

1 Measurement prospects for Higgs decays to  
2 strange quark pairs with the future International  
3 Large Detector at the International Linear  
4 Collider

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25 January 12, 2022

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29

30 **Abstract**

31 This paper describes a novel algorithm for tagging jets originating  
32 from the hadronisation of strange quarks (strange-tagging) with the future  
33 International Large Detector (ILD) at the International Linear Collider  
34 (ILC). It also presents the first application of such a strange-tagger to a

35 Higgs to strange ( $h \rightarrow s\bar{s}$ ) analysis with the initial hypothetical  $2 \text{ ab}^{-1}$  of  
36 data which will be collected by ILD during its first 10 years of data taking  
37 at  $\sqrt{s} = 250 \text{ GeV}$ . Limits on the Standard Model Higgs-strange coupling  
38 strength modifier,  $\kappa_s$ , are derived at the 95% CL to be XXX. The paper  
39 includes as well a preliminary attempt to design an ideal detector capable  
40 of maximising strange-tagging performance.

## 41 1 Introduction

42 The experimental program at the Large Hadron Collider (LHC) [1] has clearly  
43 established Yukawa couplings of the 125 GeV Higgs ( $h$ ) to the third generation  
44 of fermions. The ATLAS and CMS experiments [2, 3] have recently reported  
45 evidence that the Higgs boson decays into two muons [4, 5], which indicates for  
46 the first time that the Higgs boson interacts with second-generation leptons.  
47 At the same time, this is just a hint and not yet a complete exploration of  
48 the second generation Yukawa couplings, because these rare Higgs decay modes  
49 (i.e., to charm or strange quarks) are very challenging or nearly impossible to  
50 detect with the current detector capabilities. Furthermore, the large multi-jet  
51 background at the LHC inhibits the study of light quark couplings with inclusive  
52  $h \rightarrow q\bar{q}$  decays, in addition to the dominant  $h \rightarrow b\bar{b}$  decay mode.

53 At the LHC, new algorithms for the identification of jets originating from  
54 the hadronisation of  $c$ -quarks ( $c$ -tagging) are gradually becoming available and  
55 enabling new searches for the decay of the Higgs boson to charm quarks. Less  
56 literature, however, is available about searches of Higgs boson decays to light  
57 quarks [6, 7, 8, 9, 10, 11].

58 Searches for exclusive Higgs boson decays to a  $\phi$  or  $\rho(770)$  meson and a pho-  
59 ton have been suggested and experimentally tested [11] as a probe of the Higgs  
60 boson couplings to the strange-quark, or the up- and down-quarks, respectively.  
61 For these Higgs couplings there are no projections available and it will most  
62 likely remain out of direct experimental reach unless they are enhanced com-  
63 pared to Standard Model (SM) expectations. In fact, when considering Beyond  
64 the Standard Model (BSM) scenarios that allow for extended Higgs sectors, the  
65 possibilities open up dramatically. A class of BSM models [12], where the ori-  
66 gin of the first and second generation fermion masses is an additional source of  
67 electroweak symmetry breaking, predicts large deviations from the SM values.  
68 A simple example is the two Higgs doublet model (2HDM) where one doublet  
69 (approximately identified as the 125 GeV Higgs) couples mainly to the third  
70 generation, while the second doublet couples mainly to the first and second  
71 generation. This results in very different decay branching ratios of the addi-  
72 tional heavy Higgs bosons ( $H$ ). The largest production mode of the neutral  
73 Higgs bosons would be from a  $c\bar{c}$  initial state, while the charged Higgs bosons  
74 would be predominantly produced from a  $c\bar{s}$  initial state. The most interesting  
75 decay modes include  $H/A \rightarrow c\bar{c}$ ,  $t\bar{c}$ ,  $\mu\mu$ , and  $\tau\mu$  and  $H^\pm \rightarrow c\bar{b}$ ,  $c\bar{s}$ , and  $\mu\nu$ .

76 Tagging strange jets comes with some difficulty, however. As shown in Ta-  
77 ble 1, bottom and charm jets can be differentiated based on the presence of 2  
78 or 1 secondary vertices. Strange jets, which, excluding  $V^0$ 's, have 0 secondary  
79 vertices, are only differentiated from light (i.e., up or bottom) jets based on the  
80 ability to reliably tag the presence of a strange hadron within the jet. Strange  
81 hadrons are also most often the leading particle in strange jets, as evident from

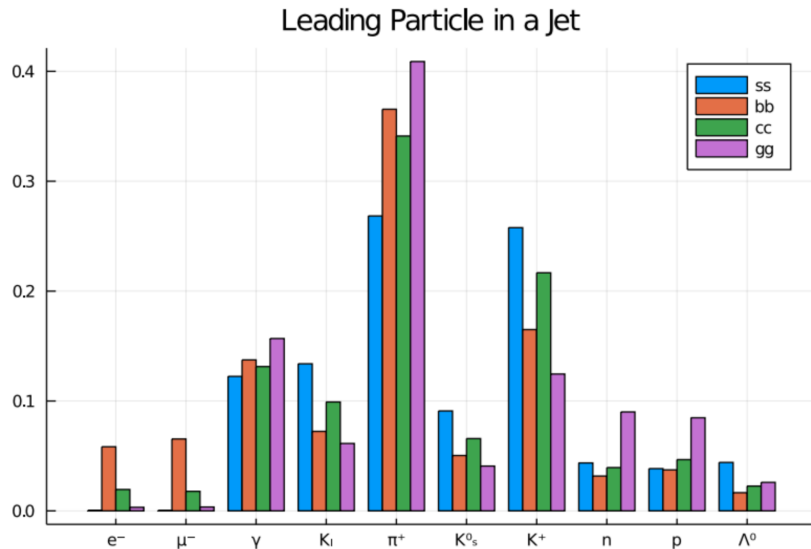


Figure 1: Leading particle fractions for reconstructed jets from  $h \rightarrow s\bar{s}/b\bar{b}/c\bar{c}/g\bar{g}$  events, generated using WHIZARD [13] and reconstructed with MARLIN [14] using a Silicon Detector [15] simulation. All of the bars of a particular colour sum to 1 by definition. Neutrinos and very soft ( $E < 0.05$  GeV) particles are excluded.

82 Figure 1. Accordingly, technology enabling kaon-pion discrimination is highly  
83 relevant at future detectors for measurements of decays to strange jets.

Table 1: Defining features for the different categories of quark jets.

Jet flavour	Number of secondary vertices (excluding $V^0$ 's)	Number of strange hadrons (e.g., $K^\pm$ , $K_{L/S}^0$ , and $\Lambda^0$ )
Bottom	2	$\geq 1$
Charm	1	$\geq 1$
Strange	0	$\geq 1$
Light	0	0

84 The work presented in this paper describes the novel development of a flavour  
85 tagging algorithm capable of tagging jets that originate from the hadronisation  
86 of strange quarks (strange-tagging). This allows us to tag for the first time  
87 exclusive Higgs decays and opens new opportunities in direct  $h \rightarrow s\bar{s}$  searches.  
88 If used in conjunction with  $c$ -tagging, it also allows to probe new physics models.  
89 **[TODO: move the previous sentence to “Conclusions and next steps”**  
90 **if we do NOT include any  $H \rightarrow cs$  studies here in the end]** The tagger  
91 is then applied to a SM (125 GeV)  $h \rightarrow s\bar{s}$  analysis estimating the prospects for  
92 Higgs-strange coupling strength measurements.

93 Strange tagging itself is of interest in the context of the ILC study ques-  
94 tions [16] proposed for Snowmass 2021 [17]. The study presented here is con-  
95 ducted in the context of the future International Linear Collider (ILC) [18], a

96 future electron-positron collider proposed to be built in Japan. Nevertheless,  
97 the results are easily applicable to future experiments at other electron-positron  
98 machines.

99 **[TODO: expand description of strange hadronisation.]**

100 The paper is organized as follows:

- 101 • Section 2 describes the International Large Detector, a proposed detector  
102 at the ILC and the detector used for the contained studies;
- 103 • Section 3 describes the Monte Carlo samples included in the study;
- 104 • Section 4 describes the development and validation of a jet flavour tagger  
105 using a neural network;
- 106 • Section 5 describes the application of the jet flavour tagger to a SM  $h \rightarrow s\bar{s}$   
107 analysis with ILD at the  $\sqrt{s} = 250$  GeV ILC run;
- 108 • Section 6 describes a detector proposal which would maximize particle  
109 identification (PID) at high momenta and thus boost strange tagging per-  
110 formance.
- 111 • Section 7 describes the conclusions and next steps.

## 112 2 The ILD detector

113 The International Large Detector (ILD) is one of two detector concepts proposed  
114 at the ILC [19, 20, 21], the other being the Silicon Detector (SiD) [20, 15].

115 Closest to the interaction point, ILD has 3 double-layer pixel detectors for  
116 vertexing followed by a time projection chamber (TPC) for tracking. The TPC  
117 additionally provides PID via measurements of energy loss from charged parti-  
118 cles due to ionisation ( $dE/dx$ ) and time-of-flight (TOF) from inner and outer  
119 layers of silicon flanking the TPC. The low material budget of the TPC is highly  
120 desirable for low momentum tracking of particles.

