Studies of Higgs couplings with the ATLAS experiment and with quantum computing

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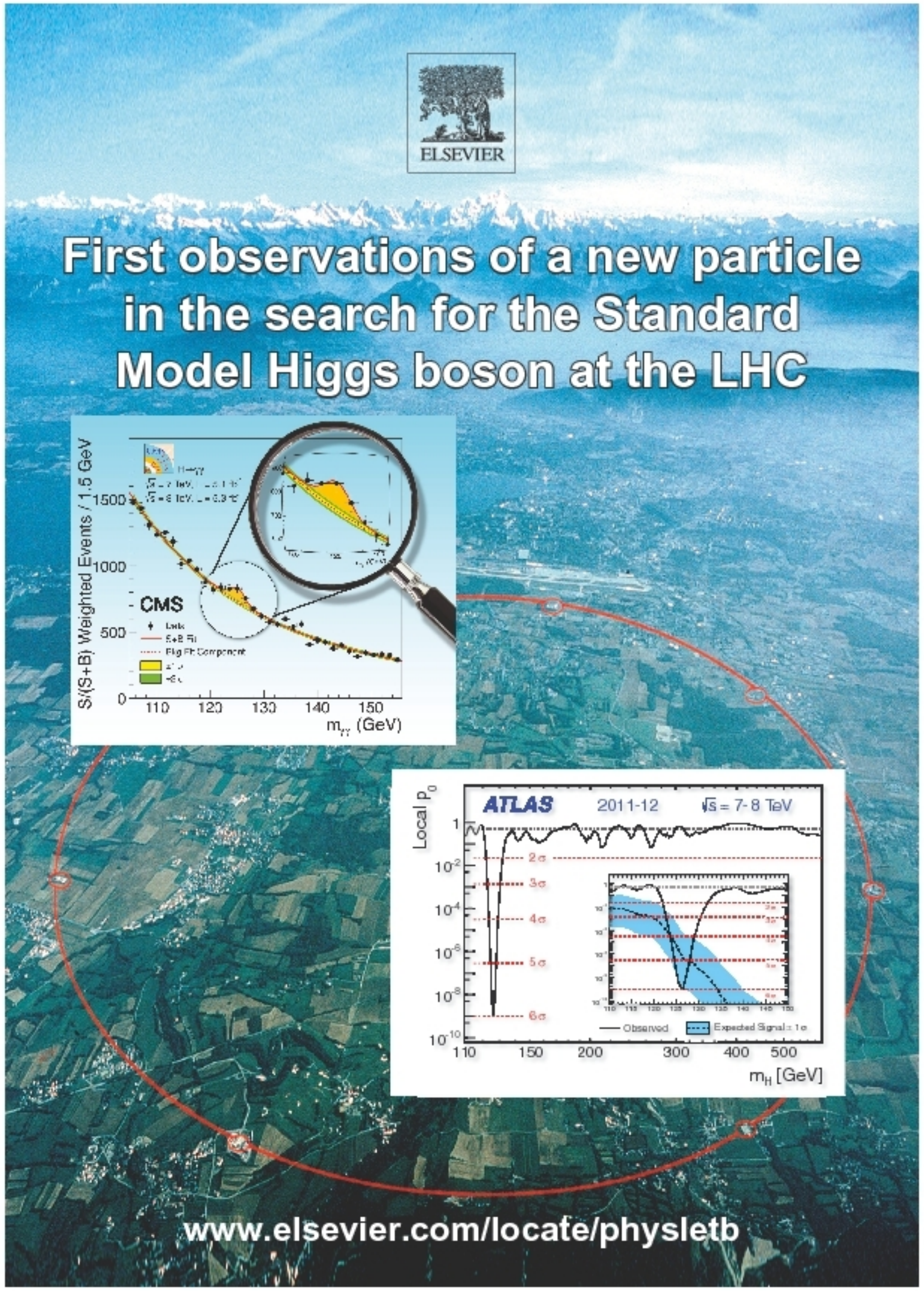
I am an assistant professor in the CMS group at Peking University (starting this month)

I was working in the ATLAS group at University of Wisconsin from 2016 to Sep 2021

In this seminar, I shall highlight several results which I recently contributed to

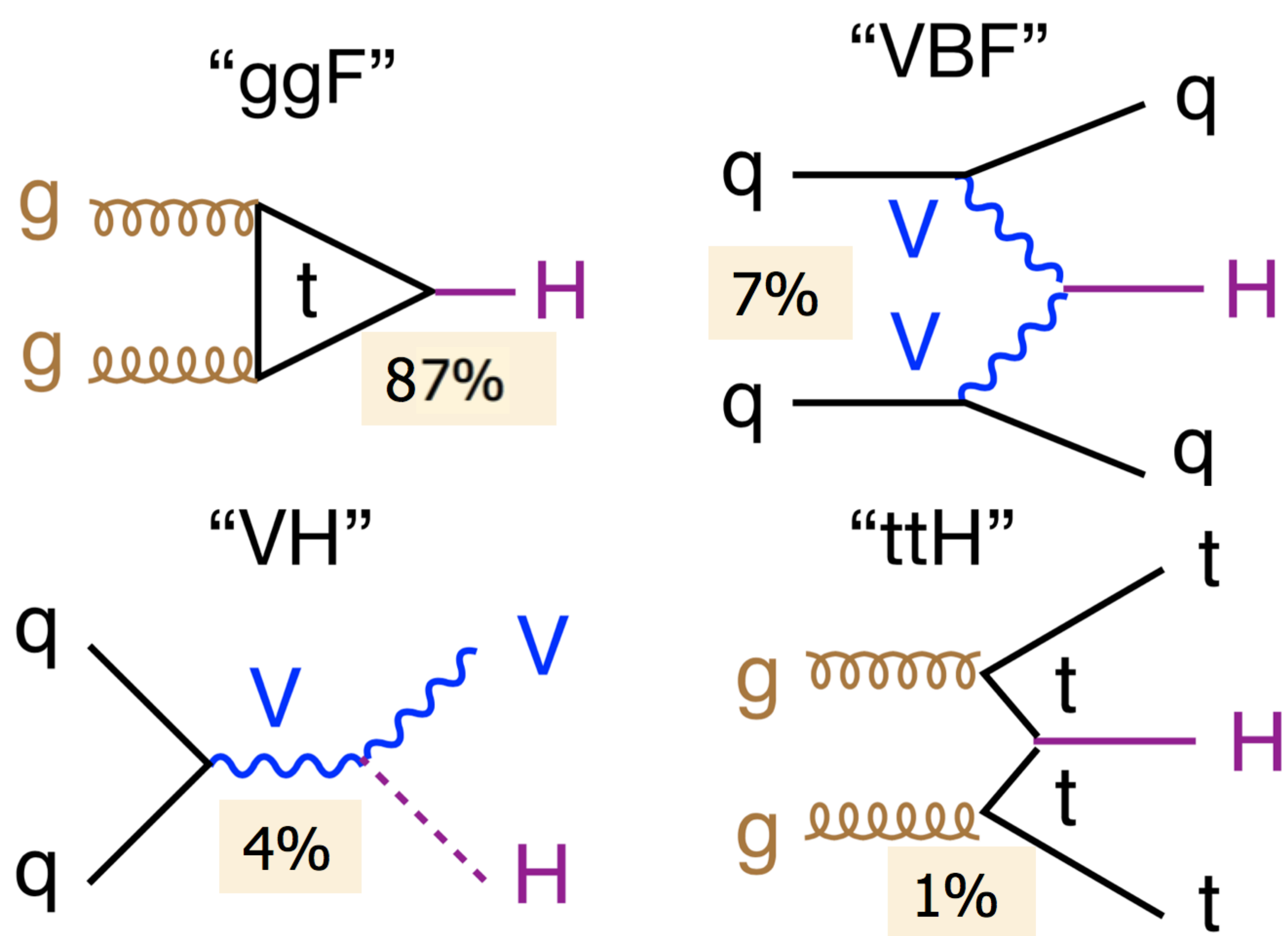
The Higgs boson

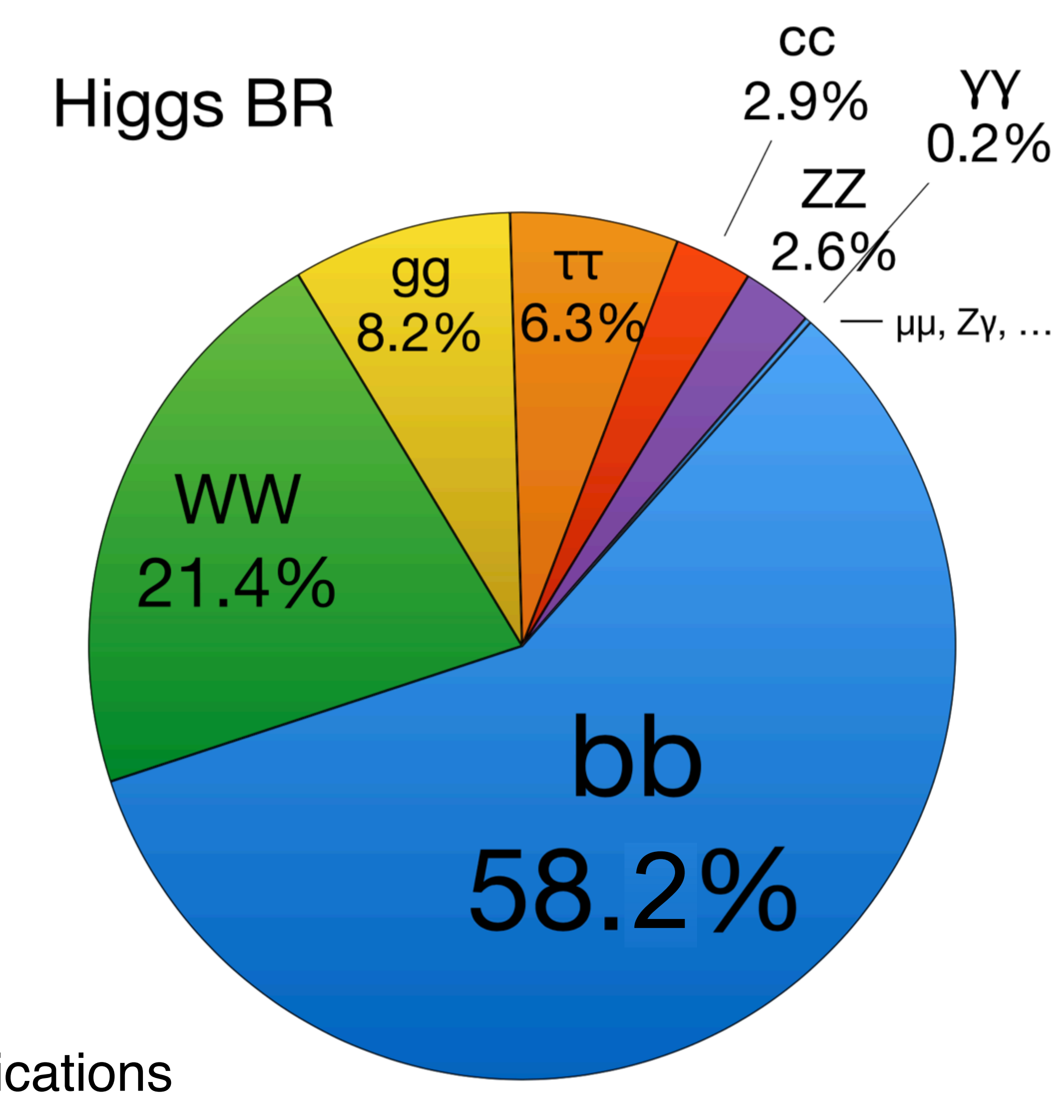
- **The Higgs boson** was discovered by the ATLAS and CMS experiments at the Large Hadron Collider (LHC) in 2012
  - a major milestone for particle physics
- It opened a new way to refine our understanding of the electroweak symmetry breaking
  - many **Higgs property studies** (mass, width, spin, parity, couplings, cross sections, etc.) have been performed
  - deviation from the Standard Model (SM) predictions on Higgs boson properties would provide clue for new physics



