ML-based shape analysis to constrain anomalous couplings in the Higgs sector

non-linear Effective Field Theory (EFT): [e.g. Buchalla et al. '13]

Lagrangian relevant for $gg \to HH$

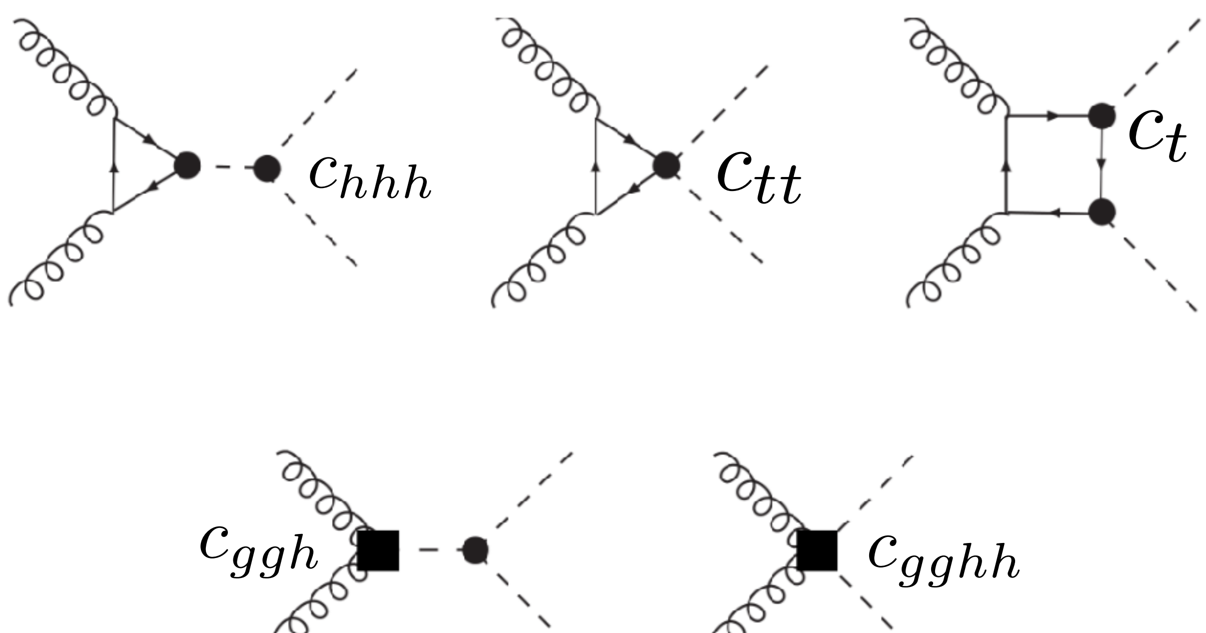
$$\Delta\mathcal{L}_{d\chi\leq 4} = -m_t \left(c_t \frac{h}{v} + c_{tt} \frac{h^2}{v^2} \right) \bar{t}\,t - c_{hhh} \frac{m_h^2}{2v} h^3 + \frac{\alpha_s}{8\pi} \left(c_{ggh} \frac{h}{v} + c_{gghh} \frac{h^2}{v^2} \right) G^a_{\mu\nu} G^{a,\mu\nu}$$

5 anomalous couplings (SM: $c_{tt} = 0, c_{ggh} = c_{gghh} = 0$)

LO diagrams:

$d\chi \leq 4$

and $\mathcal{O}(g_s^2)$

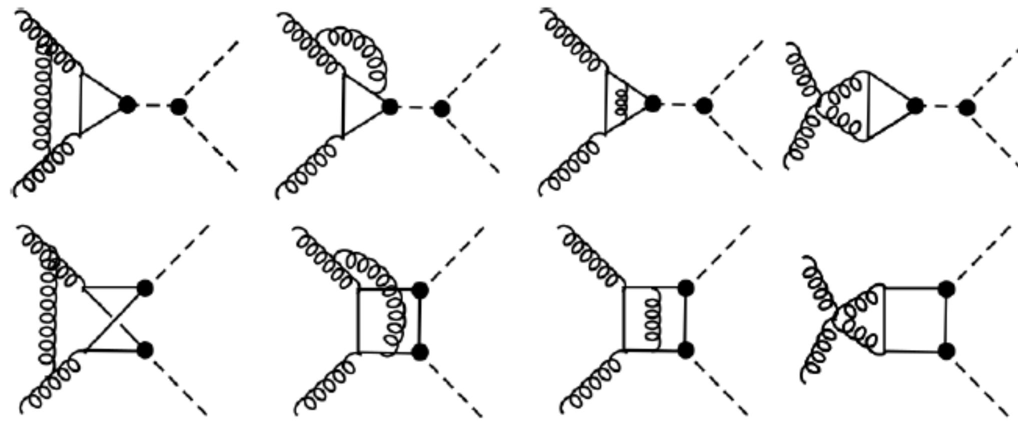


NLO QCD corrections

Buchalla, Capozi, Celis, GH, Scyboz ‘18

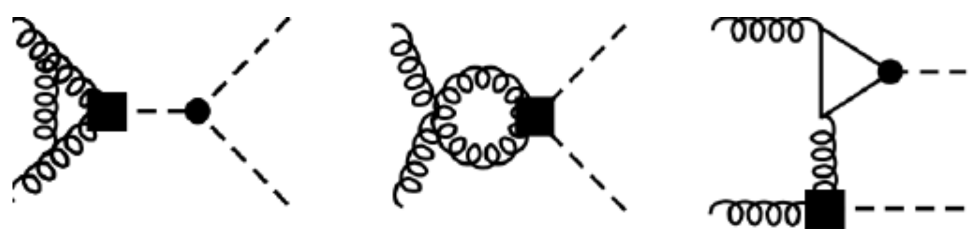
Example diagrams

virtual corrections:



2-loop SM-like

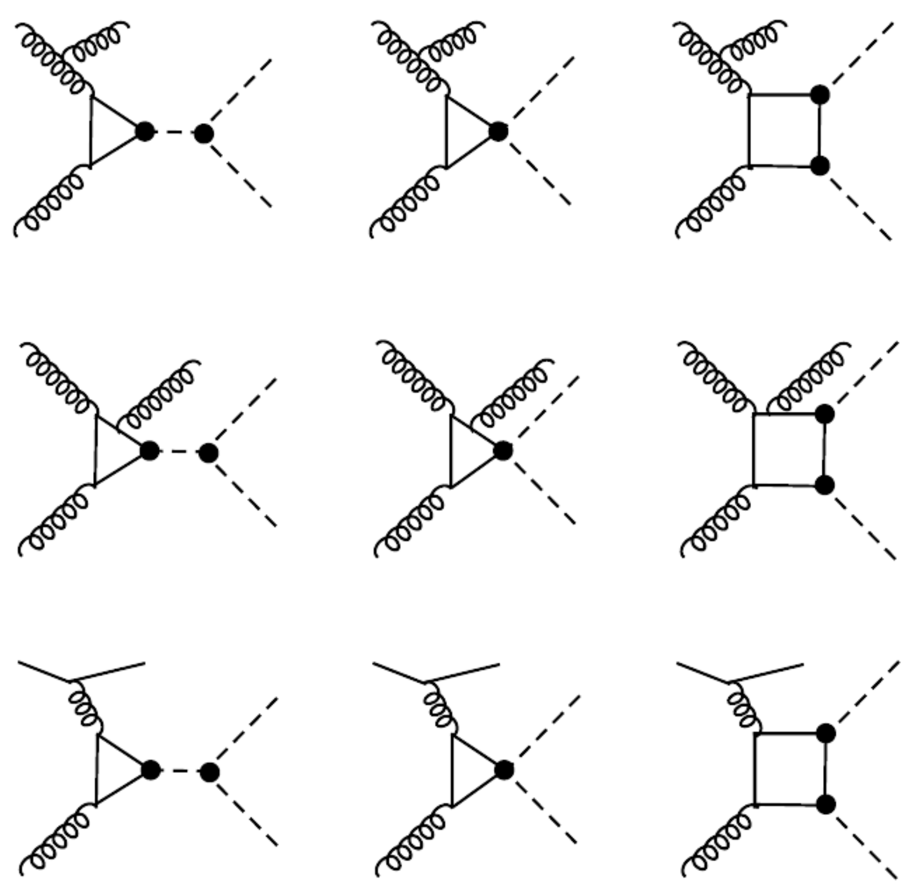
Borowka, Greiner, GH, Jones, Kerner, Schlenk, Schubert, Zirke ’16