121 Immediately beyond the tracking system, ILD has high granularity sampling  
122 calorimeters for particle flow reconstruction [22]. The precise design of the  
123 electromagnetic and hadronic calorimeters is still under study.

124 The tracking and calorimetry systems are contained within in a solenoid  
125 providing a 3.5 T magnetic field. A surrounding iron yoke instruments muon  
126 detection.

## 127 3 Monte Carlo simulation

128 The main Higgs boson production mechanism at the ILC is production in asso-  
129 ciation with a  $Z$  boson (“associated production”),  $Zh$ . Accordingly, associated  
130 production is considered in this paper for generating the signal and some of the  
131 background events in both the  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$  decay channels. To a much  
132 smaller degree,  $ZZ$ - and  $WW$ -fusion production contribute in the  $Z \rightarrow e^+e^-$   
133 and  $Z \rightarrow \nu_e\bar{\nu}_e$  decay channels, respectively; however, only  $ZZ$ -fusion is included  
134 in this paper.

135 The Monte Carlo (MC) events used in this study were generated at centre-  
136 of-mass energy  $\sqrt{s} = 250$  GeV using WHIZARD 2.8.5 [13, 23] interfaced with

137 PYTHIA 6.4 [24] for showering/hadronisation, TAUOLA for polarised  $\tau$  lepton  
 138 decays [25, 26, 27], and GUINEA-PIG [28] and CIRCE2 [29, 30] for beam spectrum  
 139 effects.

140 The generated events were reconstructed with MARLIN [14], using a full  
 141 simulation of the ILD detector based on GEANT4 [31] in the MOKKA frame-  
 142 work [32]. The reconstructed events were saved as DSTs, an LCIO<sup>1</sup> [34] event  
 143 data model, and further refined as miniDSTs [35], a slimmed version of DST  
 144 which also includes the results of the LCFIPlus [36]  $b$ -,  $c$ -, and  $o$ - (i.e., “other”  
 145 – strange, light, or gluon) jet tagger scores.

146 Low- $p_T$  pileup from  $\gamma\gamma \rightarrow$  hadrons events was simulated using the cross  
 147 section model of Chen-Barklow-Peskin [37], reconstructed using the full ILD  
 148 simulation, and overlaid onto all hard scatter events.

149 All MC samples are generated using 100% left-handed- (LH-) polarised elec-  
 150 tron beams and 100% right-handed- (RH-) polarised positron beams. As we  
 151 consider the ILC running scenario at  $\sqrt{s} = 250$  GeV using 80% LH-polarised  
 152 electron beams (i.e.,  $P_L[e^-] = -80\%$ ) and 30% RH-polarised positron beams  
 153 (i.e.,  $P_R[e^+] = +30\%$ ), the polarisation-inclusive cross section  $\sigma_{\text{inc}}$  must be cor-  
 154 rected. In particular, the 100% LH electron and 100% RH positron cross section  
 155  $\sigma_{LR}$  is given by:

$$\begin{aligned}\sigma_{LR} &= P_L P_R \sigma_{\text{inc}} \\ &= \frac{1 - P_L[e^-]}{2} \frac{1 + P_R[e^+]}{2} \sigma_{\text{inc}} \\ &= 0.585 \sigma_{\text{inc}}.\end{aligned}\tag{1}$$

156 For this particular running scenario, an integrated luminosity  $\mathcal{L}$  of  $2 \text{ ab}^{-1}$  is  
 157 expected, as per the ILC physics programme [38]. Using the corrected cross  
 158 sections and the expected luminosity, each sample is normalised prior to apply-  
 159 ing any analysis cuts, where the event weights are modified as:

$$w'_i = \frac{\mathcal{L} \sigma_{LR}}{\sum_j w_j} w_i \forall i,\tag{2}$$

160 where  $w_i$  is the weight for event  $i$ . N.B. there is no estimate available for the  
 161 SM  $h \rightarrow s\bar{s}$  branching ratio (BR),  $\text{BR}[h \rightarrow s\bar{s}]_{\text{SM}}$  – instead, it is estimated by  
 162 scaling the SM  $h \rightarrow c\bar{c}$  BR,  $\text{BR}[h \rightarrow c\bar{c}]_{\text{SM}}$ , by the square of the ratio of the  
 163 strange quark mass over the charm quark mass,  $M_s/M_c$ :

$$\begin{aligned}\text{BR}[h \rightarrow s\bar{s}]_{\text{SM}} &\approx \left(\frac{M_s}{M_c}\right)^2 \times \text{BR}[h \rightarrow c\bar{c}]_{\text{SM}} \\ &= 11.72^{-2} \times 0.0291 \\ &= 2 \times 10^{-4}.\end{aligned}\tag{3}$$

164 The ratio,  $M_s/M_c = 11.72^{-1}$ , is taken from the Particle Data Group (PDG) [39].  
 165 A similar procedure yields  $\text{BR}[h \rightarrow d\bar{d}]_{\text{SM}} \approx 5 \times 10^{-7}$  and  $\text{BR}[h \rightarrow u\bar{u}]_{\text{SM}} \approx$   
 166  $1 \times 10^{-7}$  using  $M_s/M_d \sim 20$  and  $M_u/M_d \approx 0.47$ , also taken from the PDG [39].

<sup>1</sup>LCIO version 02-15-04 [33] was used for processing all of the input miniDSTs analysed in this paper.

167 The signal and background MC samples used in this study are shown in  
 168 Table 2. Also shown are the raw numbers of events as well as the LR cross  
 169 sections, per sample. The  $h \rightarrow s\bar{s}$  comes

170 As a back-of-the-envelope calculation, assuming  $2000 \text{ fb}^{-1}$  of data collected  
 171 at the ILC after 10 years of data-taking and a Higgs boson production cross-  
 172 section of about  $200 \text{ fb}$ ,  $\sim 400,000$  Higgs bosons would be produced with only 80  
 173 of which feature a  $h \rightarrow s\bar{s}$  event.

Table 2: MC processes considered in the  $h \rightarrow s\bar{s}$  analysis, including raw statistics and cross sections. N.B. the samples were generated at  $\sqrt{s} = 250 \text{ GeV}$  and the cross sections assume electron-positron beam polarisations of  $P_L[e^-] = -80\%$  and  $P_R[e^+] = +30\%$ , respectively. The cross sections include the corresponding BRs for the indicated decays. In the non-Higgs processes, “ $nf$ ” denotes the number ( $n$ ) of fermions ( $f$ ) in the final state. In  $Z(\rightarrow \ell\ell)h(\rightarrow \text{other})$ , “other” denotes any non-hadronic decay.

Process name	Raw events [a.u.]	LR cross section [fb]
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow s\bar{s})$	500,000	0.021
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow b\bar{b})$	500,000	58.1
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow c\bar{c})$	499,800	2.9
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow u\bar{u})$	499,800	$1 \times 10^{-5}$
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow d\bar{d})$	500,000	$5 \times 10^{-5}$
$Z(\rightarrow \nu\bar{\nu})h(\rightarrow gg)$	499,800	8.6
$Z(\rightarrow \ell\ell)h(\rightarrow s\bar{s})$	373	0.011
$Z(\rightarrow \ell\ell)h(\rightarrow b\bar{b})$	872,380	29.8
$Z(\rightarrow \ell\ell)h(\rightarrow c\bar{c})$	43,334	1.5
$Z(\rightarrow \ell\ell)h(\rightarrow u\bar{u})$	0	$6 \times 10^{-6}$
$Z(\rightarrow \ell\ell)h(\rightarrow d\bar{d})$	0	$3 \times 10^{-5}$
$Z(\rightarrow \ell\ell)h(\rightarrow gg)$	123,225	4.4
$Z(\rightarrow \ell\ell)h(\rightarrow \text{other})$	460,688	15.9
$2f$ $Z$ hadronic	25,354,400	127,965
$4f$ $ZZ$ hadronic	7,099,000	1,405
$4f$ $WW$ hadronic	14,790,600	14,866
$4f$ $ZZ/WW$ hadronic	18,494,200	12,389
$2f$ $Z$ leptonic	24,500,000	21,214
$4f$ $ZZ$ semileptonic	4,199,600	838
$4f$ single $Z$ semileptonic	6,999,600	1,423

## 174 4 Jet flavour tagger

175 In order to better tag strange, light, and gluon jets, an artificial neural network  
 176 (ANN) was developed in Keras [40] using the TensorFlow backend [41]. The goal  
 177 of tagging each jet by their flavour of progenitor particle (i.e.,  $b$ ,  $c$ ,  $s$ ,  $u/d$ , or  
 178  $g$ ) inspires the use of a multiclassifier. The multiclassifier assigns a probability  
 179 of a jet belonging to each possible output class (i.e., outputs a vector of size 5),  
 180 and these probabilities logically sum up to 1 per jet.