Higgs boson production and decay modes

- In the Standard Model, the Higgs boson couples to massive bosons and fermions
- These couplings determine the Higgs boson production and decay modes:

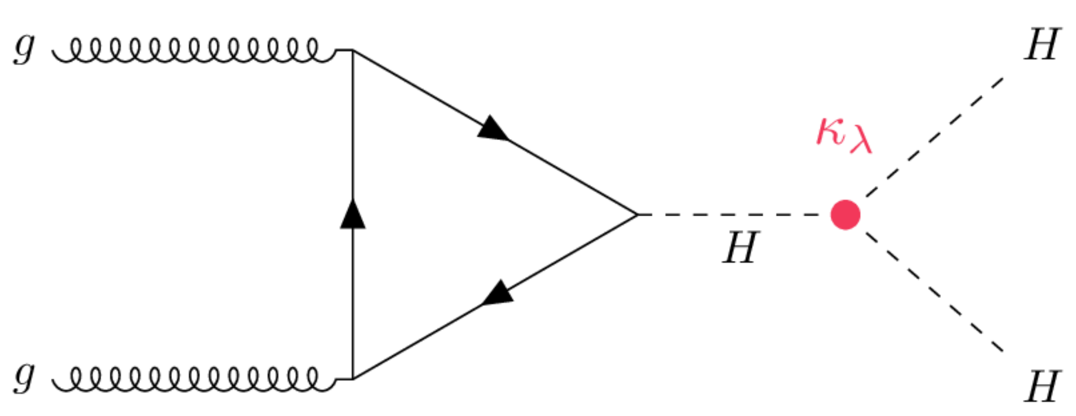


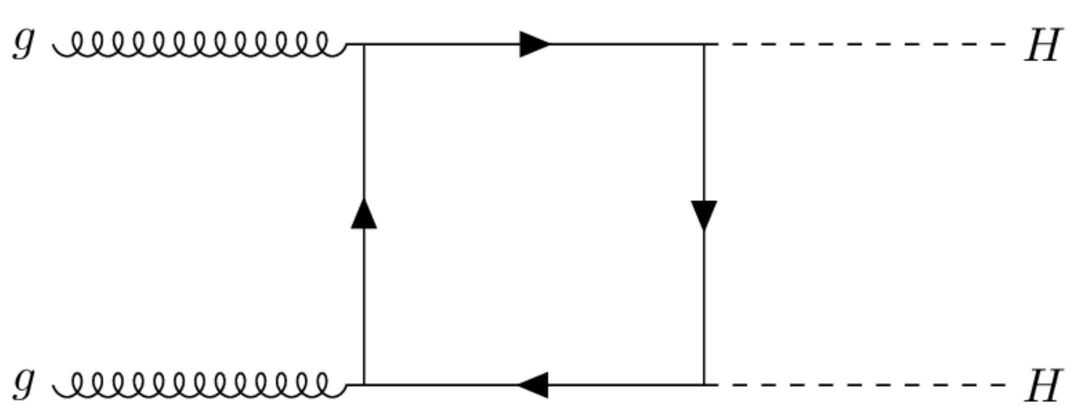


Figures from https://msneubauer.github.io with modifications

Double Higgs production

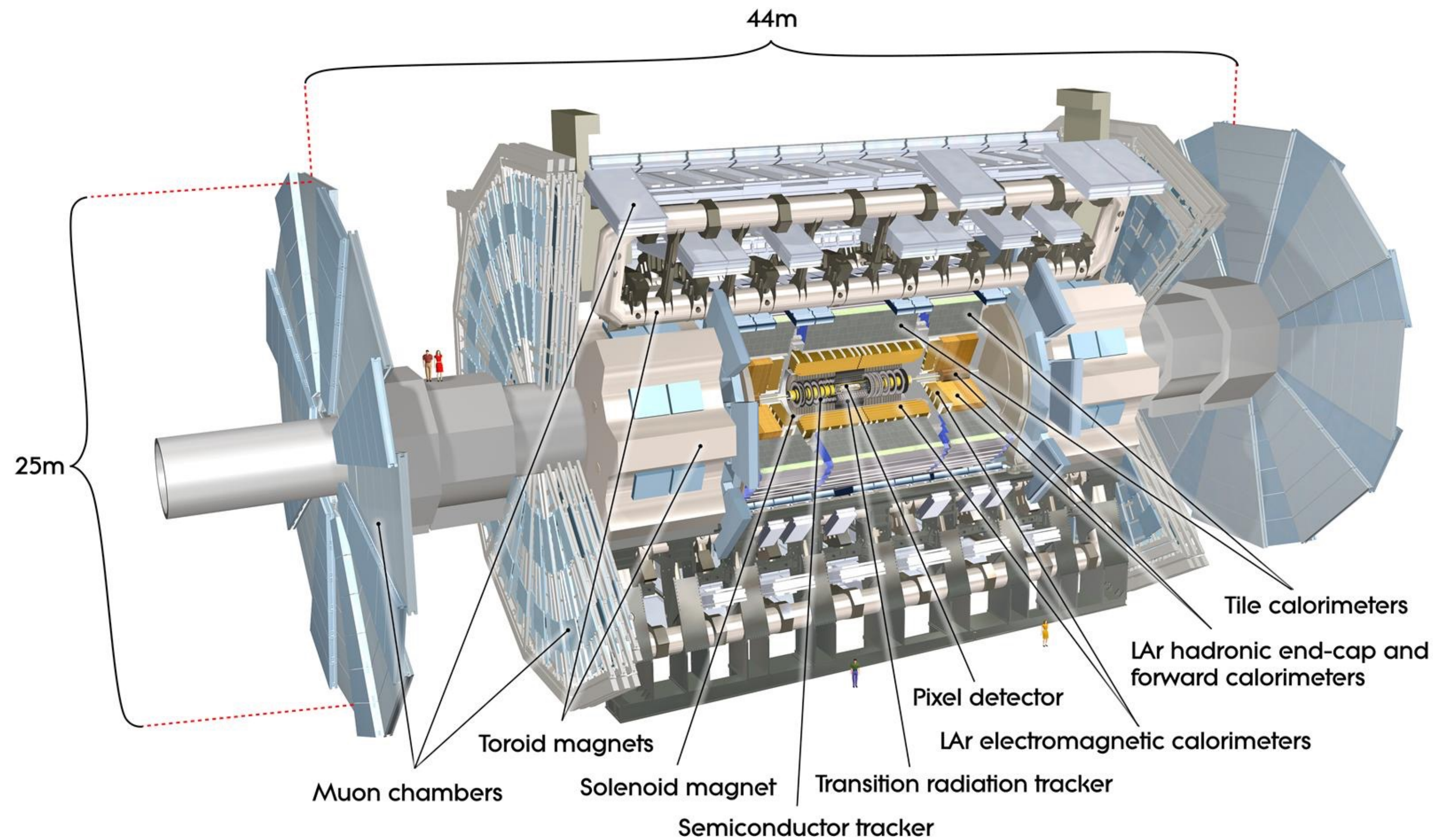
- Double Higgs production is the way to directly probe **Higgs self-couplings** at the LHC
- Extremely low cross-section in the SM (one double-Higgs event every 1000 single-Higgs events)
- Non-SM self-coupling strength κ_λ can change cross-section and kinematics of double Higgs production