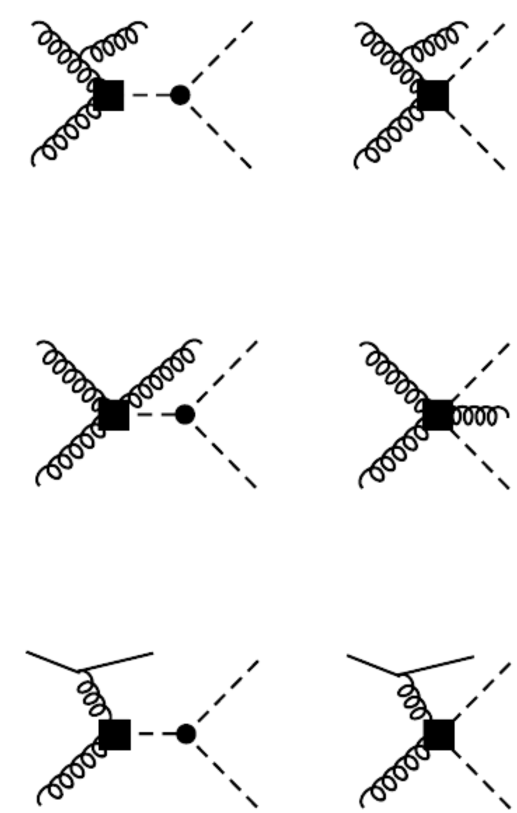
1-loop EFT

real corrections:

5-point 1-loop diagrams



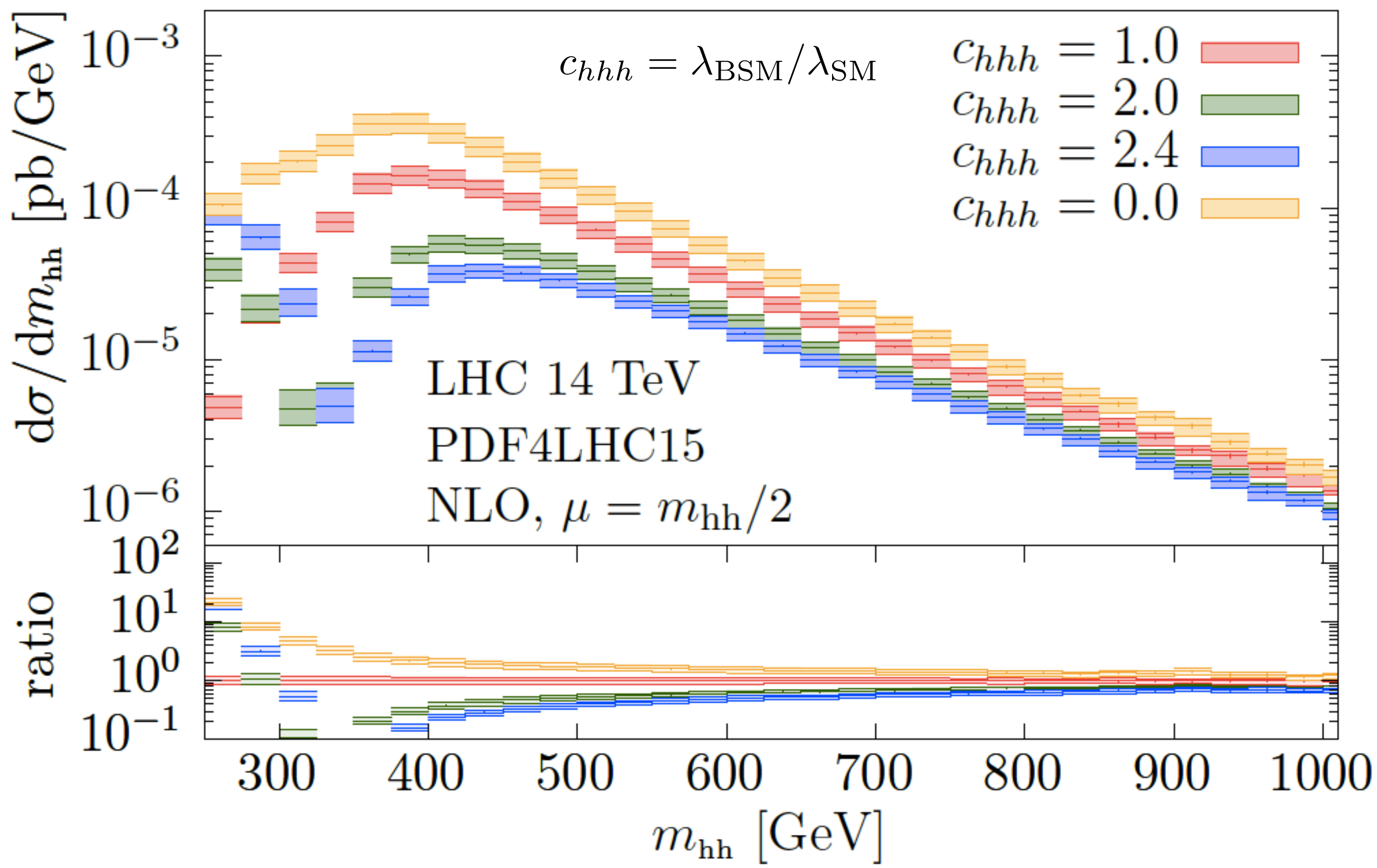
tree diagrams $\propto c_{ggh},\ c_{gghh}$



m_{hh} shape analysis

Values of c_{hhh} around 2.4 lead to

a dip/double peak structure in the m_{hh} distribution



Is this feature preserved once variations of the other couplings are taken into account?

m_{hh} shape analysis

Aim:

get a clearer idea how the different anomalous couplings affect the shape of the m_{hh} distribution

How?

- focus on characteristic shape features
- visualise underlying parameter space in 2-dim. projections
- analyse how the different parameters affect the shape
- crucial: find a suitable “measure” defining a characteristic shape type

used in 1908.08923:

(a) bin-by-bin analyser script

(b) unsupervised learning

Shape analysis

- use unsupervised learning to identify shape types
- autoencoder from KERAS (tensorflow)
- input: 10000 m_{hh} distributions with 30 bins of width 20 GeV