## 181 4.1 Inputs

182 The training is performed on the  $Z(\rightarrow \nu\bar{\nu})h(\rightarrow q\bar{q}/gg)$  samples from Table 2. All  
183 events are required to have  $N_{\text{jets}} \geq 2$  and  $N_{\text{leptons}} = 0$ . The training is performed  
184 using only one jet per event, where the leading or subleading momentum jet is  
185 randomly chosen. Per process, 250,000 raw MC events are used – additionally,  
186 the  $h \rightarrow u\bar{u}$  and  $h \rightarrow d\bar{d}$  processes are combined into a single class,  $h \rightarrow \text{light}$ .

187 As input to the ANN, several jet-level variables are chosen:

- 188 • kinematics: momentum  $p$ , pseudorapidity  $\eta$ , polar angle  $\phi$ , and mass  $m$ ;
- 189 • LCFIPlus tagger results:  $b$ -,  $c$ - and  $o$ -tag scores as well as jet category;
- 190 • number of Particle Flow Objects (PFOs – these are the particles which  
191 are grouped into the jet).

192 In addition to jet-level variables, it is prudent to include variables at the level  
193 of the PFOs contained within the jet. The 10 leading momentum particles  
194 contained within the jet have their kinematics redefined relative to the jet’s axis  
195 and their momentum and mass scaled by the momentum of the jet. Per-particle,  
196 the following variables are also chosen as inputs:

- 197 • kinematics:  $p$ ,  $\eta$ ,  $\phi$ , and  $m$ ;
- 198 • charge  $q$ ;
- 199 • truth likelihoods:  $L(e^\pm)$ ,  $L(\mu^\pm)$ ,  $L(\pi^\pm)$ ,  $L(K)$ ,  $L(p^+)$ .

200 The ILD detector will provide PID information per PFO, including electron  
201 ( $e^\pm$ ), muon ( $\mu^\pm$ ), pion ( $\pi^\pm$ ), kaon ( $K$ ), and proton ( $p^+$ ) likelihoods,  $L$ . How-  
202 ever, the reconstructed likelihoods utilising the  $dE/dx$  and TOF information  
203 were not available in the inputs at the time of the study. *Truth* likelihoods are  
204 assigned instead, representing a best-case scenario in terms of PID. The 5 truth  
205 likelihoods are assigned a binary number by comparing the absolute value of  
206 PDG ID [39] of the PFO to the PDG ID(s) of each particle class:

- 207 • electrons: 11;
- 208 • muons: 13;
- 209 • pions: 211;
- 210 • kaons: 310, 321, and 3122 (includes  $V^0$ ’s:  $K_s^0$  and  $\Lambda^0$ );
- 211 • protons: 2212;

212 where 1 is assigned if one of the PDGs match and 0 is assigned otherwise.

## 213 4.2 Architecture

214 PFO-level inputs motivates the use of a recurrent neural network (RNN), which  
215 can handle input events where the jet has fewer than 10 constituent particles  
216 (in these rare cases, the input vectors of particles are padded to size 10 with  
217 zero-initialised variables). A similar architecture (using a different flavour of

218 RNN) has been used for studying the maximum strange tagging performance  
 219 at hadron machines [42]. The RNN consist of 3 layers using gated recurrent  
 220 units (GRUs) [43]. The output from the RNN is concatenated with the jet-level  
 221 inputs and serve as inputs to a multilayer perceptron (MLP) with 3 layers. Each  
 222 layer of the MLP uses a scaled exponential linear unit (SELU) [44] activation,  
 223 which has the nice property of self-normalising inputs. As the network is a  
 224 multiclassifier, the sensible choice of output activation is the softmax function:

$$[f(\vec{x})]_i = \frac{\exp([\vec{x}]_i)}{\sum_{i=1}^5 \exp([\vec{x}]_i)} \quad \forall i = 1, \dots, 5, \quad (4)$$

225 where  $f$  is the softmax activation function,  $\vec{x}$  is the input vector, and  $[\dots]_i$   
 226 denotes the  $i$ -th value of a vector. The output vector is of size 5, as there are 5  
 227 jet flavour classes, and sums to 1, by definition.

228 A pictorial representation of the network’s architecture, including the num-  
 229 ber of nodes per layer, is shown in Figure 2.

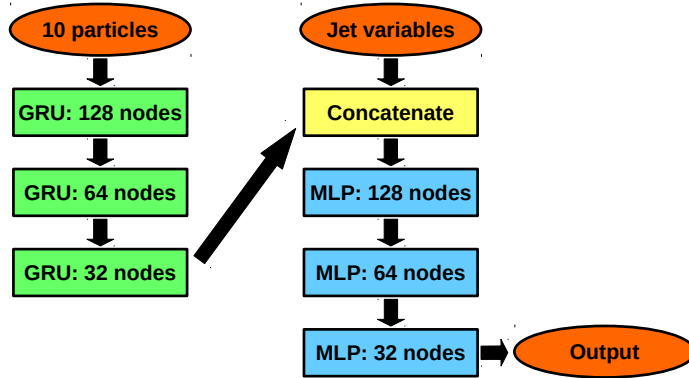


Figure 2: A cartoon of the network architecture used for the jet flavour tagger ANN. The arrows denote the flow of vectors through the network.

### 230 4.3 Training and validation

231 To train the network, input events are first split, where 90% of all events per  
 232 class are reserved for training and 10% are reserved for testing. Within the  
 233 training dataset, events are split according to even and odd event numbers. A  
 234 two-way  $k$ -folding procedure is used, where the network is trained using only  
 235 odd events and simultaneously validated using only even events (“ $k$ -fold 0”), and  
 236 then the network is trained using only even events and simultaneously validated  
 237 using only odd events (“ $k$ -fold 1”). In this way, the entire training dataset may  
 238 be used. If the input vector for a given event is  $\vec{x}$  and that same event has an  
 239 event number  $n$ , then the output of the tagger,  $F$  is:

$$F(\vec{x}) = \begin{cases} F_{k\text{-fold } 0}(\vec{x}), & n \bmod 2 = 0 \\ F_{k\text{-fold } 1}(\vec{x}), & n \bmod 2 = 1 \end{cases}, \quad (5)$$

240 where  $F_{k\text{-fold } 0}$  is the output of network trained on  $k$ -fold 0 and  $F_{k\text{-fold } 1}$  is the  
241 output of network trained on  $k$ -fold 1. In this way, we avoid bias by ensuring  
242 the tagger is *never* applied to the same events it was trained on.

243 A categorical cross-entropy loss function is chosen, and the network is trained  
244 using the Adam [45] optimizer with a learning rate of 0.0005 and a batch size  
245 of 1024. Each class is re-normalised to have the same sum-of-weights. Early  
246 stopping is applied to prevent overtraining.

247 The output scores for each node of the  $k$ -fold 0 and 1 networks are shown  
248 in Figures 3 and 4, respectively. Each network is applied to both the “training”  
249 events (90% – includes both the actual events used in training as well as those  
250 used in validation) and to the testing events (10%). In all distributions, the  
251 training and testing are in good agreement with one another, indicating no  
252 overfitting occurred.

253 For both  $k$ -fold’s 0 and 1, there is clear discrimination of  $b$ - and  $c$ -jets.  
254 Additionally, there is a capacity for *independently* tagging light-,  $s$ - and  $g$ -jets,  
255 but the separation power is somewhat reduced in comparison to  $b$ - and  $c$ -jets as  
256 these classes are more often confused with one another. This demonstrated by  
257 the confusion matrix shown in Figure 5, where there off-diagonal terms of order  
258 10–20% in the upper  $3\times 3$  (i.e., gluon, light, and strange) matrix compared to  
259 off-diagonal terms of order 5–10% in the lower  $2\times 2$  (i.e., charm and bottom)  
260 matrix.

261 In order to quantify the performance of each network, the receiver-operator  
262 characteristic (ROC) curves (i.e., background rejection as a function of signal  
263 efficiency) are also calculated using Eq. 5 and shown in Figure 6. Alongside the  
264 tagger’s ROC curves, the corresponding LCFIPlus results are also shown. Small  
265 improvements are seen for the  $b$ - and  $c$ -jet output nodes – likely, the tagger is  
266 simply returning the input LCFIPlus tagger scores with small enhancements due  
267 to the truth PID on the jet’s constituent PFOs. However, large improvements  
268 are observed for light-,  $s$ -, and  $g$ -jet tagging when using the multiclassifier over  
269 the LCFIPlus OTagger.