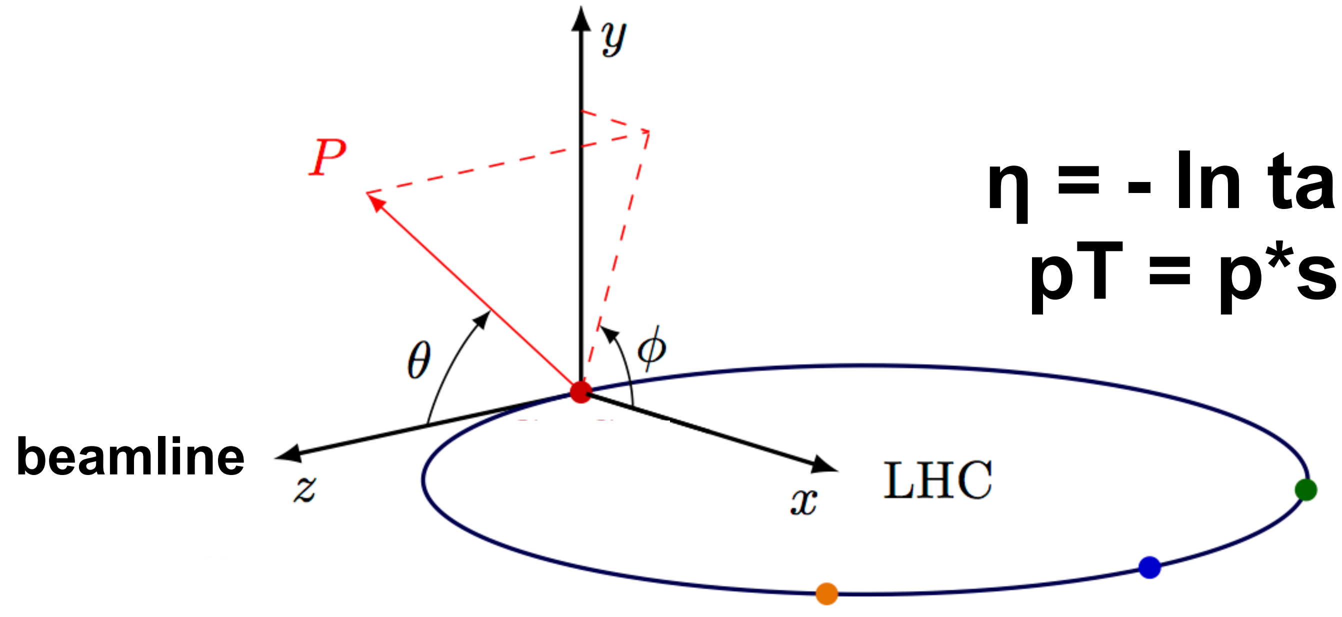




ATLAS Detector

- Collect collision data at the LHC
  - Run 1 (2010-2012): proton-proton collisions at 7-8 TeV
  - Run 2 (2015-2018): proton-proton collisions at 13 TeV
- Three sub-detectors:
  - Inner tracker
  - Calorimeter
  - Muon spectrometers

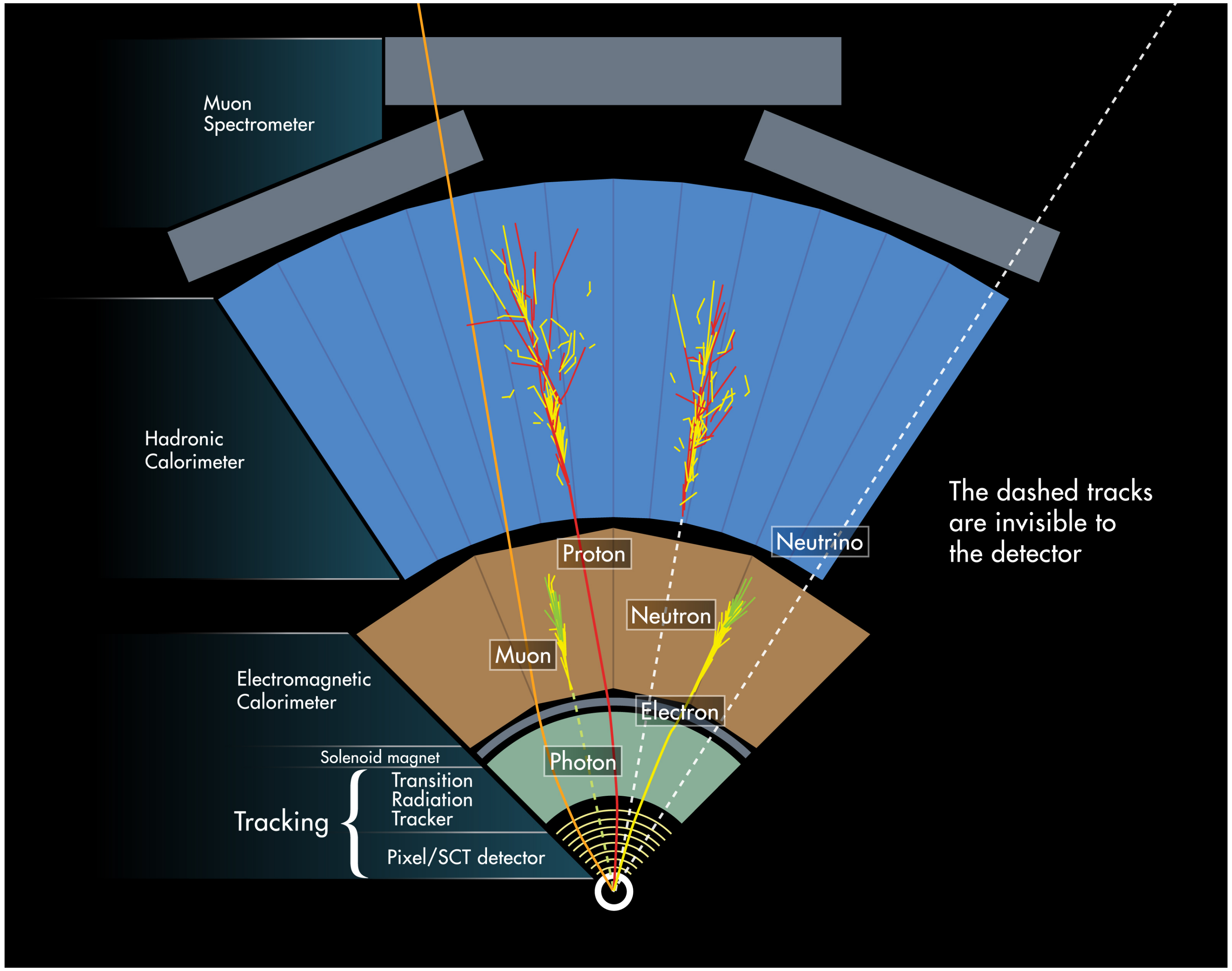




η = - ln tan(θ/2)

pT = p*sin(θ)

ATLAS Object Reconstruction



- ATLAS reconstructs photons, electrons, muons, jets, etc.
- Jets from b-quarks or taus can be tagged
- Missing transverse momentum (MET): negative vector sum of transverse momenta of all reconstructed objects

Contents of this talk

- Part 1: ATLAS Higgs coupling measurements using the $H \rightarrow \gamma\gamma$ decay
- Part 2: ATLAS $H \rightarrow \mu\mu$ search (probing Higgs couplings to second generation fermions)
- Part 3: ATLAS Higgs coupling measurements with the combination of various channels
- Part 4: Application of quantum machine learning to LHC Higgs physics analyses

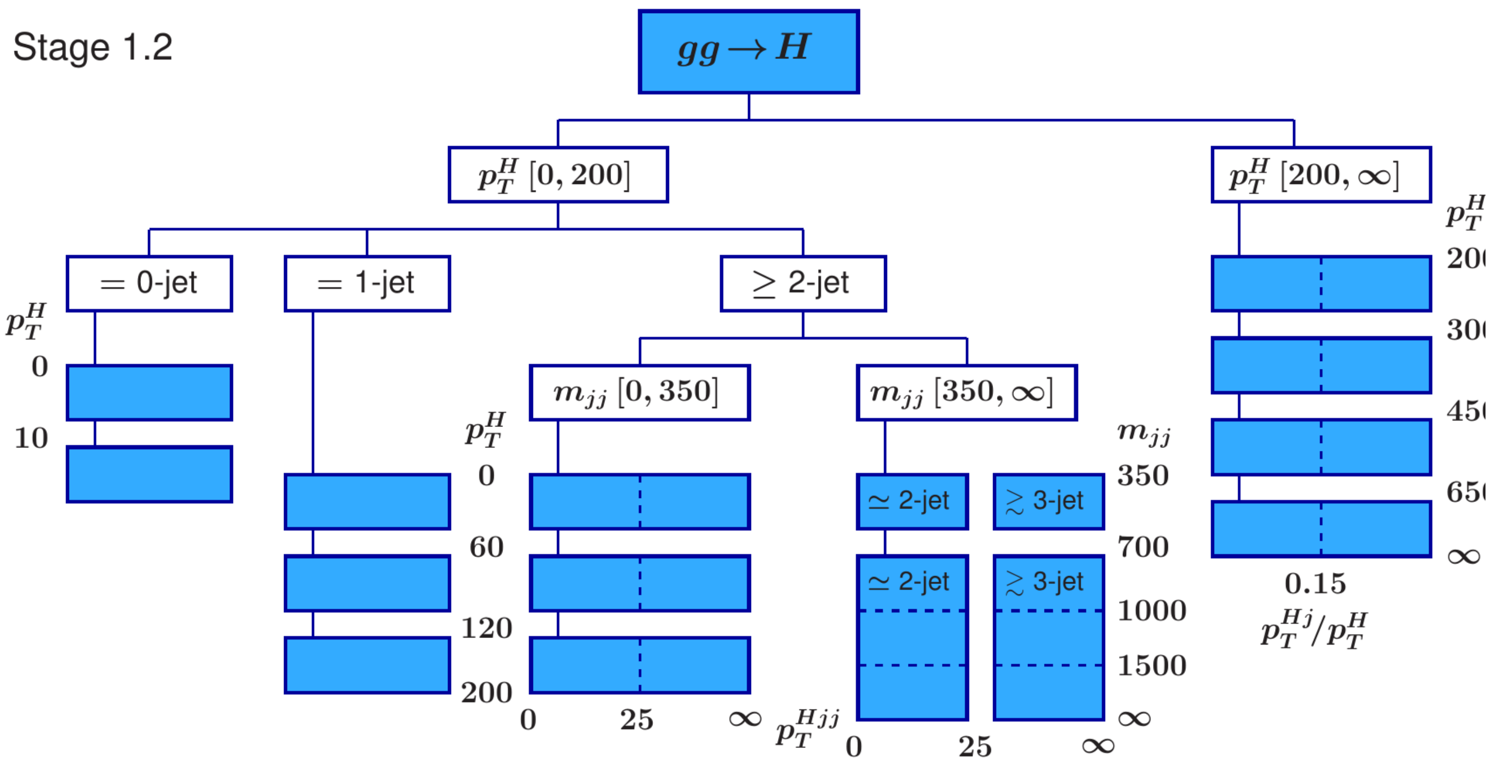
Part 1: ATLAS Higgs coupling measurements using the $H\rightarrow\gamma\gamma$ decay