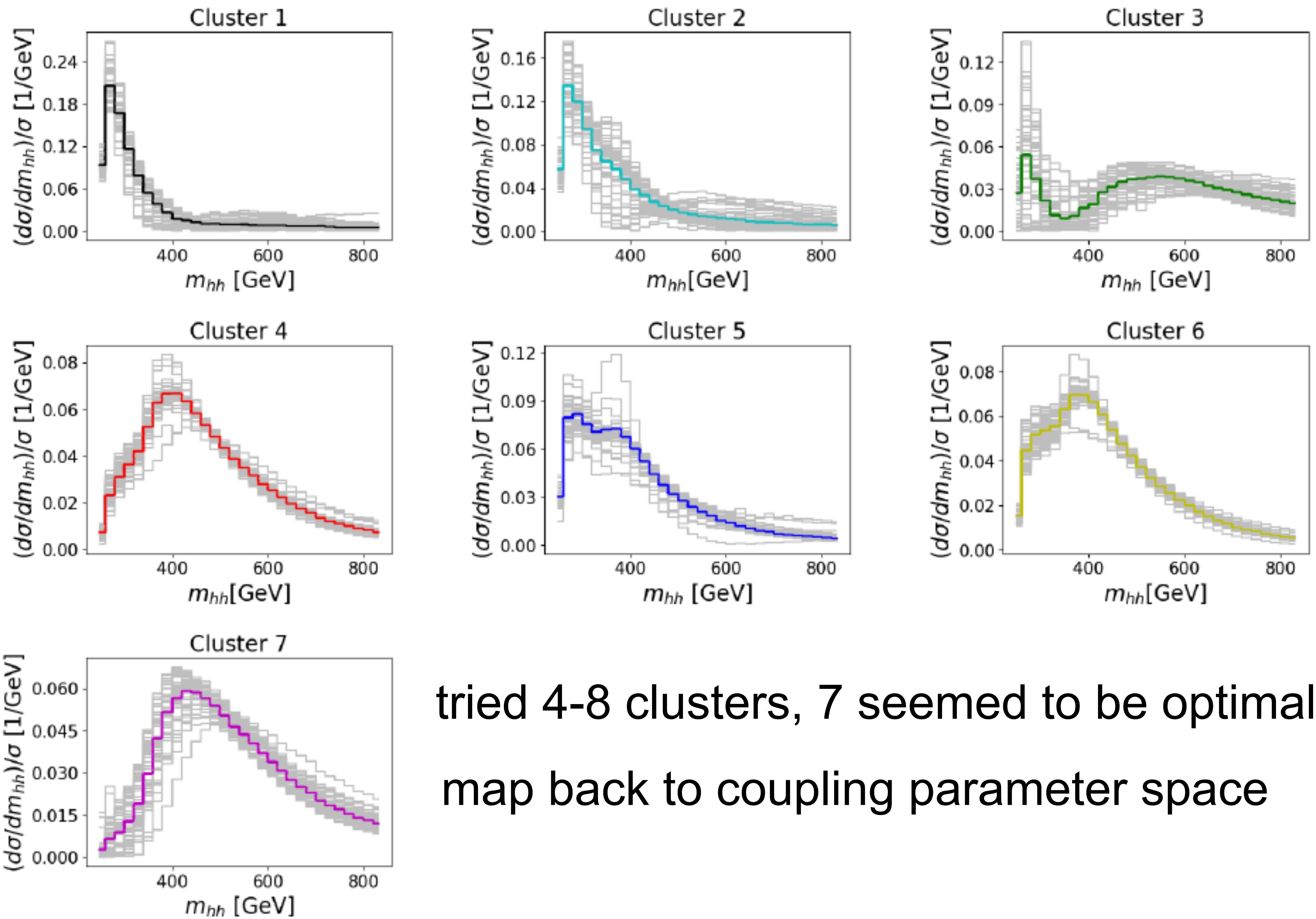
use 7000 distributions for training, retain 3000 for validation

encoder will try to find common patterns in order to achieve a compressed representation of the data

```
input_data = Input(shape=(30,))
encoded = Dense(20, activation='relu')(input_data)
encoded = Dense(20, activation='relu')(encoded)
encoded = Dense(4, activation='relu')(encoded)
decoded = Dense(20, activation='relu')(encoded)
decoded = Dense(20, activation='relu')(decoded)
decoded = Dense(30, activation='sigmoid')(decoded)
autoencoder = Model(input_data, decoded)
```

then use KMeans algorithm (scikit-learn) for clustering into given number of clusters