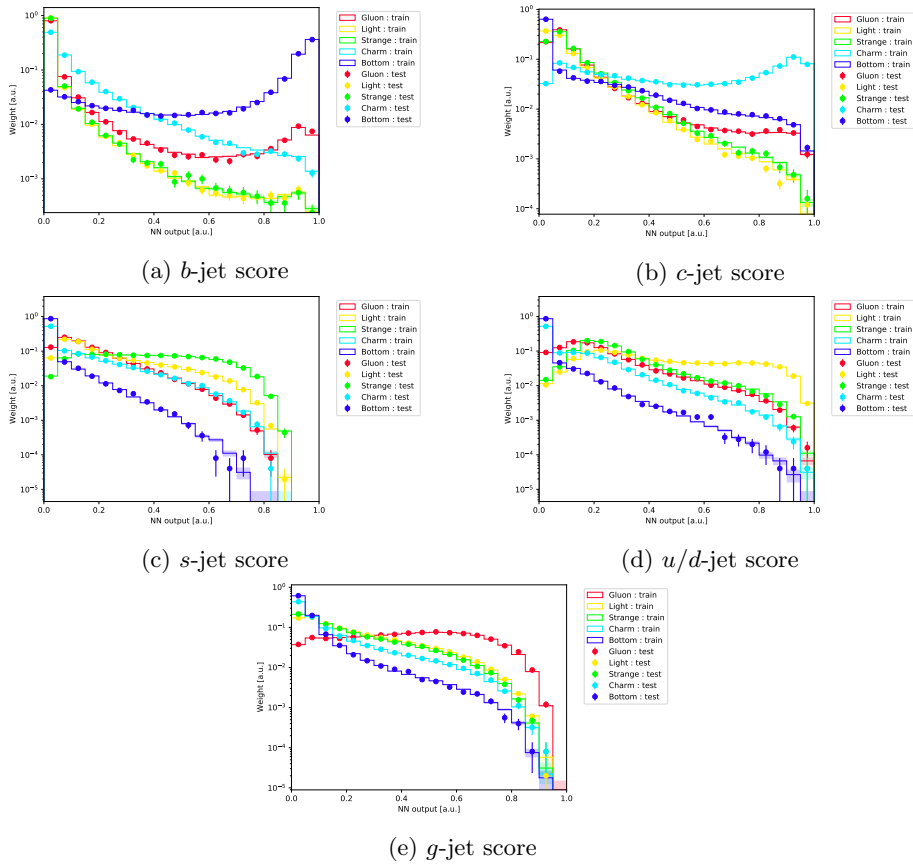


Figure 3: Distributions of the ANN's output nodes for the training and testing slices of  $k$ -fold 0. N.B. each class of each slice is normalised to the same sum-of-weights (i.e., 1) and logarithmic  $y$ -axis scales are used. The error bars correspond to Poisson counting statistics.

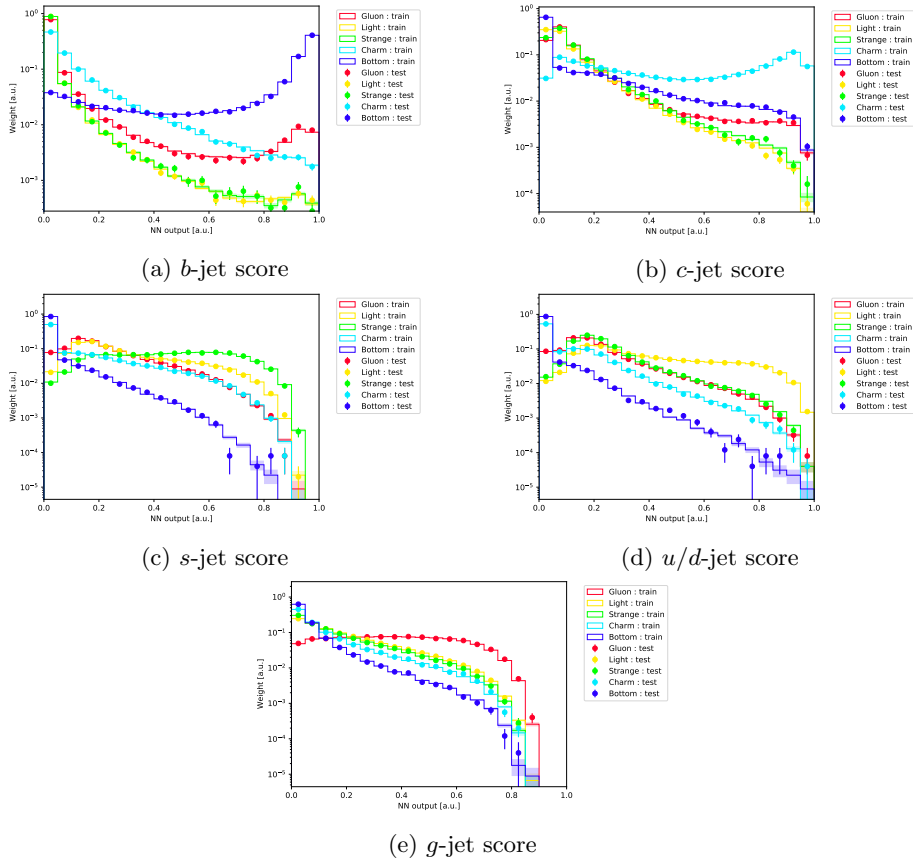


Figure 4: Distributions of the ANN's output nodes for the training and testing slices of  $k$ -fold 1. N.B. each class of each slice is normalised to the same sum-of-weights (i.e., 1) and logarithmic  $y$ -axis scales are used. The error bars correspond to Poisson counting statistics.

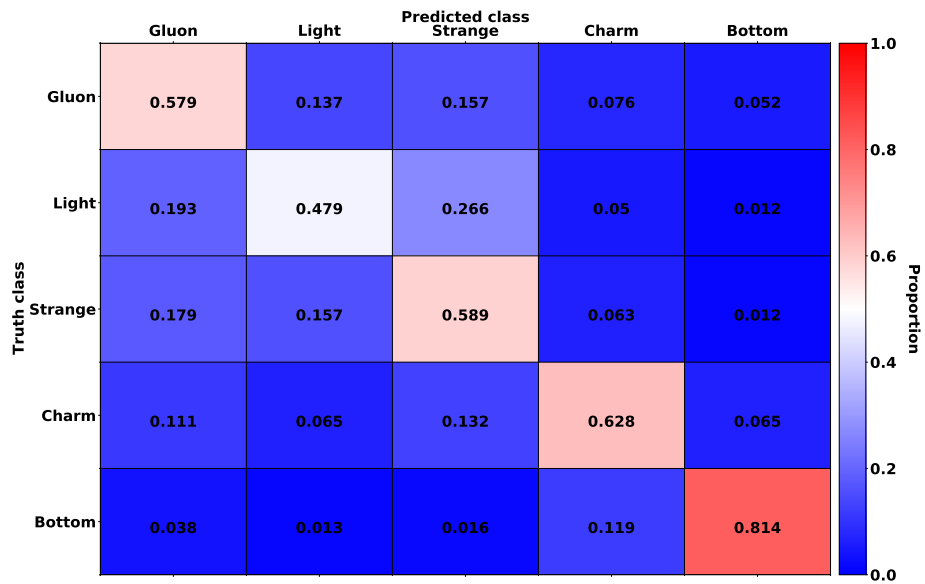
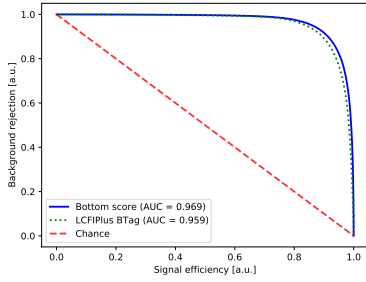
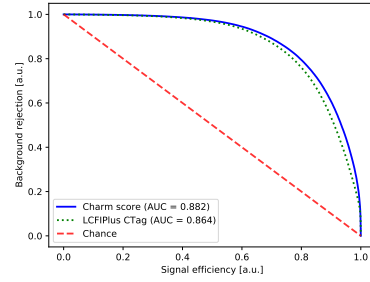


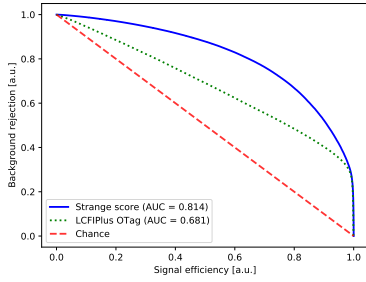
Figure 5: Confusion matrix for the output of the described jet flavour tagger, Eq. 5. Each truth class (i.e., row) is normalised to 1.



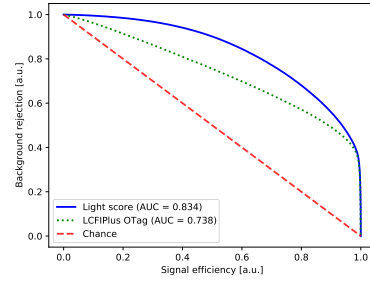
(a)  $b$ -jet score



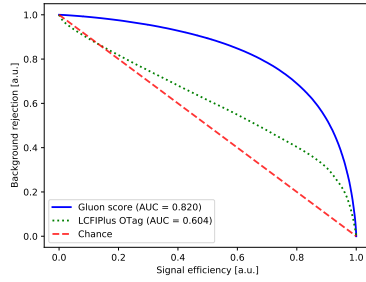
(b)  $c$ -jet score



(c)  $s$ -jet score



(d)  $u/d$ -jet score



(e)  $g$ -jet score

Figure 6: ROC curves for each output node of the described jet flavour tagger, Eq. 5. Also shown on each graph is the ROC curve for the appropriate LFCIPlus tagger: “BTagger” for  $b$ -jet node, “CTagger” for  $c$ -jet node, and “OTagger” for light-,  $s$ -, and  $g$ -jet nodes. The area under the curve (AUC) is given for each tagger – ideally,  $AUC = 1$  (i.e., 100% background rejection with 100% signal efficiency).