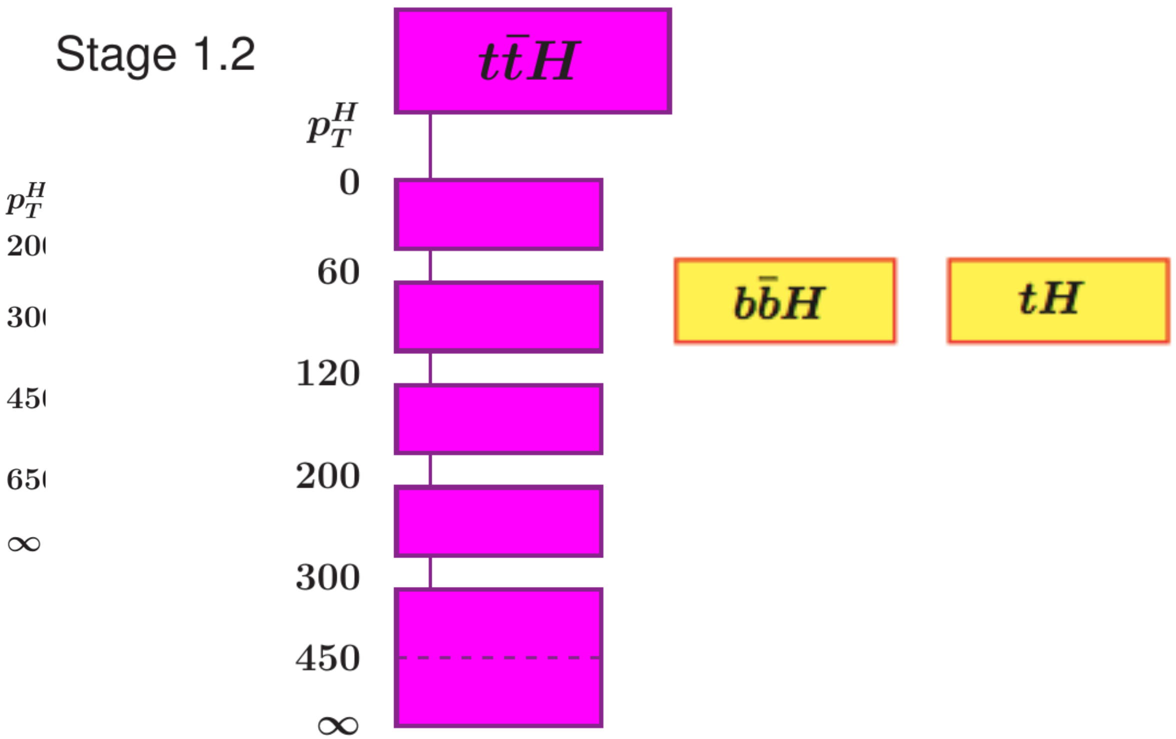
(ATLAS Run 2, 139 fb^{-1})

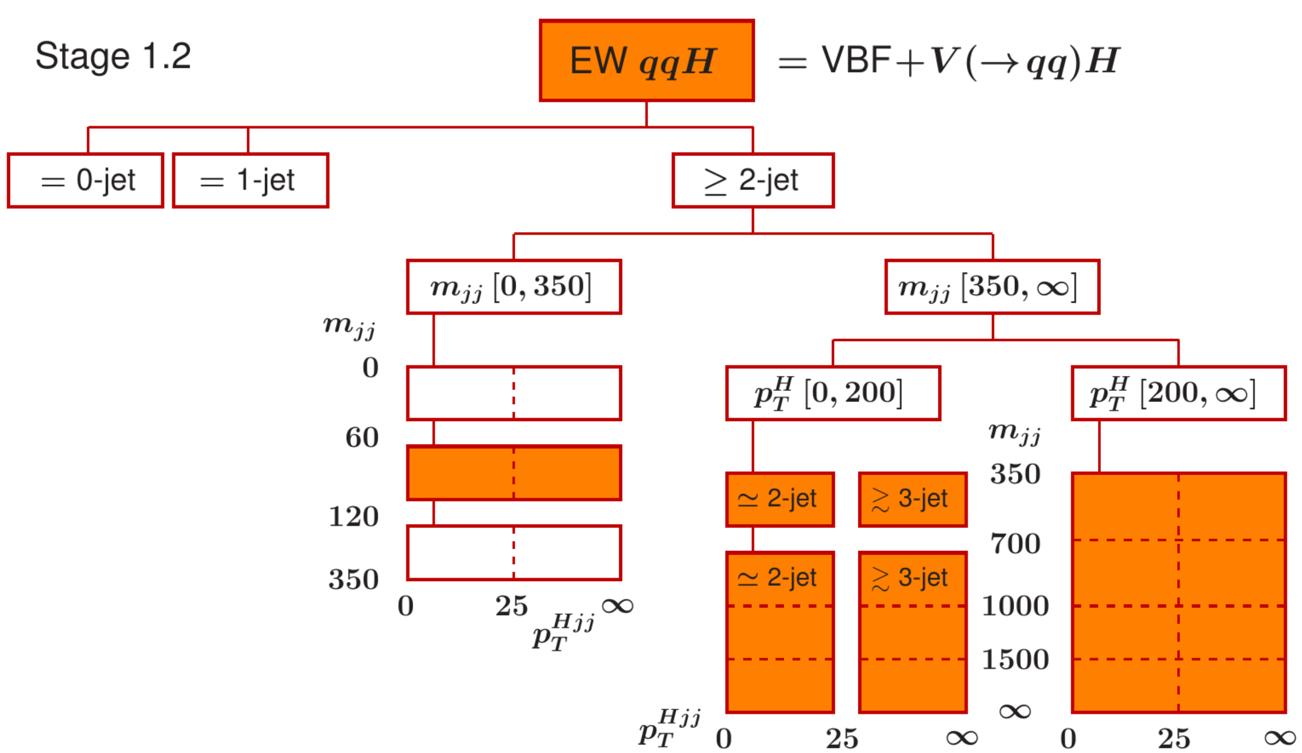
Higgs coupling property measurements

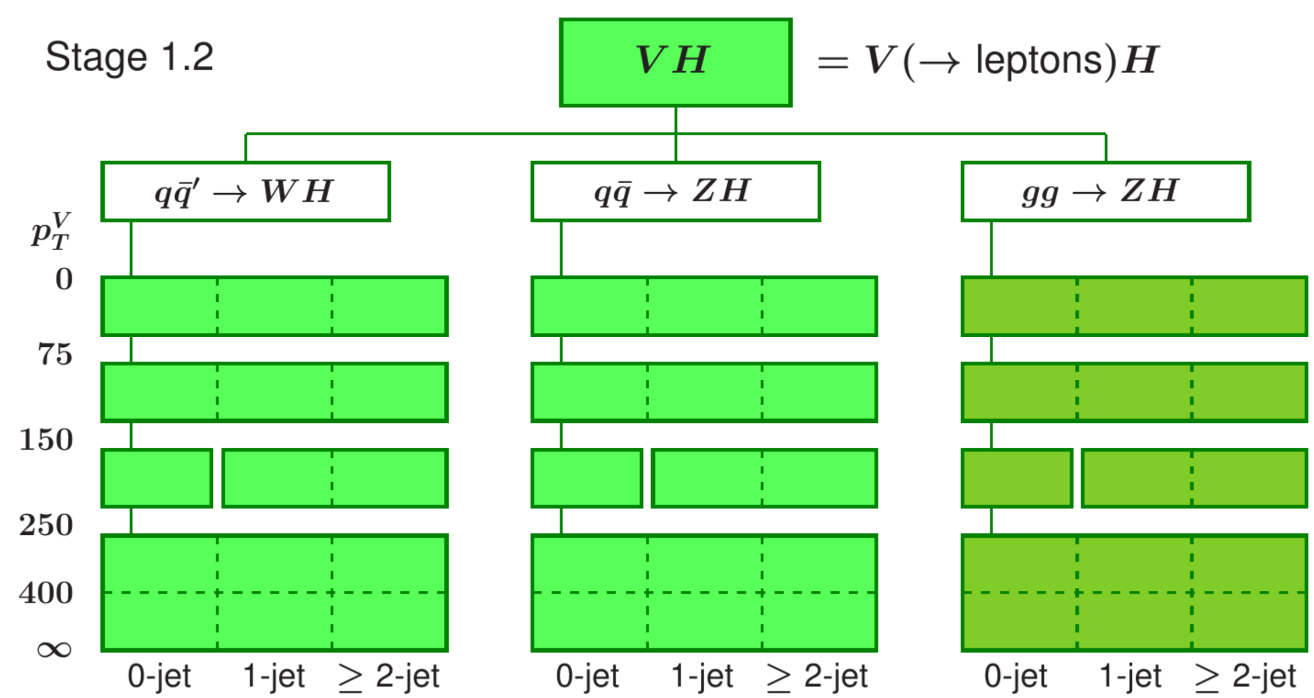
- ATLAS and CMS performed measurements of Higgs boson coupling properties:
  - provide stringent test of the Standard Model
- Simplified template cross section (STXS) is the common framework for the LHC Higgs coupling property measurements in Run 2
  - Split production mode cross-sections into various phase-space regions, which are chosen according to sensitivity to beyond Standard Model effects, avoidance of large theory uncertainties, matching to experimental selections
  - STXS measurements can be used to probe coupling modifiers (“kappa”) and effective field theories (EFT)
  - Various stages; stage 0 is basically production mode cross-sections

Stage 1.2 STXS

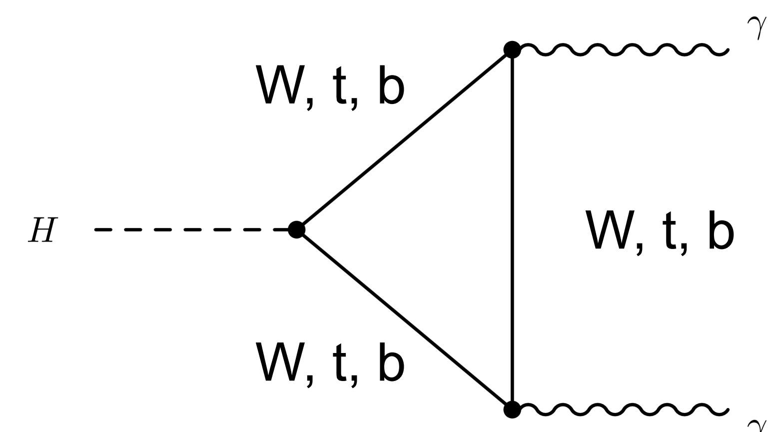








H→γγ analysis strategy



Small BR, but good S/B and resolution

Select events with **two photons** (at both trigger and offline levels)

➔Separate events to **many categories**

- target different STXS regions

➔Fit **diphoton mass** over all categories

- Signature: a narrow resonance with a width consistent with detector resolution above a smooth background in the diphoton invariant mass distribution

➔Measure production mode cross sections, simplified template cross sections, etc.

