8   0.003213
9   0.003601
10  0.002706
```

```
11  0.000754
12    0.0024
13  0.001971
14  0.005523
15  0.003974
16  0.002796
17  0.004809
18  0.011238
```