## 5 Higgs to strange analysis

The jet flavour tagger described in Section 4 is applied to a search for SM Higgs decaying to strange quarks ( $h \rightarrow s\bar{s}$ ), using all of the MC samples described in Table 2. The parameter of interest (POI) for the analysis is the Higgs-strange quark coupling strength modifier,  $\kappa_s$ , which tunes the SM  $h \rightarrow s\bar{s}$  BR,  $\text{BR}[h \rightarrow s\bar{s}]_{\text{SM}}$ , as:

$$\text{BR}[h \rightarrow s\bar{s}] = \mu(\kappa_s) \times \text{BR}[h \rightarrow s\bar{s}]_{\text{SM}}, \quad (6)$$

where  $\text{BR}[h \rightarrow s\bar{s}]$  is the modified BR and  $\mu(\kappa_s)$  is our POI as a function of  $\kappa_s$ , given by<sup>2</sup>:

$$\mu(\kappa_s) = \frac{\kappa_s^2}{\kappa_s^2 \times \text{BR}[h \rightarrow s\bar{s}]_{\text{SM}} + (1 - \text{BR}[h \rightarrow s\bar{s}]_{\text{SM}})}. \quad (7)$$

The coupling strength modifier is understood within the context of the kappa framework, the experimental tool for exploring the properties of the Higgs [47, 48]. When  $\kappa_s = 1$ , the SM BR is recovered.

### 5.1 Kinematic selections

The measurement of  $h \rightarrow s\bar{s}$  is performed using the associated production mode in two channels based on the decay of the  $Z$ :  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$ . The kinematic selections for each channel, detailed in Table 3, are designed to be orthogonal and to reduce the dominant  $Z$ ,  $VV$ , and  $h \rightarrow b\bar{b}/c\bar{c}/gg$  backgrounds. The cuts on the number of PFOs per event and per jet reduce the  $h \rightarrow gg$  backgrounds – in general, gluon jets have a higher track multiplicity than quark jets. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \nu\bar{\nu})$  and  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell)$  are combined to define the signal template for both channels (with orthogonality applied via the object counting cuts).

The cutflow for the  $Z \rightarrow \nu\bar{\nu}$  channel is shown in Table 4. Histograms of the variables included as part of this channel’s selections (showing the evolution of the yields as previous selection are applied) are shown in Figures 7 and 8.

From Table 4, we see the signal efficiency for our selections is 14% while our background efficiency is 0.005%. Even with the high background rejection,  $Z \rightarrow q\bar{q}$  is still highly dominant with  $\sim 16,000$  events compared to the  $\sim 9$  events expected for  $h \rightarrow s\bar{s}$ . Therefore, improvements to the sensitivity of the analysis are expected to be accompanied by improved rejection of  $Z \rightarrow q\bar{q}$ . The  $h \rightarrow gg$  process is the dominant Higgs background with  $\sim 400$  events.

The cutflow for the  $Z \rightarrow \ell\ell$  channel is shown in Table 5. Histograms of the variables included as part of this channel’s selections (showing the evolution of the yields as previous selection are applied) are shown in Figures 9, 10, and 11.

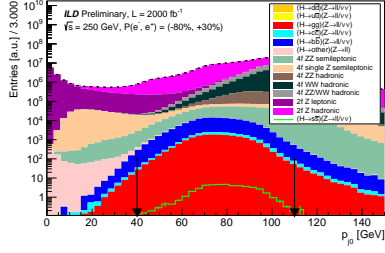
From Table 5, the hadronic backgrounds are almost entirely removed by cutting on the number of leptons. The signal efficiency for our selections is 7% while our background efficiency is 0.002%. The  $4f$  single  $Z$  and  $ZZ$  backgrounds

<sup>2</sup>The POI has the same form as that used by ATLAS for measuring the Higgs-charm quark coupling strength modifier – for instance, see Eq. 1 of Ref. [46].

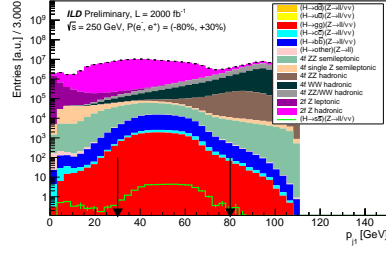
<sup>3</sup>“SFOS” stands for “same-flavour, opposite-sign”.

<sup>4</sup> $\Delta R \equiv \sqrt{\Delta\eta^2 + \Delta\phi^2}$ .

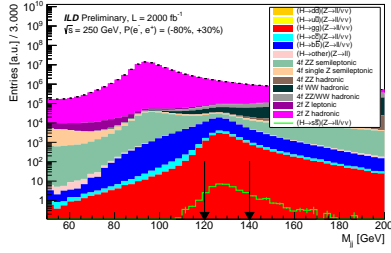
<sup>5</sup>If the 4-vectors of jets summed to  $(\sqrt{s}, 0, 0, 0)$ , then  $\Delta R_{jj, \text{miss}} = \pi$  – the fact that this isn’t true implies there are additional PFOs/tracks in the event not grouped into either jet.



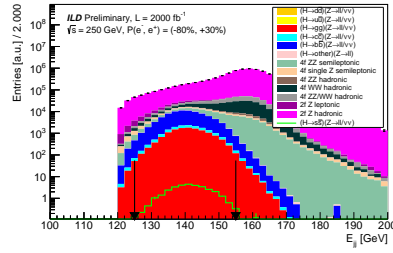
(a) Leading jet momentum  $p_{j_0}$



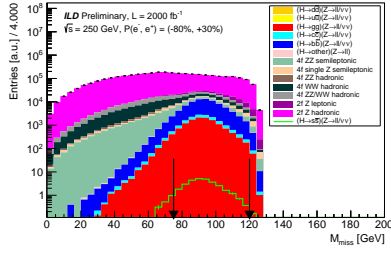
(b) Subleading jet momentum  $p_{j_1}$



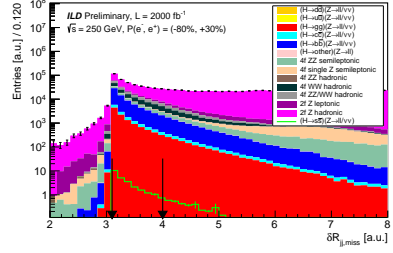
(c) Dijet mass  $M_{jj}$



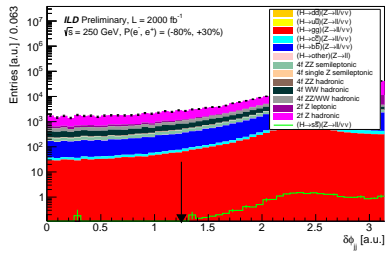
(d) Dijet energy  $E_{jj}$



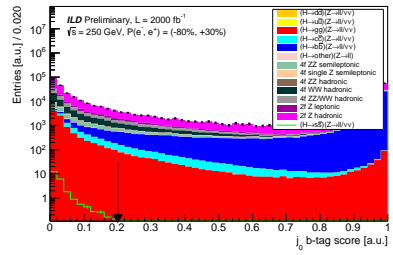
(e) Missing mass  $M_{miss}$



(f) Angular separation  $\Delta R_{jj,miss}$



(g) Dijet azimuthal separation  $\Delta\phi_{jj}$



(h) Leading jet BTag score

Figure 7: Histograms of the variables used in the kinematic selections of the  $Z \rightarrow \nu\bar{\nu}$  channel, as described in Table 3. Each histogram is given at the level of its corresponding selection but *before* that selection is applied. The arrows represent the placement of the selection cuts, and the error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked.