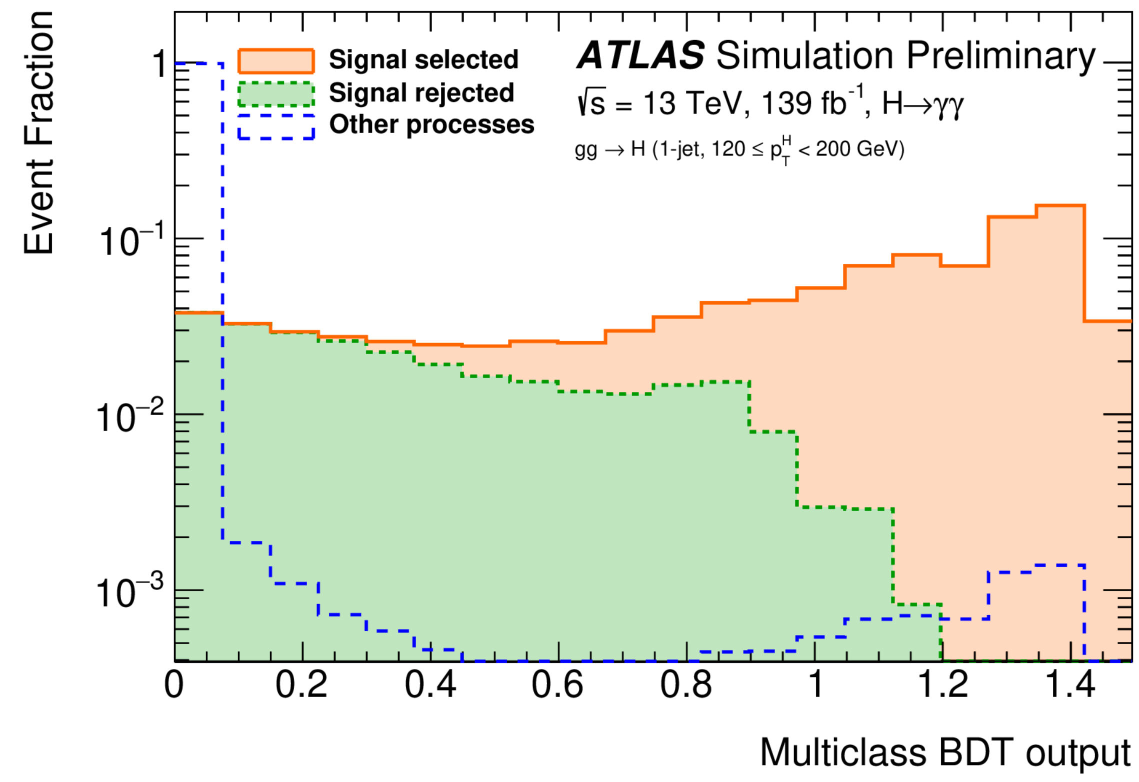
Event categorization

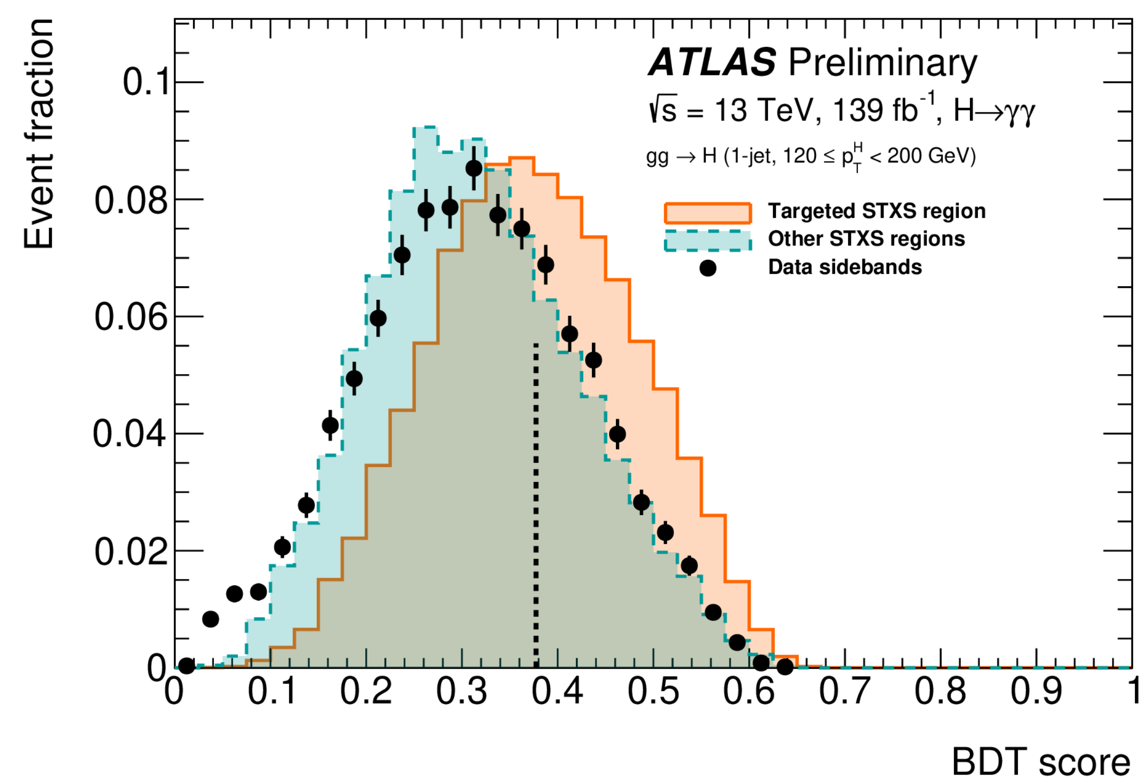
Designed to maximize the global sensitivity to all STXS regions

- Step 1: A multi-class boosted decision tree (BDT) is trained to separate signal events from different STXS regions.
  - Then, the output discriminant values are used to assign events into different classes.
- Step 2: Each class of events is further divided into multiple *categories* based on a binary BDT classifier.
  - This binary BDT is trained to separate signal from continuum background in each class.

Finally, 88 event categories in total

- S/(S+B) ranges from 3% to 83%

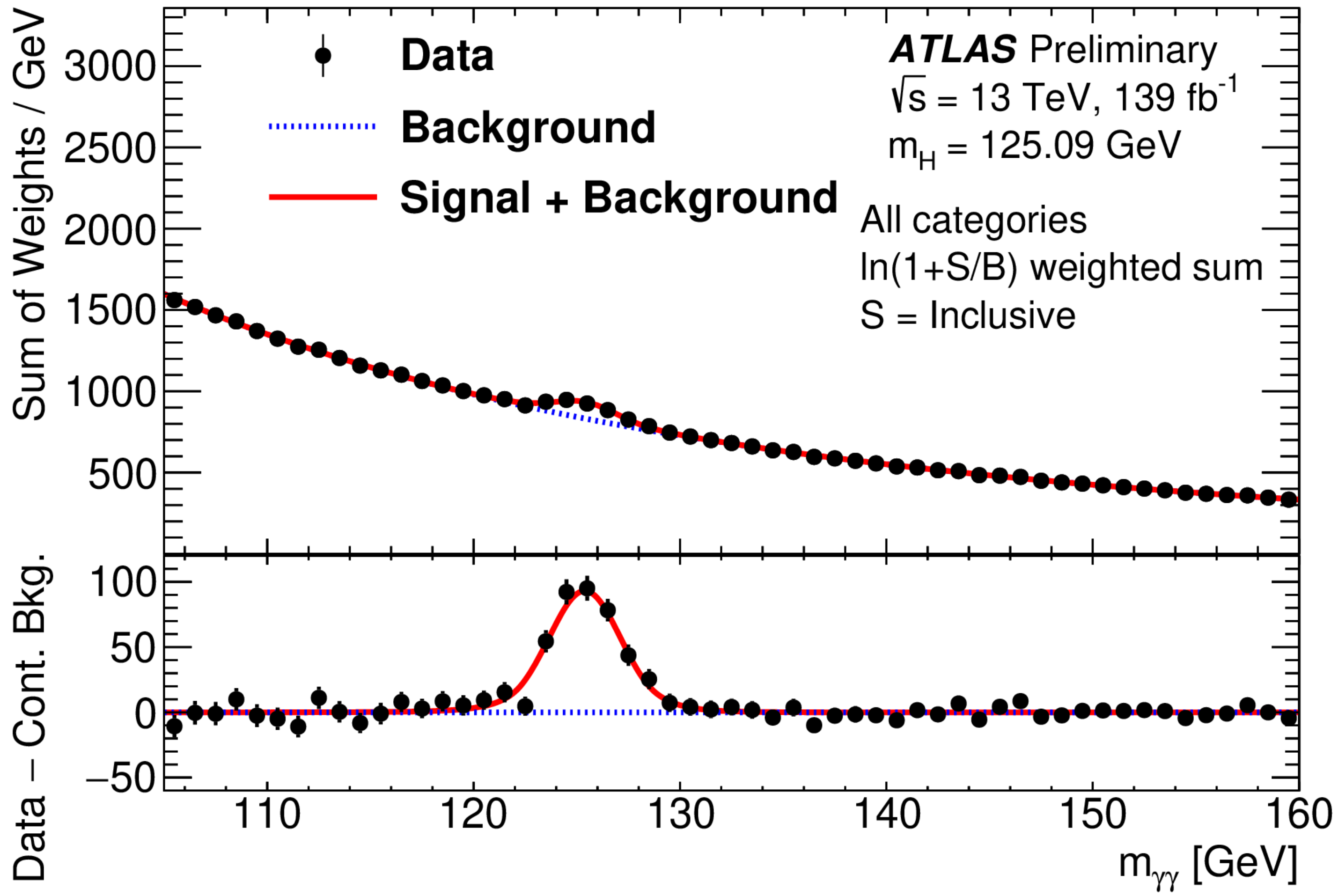




Signal and background modeling $H \to \gamma\gamma$

- **For each event category, need to model diphoton mass distributions of signal and backgrounds**
- **Model of Higgs signal**
    - Expected yields of Higgs production modes: estimated from simulation
    - Mass shapes: parametrized from simulation with double-sided crystal ball functions
- **Model of continuum background (QCD γγ, etc.)**:
    - Analytical functions fitted on data
    - Using dedicated background-only samples
        - studied functional forms and associated uncertainties