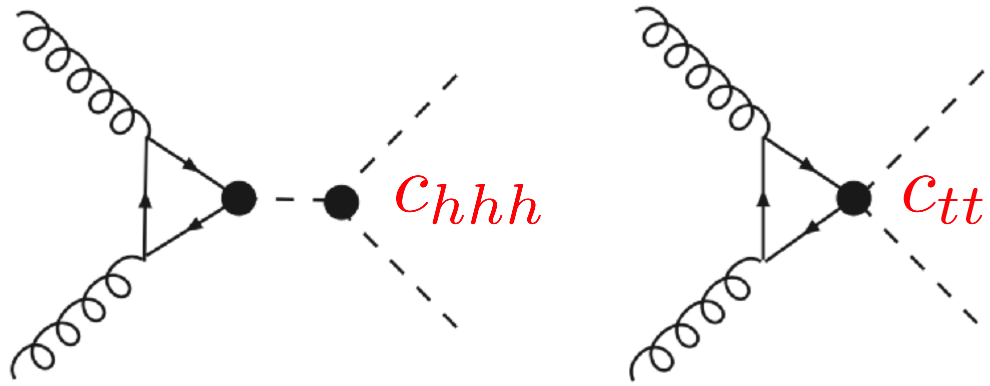
Shape analysis

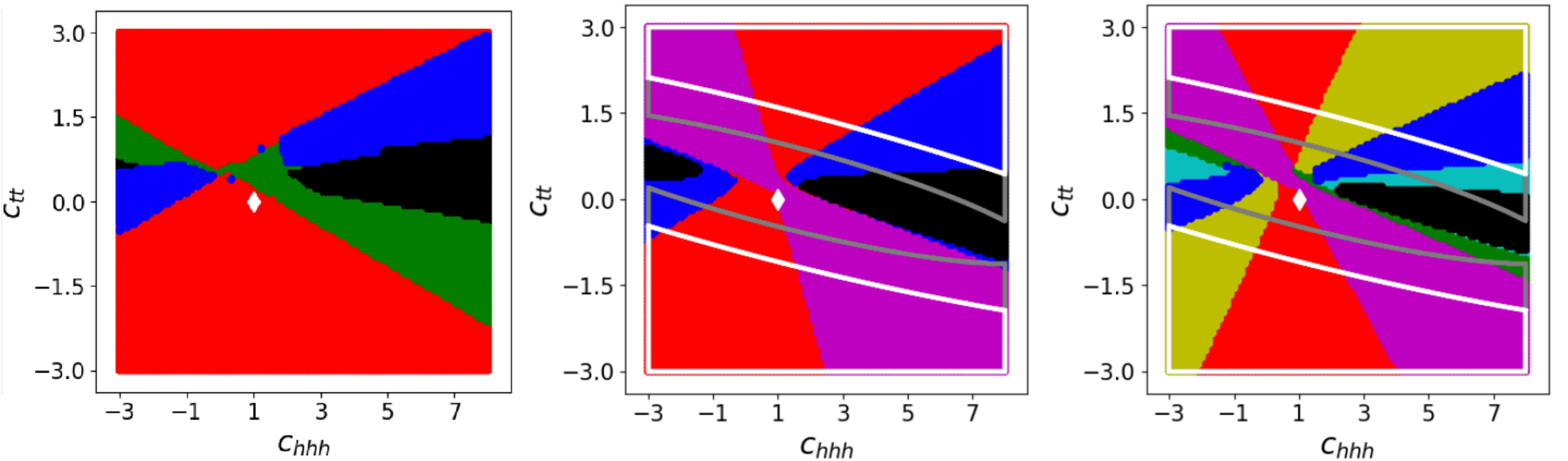


tried 4-8 clusters, 7 seemed to be optimal

map back to coupling parameter space

Shape analysis





c_{tt} and c_{hhh} have strong influence on shape

shape combined with bounds on total σ puts constraints on c_{tt}

Projects

(1) combine with shape analysis of

- H+jet (p_T^H) for constraints on c_g, c_t
- maybe also VBF di-Higgs

(2) new method to model complicated matrix elements based on ML