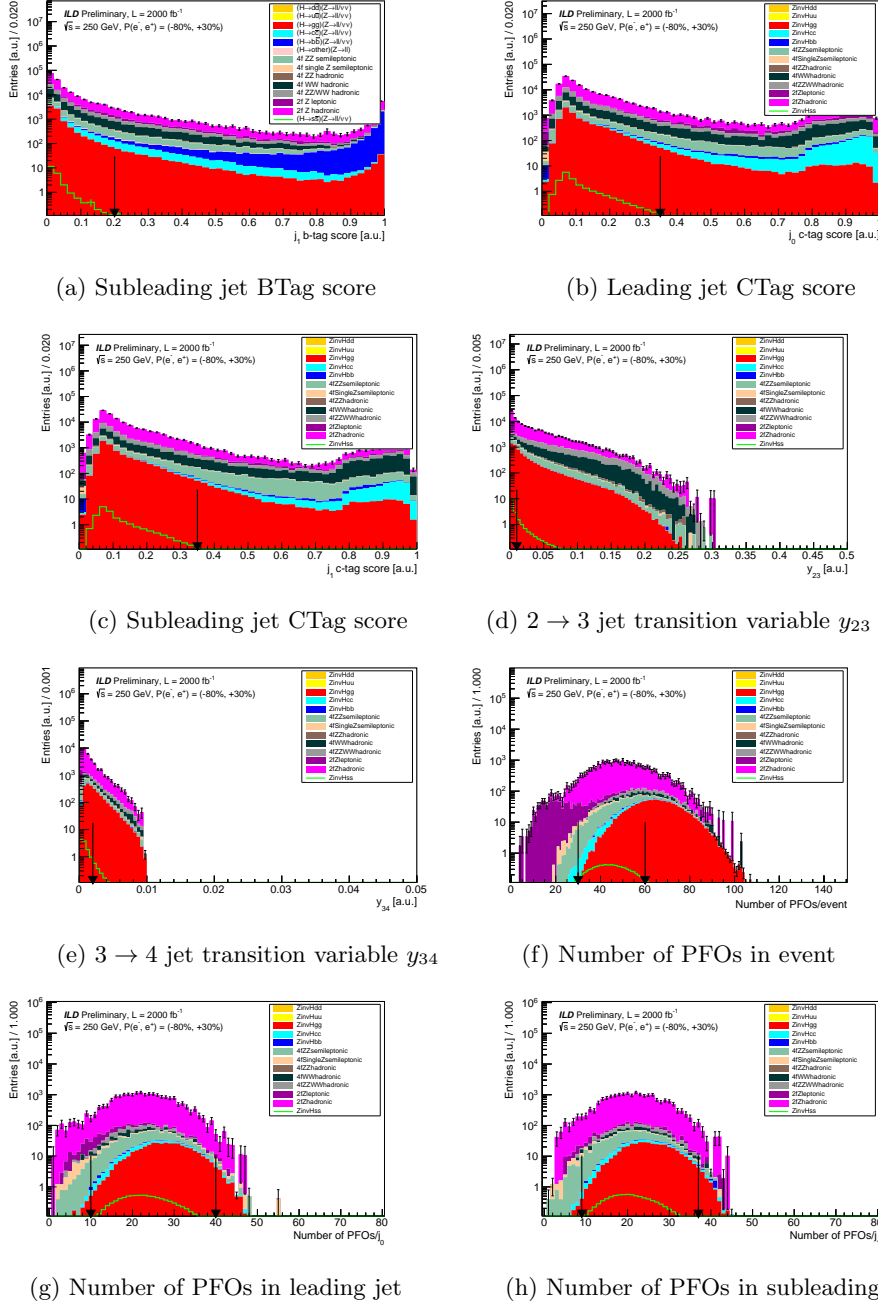


Figure 8: Histograms of the variables used in the kinematic selections of the  $Z \rightarrow \nu\bar{\nu}$  channel, as described in Table 3. Each histogram is given at the level of its corresponding selection but *before* that selection is applied. The arrows represent the placement of the selection cuts, and the error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked. A continuation of Figure 7.

Table 3: Kinematic selections for  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$  channels of the  $h \rightarrow s\bar{s}$  analysis. The selections are grouped into categories serving specific purposes.

Category	Selection	$Z \rightarrow \nu\bar{\nu}$	$Z \rightarrow \ell\ell$
Object counting	Number of leptons, $N_{\text{leptons}}$	0	$\geq 2$
	Number of jets, $N_{\text{jets}}$	$\geq 2$	$\geq 2$
	Leading 2 leptons are SFOS <sup>3</sup>	-	True
$2f$ $Z$ rejection	Leading jet momentum, $p_{j_0}$	$\in [40, 110]$ GeV	$\in [60, 110]$ GeV
	Subleading jet momentum, $p_{j_1}$	$\in [30, 80]$ GeV	$\in [30, 75]$ GeV
	Dijet mass, $M_{jj}$	$\in [120, 140]$ GeV	$\in [115, 145]$ GeV
	Dijet energy, $E_{jj}$	$\in [125, 155]$ GeV	$\in [130, 160]$ GeV
	Missing mass, $M_{\text{miss}}$	$\in [75, 120]$ GeV	-
	Dijet/missing- $p^T$ angular separation, $\Delta R_{jj,\text{miss}}$ <sup>4</sup>	$\in [3.1, 4.0]$ <sup>5</sup>	-
	Dijet azimuthal separation, $\Delta\phi_{jj}$	$> 1.25$	$> 1.75$
	Leading lepton momentum, $p_{\ell_0}$	-	$\in [40, 90]$ GeV
	Subleading lepton momentum, $p_{\ell_1}$	-	$\in [20, 60]$ GeV
	Dilepton mass, $M_{\ell\ell}$	-	$\in [70, 100]$ GeV
Dilepton energy, $E_{\ell\ell}$	-	$\in [85, 115]$ GeV	
$h \rightarrow b\bar{b}/c\bar{c}$ rejection	Leading jet LCFIPlus BTag score, $\text{score}_b^{j_0}$	$< 0.20$	$< 0.1$
	Subleading jet LCFIPlus BTag score, $\text{score}_b^{j_1}$	$< 0.20$	$< 0.1$
	Leading jet LCFIPlus CTag score, $\text{score}_c^{j_0}$	$< 0.35$	$< 0.3$
	Subleading jet LCFIPlus CTag score, $\text{score}_c^{j_1}$	$< 0.35$	$< 0.3$
$4f$ $VV$ rejection	$2 \rightarrow 3$ jet transition variable, $y_{23}$	$< 0.010$	$< 0.050$
	$3 \rightarrow 4$ jet transition variable, $y_{34}$	$< 0.002$	$< 0.005$
$h \rightarrow gg$ rejection	Number of PFOs in event, $N_{\text{PFOs}}^{\text{event}}$	$\in [30, 60]$	$\in [20, 80]$
	Number of PFOs in leading jet, $N_{\text{PFOs}}^{j_0}$	$\in [10, 40]$	$\in [5, 50]$
	Number of PFOs in subleading jet, $N_{\text{PFOs}}^{j_1}$	$\in [9, 37]$	$\in [5, 50]$

are the dominant backgrounds, with  $\sim 7,000$  events compared to the  $\sim 4$  events expected for  $h \rightarrow s\bar{s}$ . As with the  $Z \rightarrow \nu\bar{\nu}$  channel, the  $h \rightarrow gg$  process is the dominant Higgs background with  $\sim 700$  events.

## 5.2 Limits on Higgs-strange coupling strength modifier

The estimated significance of discovery,  $Z_0 \approx s/\sqrt{b}$ , using the signal and background yields at the level of the last selection in Table 3 is  $\sim 0.1\sigma$ . Therefore, a discovery measurement of  $h \rightarrow s\bar{s}$  is *unlikely*, given the use of a best-case jet flavour tagger. However, limits on  $\kappa_s$ , and accordingly  $\text{BR}[h \rightarrow s\bar{s}]$ , may be set instead, allowing to reduce the phase space for BSM enhancements to the  $h \rightarrow s\bar{s}$  rate.

The chosen fit discriminant for  $h \rightarrow s\bar{s}$  is the sum of strange jet tagger scores for the leading and subleading momentum jets, using the jet flavour tagger described in Section 4, as shown in Figure 12. A higher sum of scores corresponds to a higher probability of an event containing an  $s\bar{s}$  system.

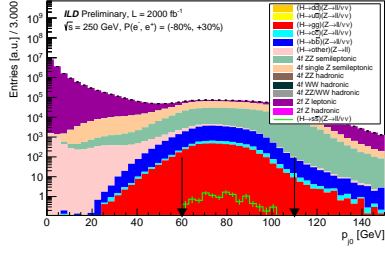
The fitted likelihood is a simple Poisson probability density function (PDF):

$$L(\kappa_s; \vec{n}, \vec{s}, \vec{b}) = \prod_{i=1}^N \frac{(\mu(\kappa_s) \times s_i + b_i)^{n_i} \times \exp(-\mu(\kappa_s) \times s_i - b_i)}{n_i!}, \quad (8)$$

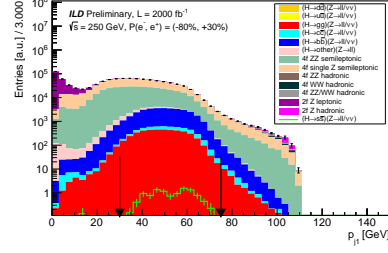
where our POI,  $\mu(\kappa_s)$ , is given by Eq. 7,  $\vec{s}$  is the vector of expected signal yields (in  $N$  bins –  $s_i \in [\vec{s}]_i$  is the expected signal yield in  $i$ -th bin),  $\vec{b}$  is the vector of expected background yields, and  $\vec{n}$  is the vector of observed yields. As observed yields are unavailable, ‘‘Asimov’’ [49] data is assumed. The Python package `pyhf` [50, 51] is used to set the limits.