Diphoton mass: all categories

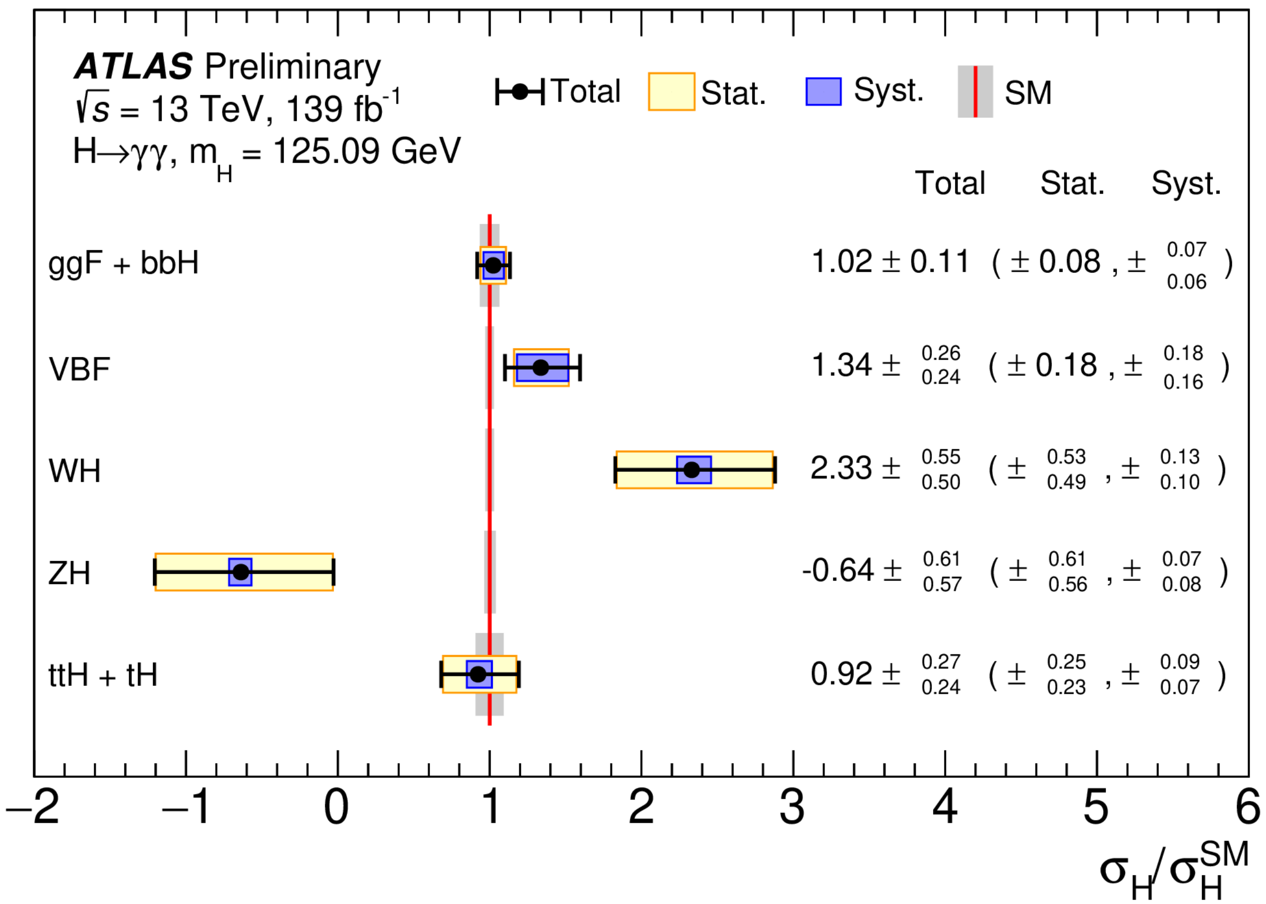


ATLAS-CONF-2020-026

- Diphoton mass spectrum peaks at the Higgs mass around 125 GeV
- ~6,900 H→γγ events fitted over 88 categories (~1.2 million data events are selected)

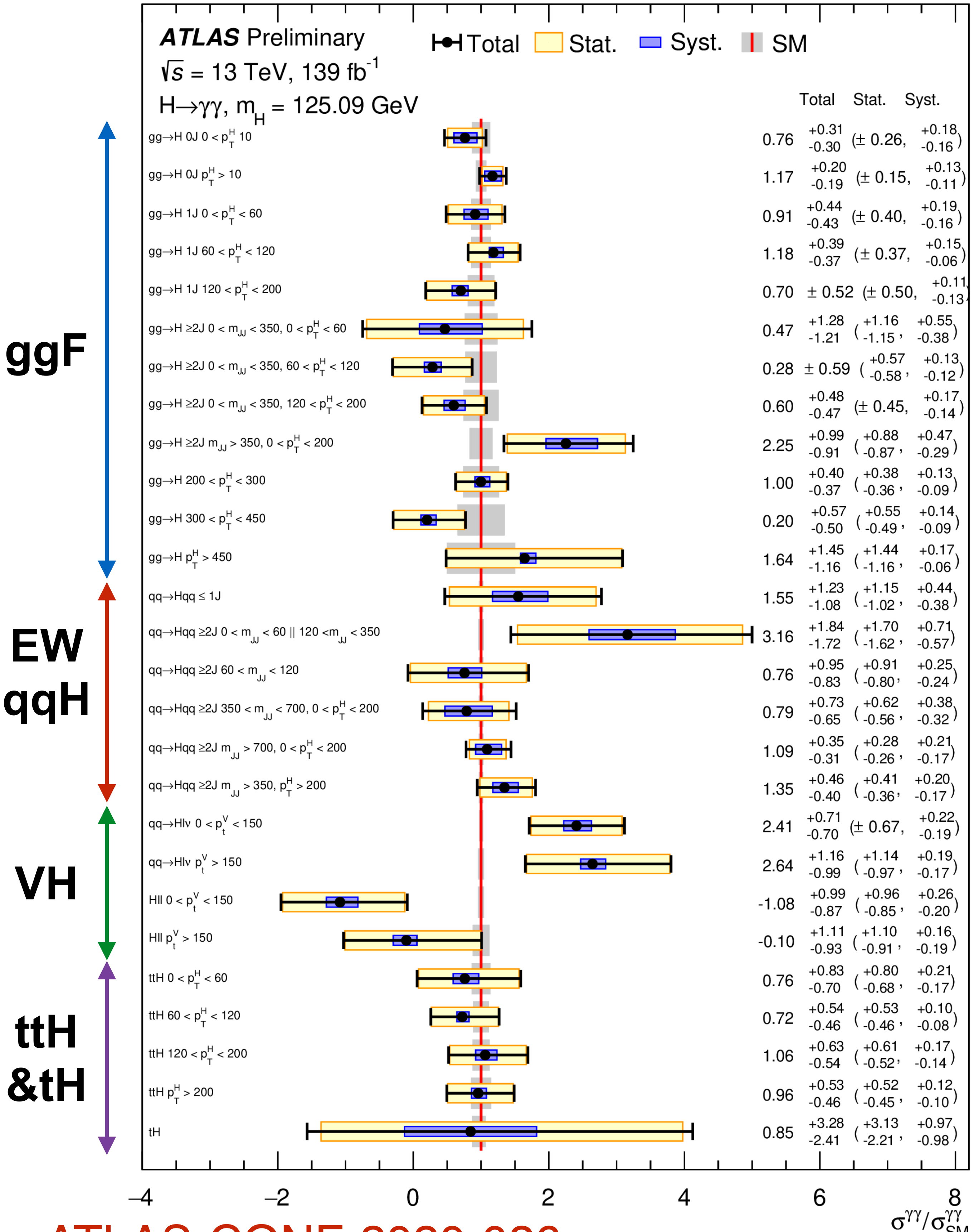
Production mode cross sections $H \to \gamma\gamma$

ATLAS-CONF-2020-026



- ggF cross section is measured with 11% precision
- The observed (expected) significance of other modes:
  - VBF: 7.5σ (6.1σ), WH: 5.6σ (2.8σ), ZH: 0σ (1.7σ), $t\bar{t}H$+tH: 4.7σ (5.0σ)
- An upper limit of 8 times the SM prediction is set for tH production
  - the most stringent single-channel constraint on tH
- The compatibility with SM prediction corresponds to a p-value of 3%
  - Difference is mainly due to the larger than expected yield for WH, and smaller than expected yield for ZH

Simplified template cross sections H→γγ



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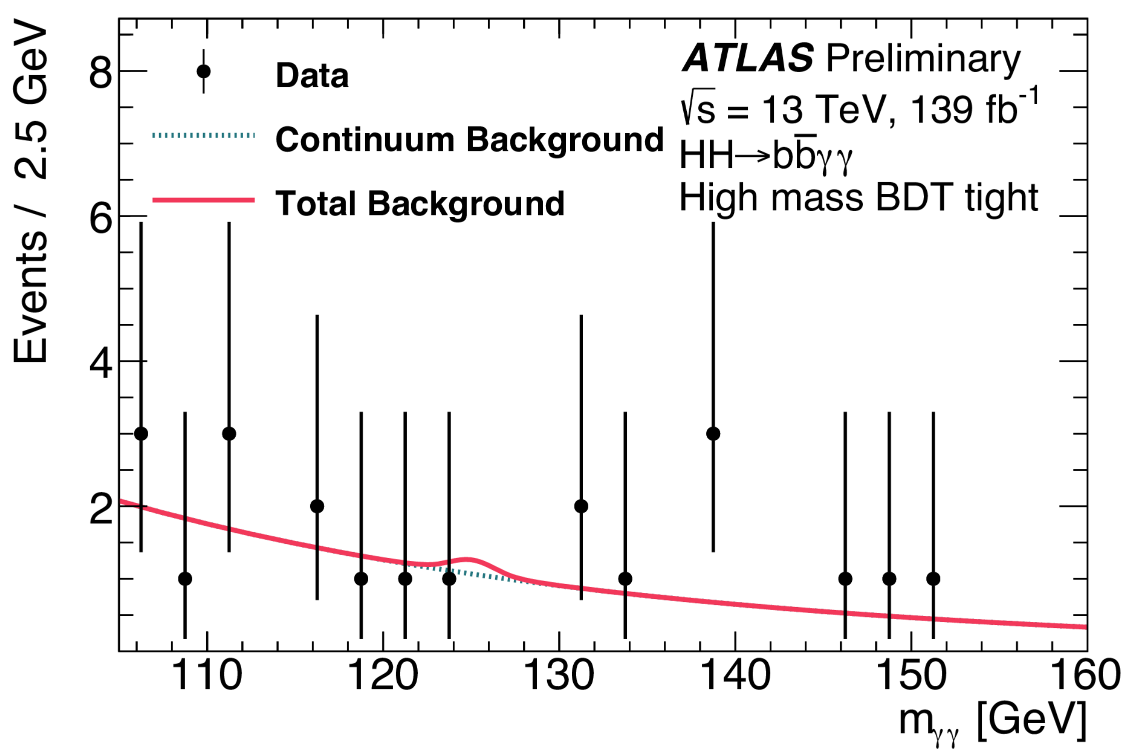
- Higgs production measured granularly
  - 27 merged STXS regions are measured
  - Uncertainties range from 20% to more than 100%, mostly statistically dominated
- $t\bar{t}H$ production measured differentially in Higgs pT (two years after its observation)
  - sensitive to self-couplings of the Higgs
- Good compatibility with the SM prediction (p-value of 60%)