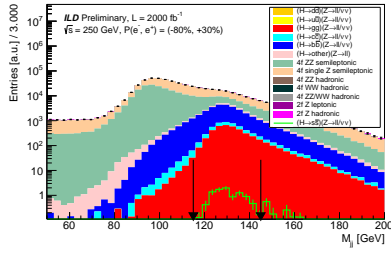




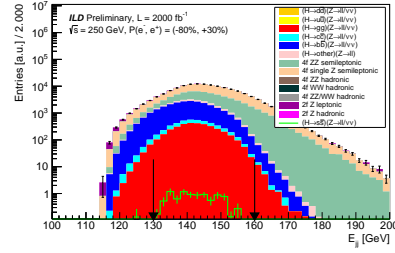
(a) Leading jet momentum  $p_{j_1}$



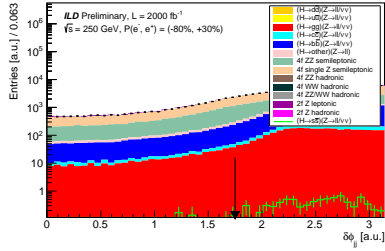
(b) Subleading jet momentum  $p_{j_2}$



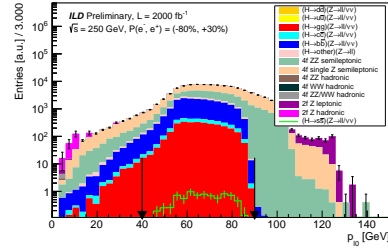
(c) Dijet mass  $M_{jj}$



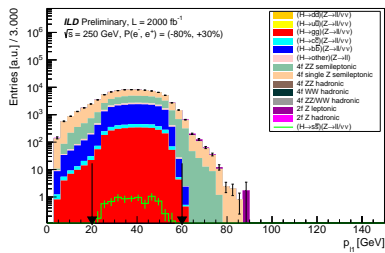
(d) Dijet energy  $E_{jj}$



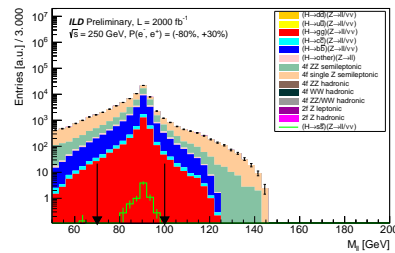
(e) Dijet azimuthal separation  $\Delta\phi_{jj}$



(f) Leading lepton momentum  $p_{\ell_0}$



(g) Leading lepton momentum  $p_{\ell_1}$



(h) Dilepton mass  $M_{\ell\ell}$

Figure 9: Histograms of the variables used in the kinematic selections of the  $Z \rightarrow \ell\ell$  channel, as described in Table 3. Each histogram is given at the level of its corresponding selection but *before* that selection is applied. The arrows represent the placement of the selection cuts, and the error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked.

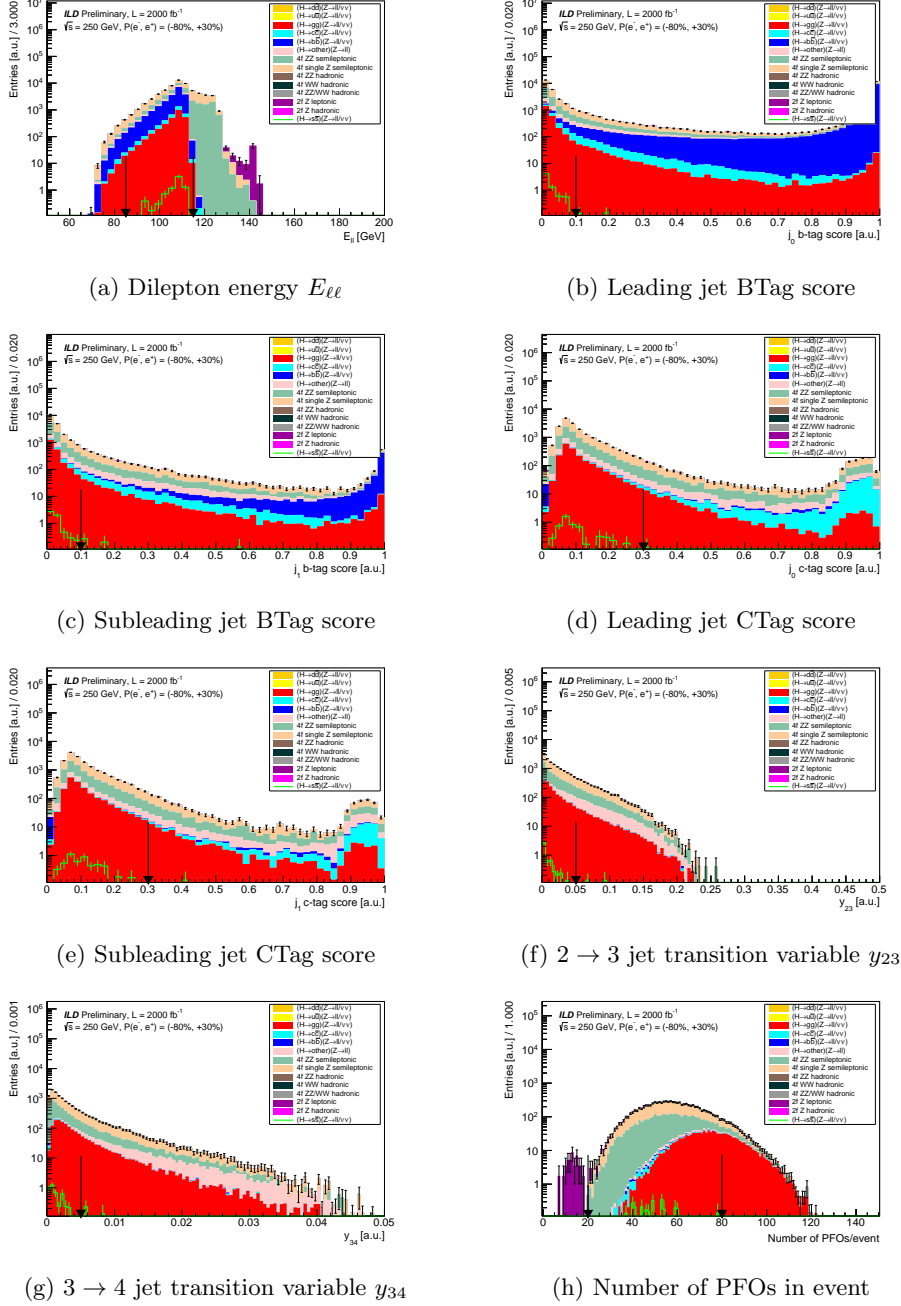
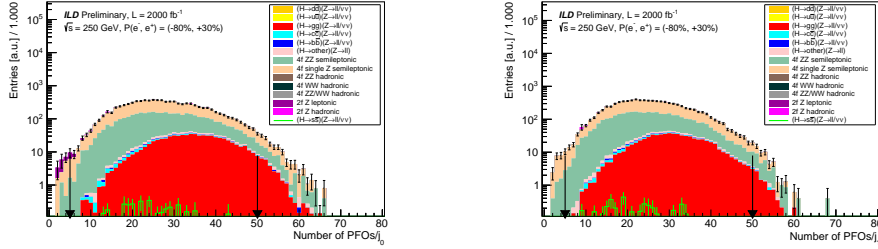


Figure 10: Histograms of the variables used in the kinematic selections of the  $Z \rightarrow \ell\ell$  channel, as described in Table 3. Each histogram is given at the level of its corresponding selection but *before* that selection is applied. The arrows represent the placement of the selection cuts, and the error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked. A continuation of Figure 9.



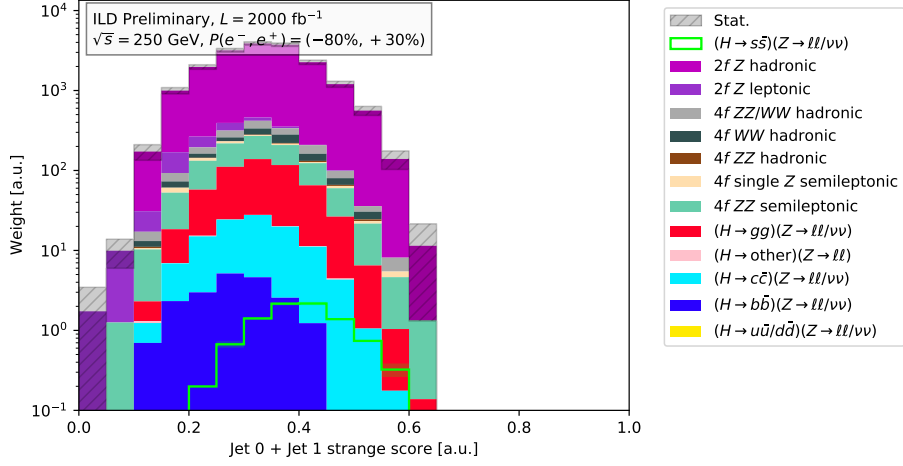
(a) Number of PFOs in leading jet

(b) Number of PFOs in subleading jet

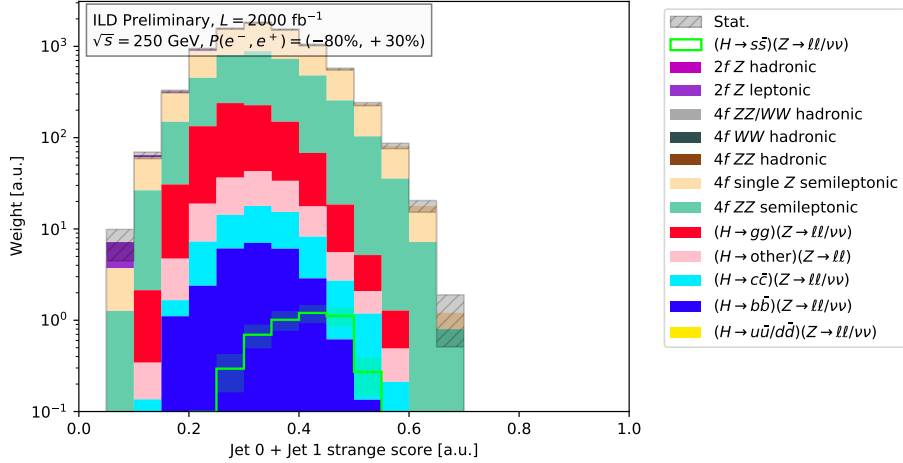
Figure 11: Histograms of the variables used in the kinematic selections of the  $Z \rightarrow \ell\ell$  channel, as described in Table 3. Each histogram is given at the level of its corresponding selection but *before* that selection is applied. The arrows represent the placement of the selection cuts, and the error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked. A continuation of Figure 10.