Part 1*: ATLAS Higgs self-coupling study using $HH \rightarrow bb\gamma\gamma$

(ATLAS Run 2, 139 fb^{-1})

- General strategy similar with single Higgs→γγ analyses
- Event categorization with diphoton and b-jet variables
  - 4 categories based on 4-body mass and BDT
- Using diphoton mass, compare observed data with single Higgs + continuum background



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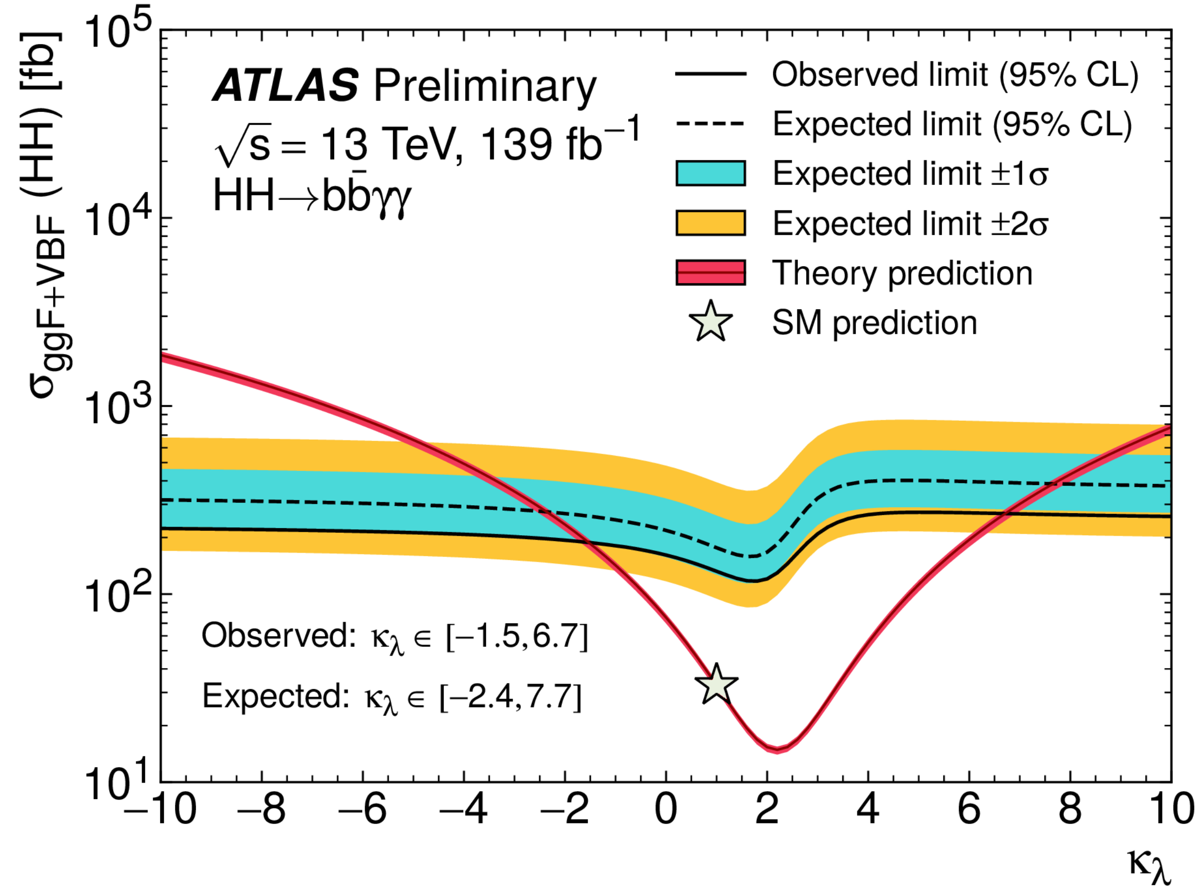
HH→bbγγ analysis result

- Observed (expected) limit of double Higgs cross section: 4.1 (5.5) times SM prediction
- Observed (expected) constrain on self-coupling strength: $-1.5<\kappa_\lambda<6.7$ ($-2.4<\kappa_\lambda<7.7$)
- Sensitivity significantly improved mainly due to better categorization



ATLAS-CONF-2021-016

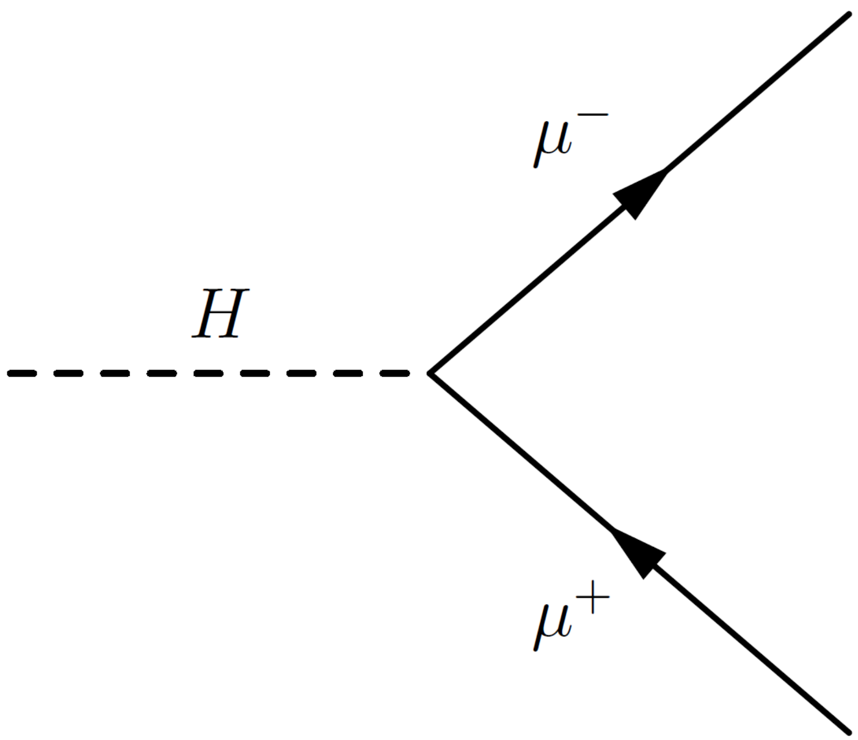
Part 2: $H \rightarrow \mu\mu$ search

(probing Higgs boson couplings to second generation fermions)

(ATLAS Run 2, 139 fb^{-1})

H→μμ decay mode

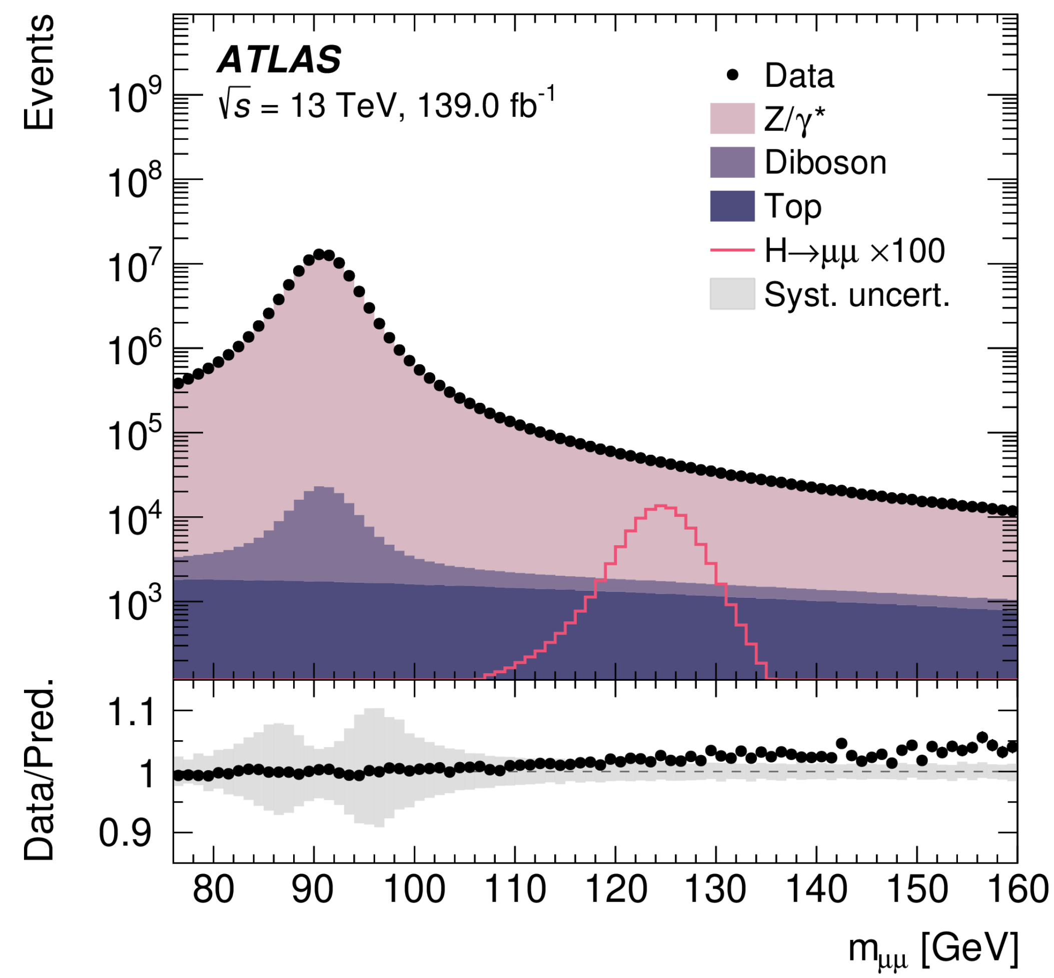
- The couplings between the Higgs boson and the third-generation fermions (top quark, bottom quark, τ lepton) have already been observed
  - The Higgs couplings with fermions of the other generations have not been established
- The Higgs decay to two muons offers the best opportunity to observe the Higgs couplings with the second-generation fermions at the LHC
  - Small branching ratio in SM (2×10^{-4}), physics beyond the SM could modify it