326 Signal regions are built by requiring  $0.5 \times (\text{score}_{j_0}^s + \text{score}_{j_1}^s)$  to be greater than  
 327 some threshold – these thresholds are chosen such that the best (i.e., strongest)  
 328 95% CL<sub>s</sub> upper limits [52] are obtained for the  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$  channels  
 329 independently. Scans on the choice of threshold are shown in Figure 13, which  
 330 are found to be 0.35 and 0.40 for the  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$  channels, respectively,  
 331 a trade-off between reducing the dominant backgrounds and the finiteness of  
 332 MC statistics. The resulting limit plots on  $\kappa_s$  for these particular thresholds are  
 333 shown in Figure 14, including both the single-channel and combined results.

334 From Figure 14, the 95% upper confidence bound on  $\kappa_s$  is found to be 8.97  
 335 for the  $Z \rightarrow \nu\bar{\nu}$  channel and 6.28 for the  $Z \rightarrow \ell\ell$  channel, leading to a combined  
 336 limit of 5.95. This number is comparable to what has been estimated for the  
 337 ILC (all data,  $\sqrt{s} = 250$  GeV as well as  $\sqrt{s} = 500$  GeV) from other studies [53]  
 338 using indirect measurements,  $\kappa_s \lesssim 10$  at 95% confidence level (CL). However,  
 339 the study here includes only two measurement channels and approximately 50%  
 340 of the expected dataset for ILD. The limits are therefore expected to improve  
 341 even more. [TODO: other comparisons, discussion, etc.]

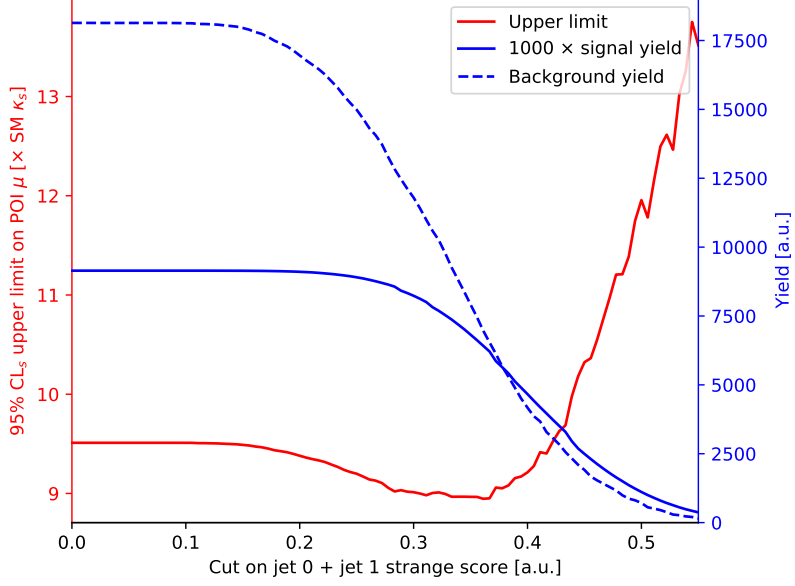


(a)  $Z \rightarrow \nu\bar{\nu}$  channel

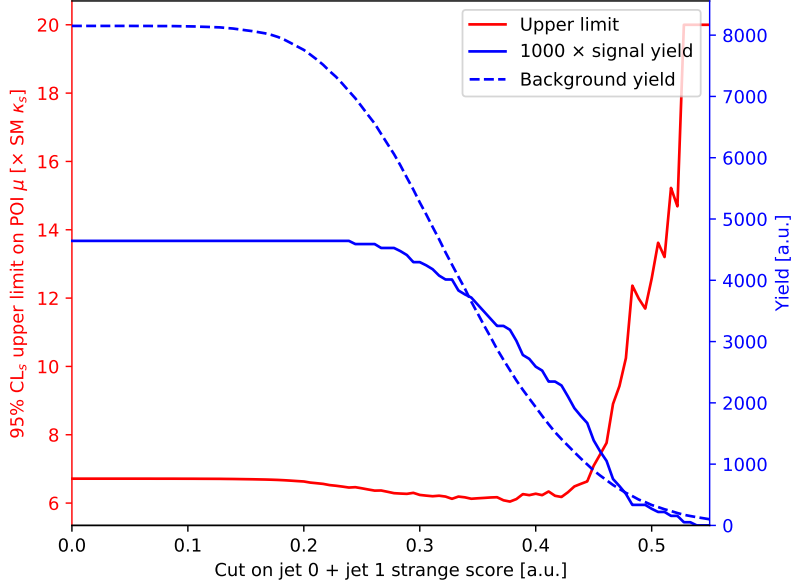


(b)  $Z \rightarrow \ell\ell$  channel

Figure 12: Fit discriminant for the SM  $h \rightarrow s\bar{s}$  analysis:  $(0.5\times)$  the sum of the strange scores for leading and subleading jets, using the jet flavour tagger described in Section 4. Each histogram is produced at the level of the last selection of their respective channel in Table 3. The error bars represent the Poisson counting uncertainties on those yields. The sum-of-weights per process is normalised to the SM cross-section. N.B. the  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$  signal is unstacked.

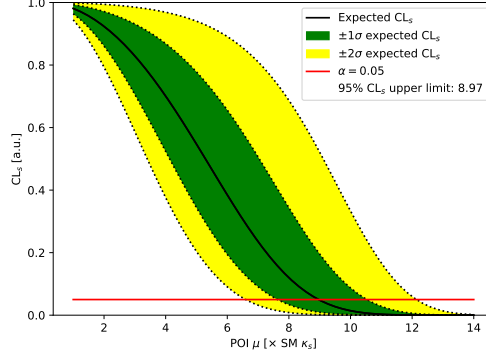


(a)  $Z \rightarrow \nu\bar{\nu}$  channel

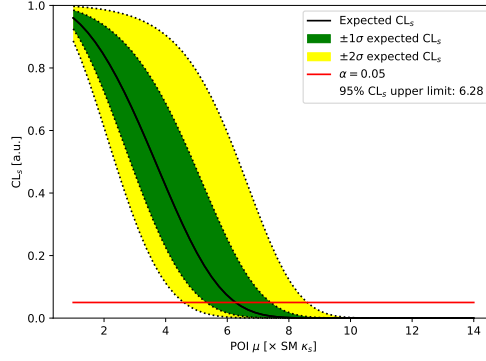


(b)  $Z \rightarrow \ell\ell$  channel

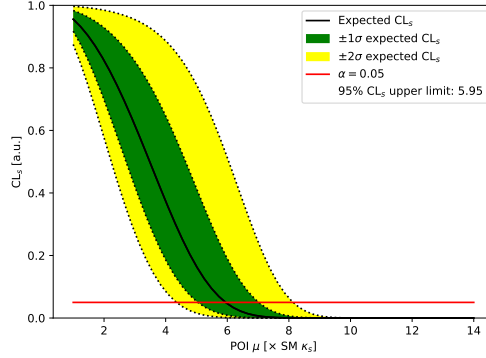
Figure 13: Scans of the 95%  $CL_s$  upper limit for the Higgs-strange coupling strength modifier  $\kappa_s$ , obtained by varying the choice of the lower thresholds on the discriminants shown in Figure 12. Also shown are the signal (i.e.,  $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$ ) and background (i.e., non- $h(\rightarrow s\bar{s})Z(\rightarrow \ell\ell/\nu\bar{\nu})$ ) yields in the resulting regions.



(a)  $Z \rightarrow \nu\bar{\nu}$  channel



(b)  $Z \rightarrow \ell\ell$  channel



(c) Combined

Figure 14:  $CL_s$  upper limit plots for the Higgs-strange coupling strength modifier  $\kappa_s$  obtained from fitting the discriminants (in the regions  $>0.35$  and  $>0.4$  for the  $Z \rightarrow \nu\bar{\nu}$  and  $Z \rightarrow \ell\ell$  channels, respectively) shown in Figure 12. Only a single bin is used for each channel – the combination fit using both of these bins is also shown. The crossing of the black and red lines indicates the 95% confidence level.

## 342 **6 Proposal for an alternative detector layout**

343 [TODO: Add studies on RICH etc]

## 344 **7 Conclusion**

345 [TODO: Write a conclusion...]

## 346 **References**

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