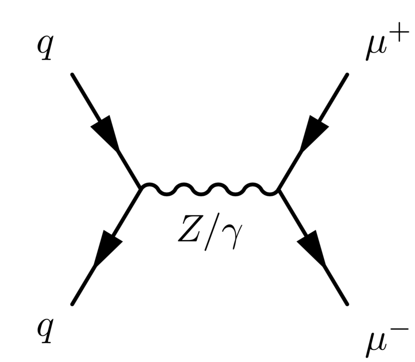


H→μμ analysis general strategy

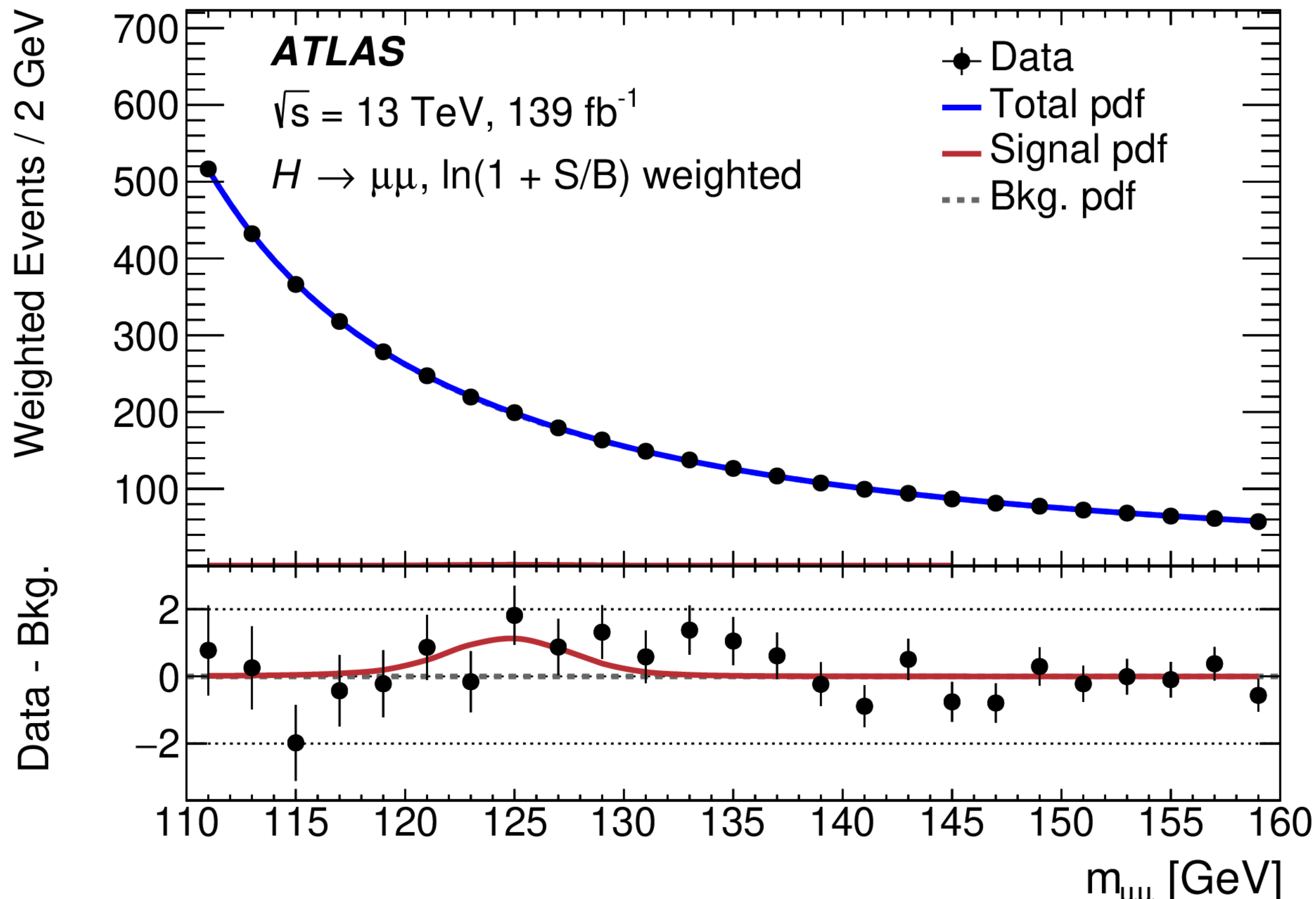
- Select events with **two opposite-sign muons**
- The main challenge is a very small signal over background ratio (~0.2% in 120-130 GeV)
  - the dominant background is **Drell-Yan process (Z/γ*→μμ)**
- Analysis strategy is somewhat similar to H→γγ analysis, but
  - categories are defined to target major Higgs production modes (instead of STXS regions)
  - more sophisticated background modeling is adopted

Phys. Lett. B 812 (2021) 135980





Dimuon mass: all categories



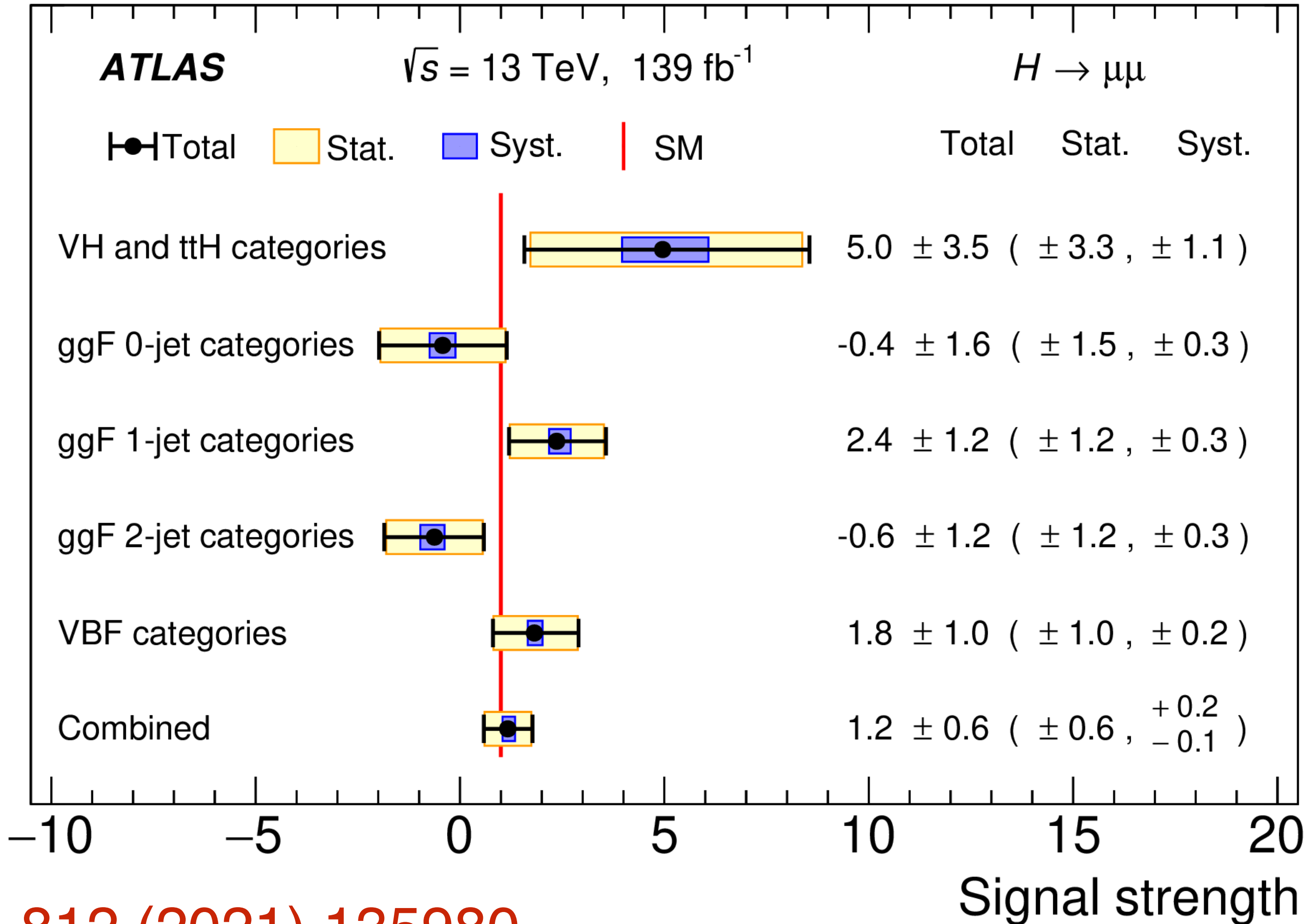
Phys. Lett. B 812 (2021) 135980

- Dimuon mass spectrum: small excess at the Higgs mass around 125 GeV
- ~1,000 H→μμ events fitted over 20 categories

Results: $H\rightarrow\mu\mu$ significance

- The observed $H\rightarrow\mu\mu$ significance is **2.0σ** (expected 1.7σ) in ATLAS full Run 2 results
- Large improvement in expected sensitivity compared with the previous ATLAS publication, due to
  - Larger dataset (a factor of 2)
  - Advanced analysis techniques (~25%): mainly from categorization and background modeling
- The observed $H\rightarrow\mu\mu$ significance is **3.0σ** (expected 2.5σ) in CMS full Run 2 results
- **These results on the $H\rightarrow\mu\mu$ decay provide first evidence for the Higgs couplings to second generation fermions**

Results: H→$\mu\mu$ signal strength



Phys. Lett. B 812 (2021) 135980

- The measured H→μμ signal strength at 13 TeV is 1.2 +/- 0.6 (stat.) $^{+0.2}_{-0.1}$ (syst.)
    - Dominated by statistical uncertainties
    - In agreement with the SM prediction

CERN experiments announce first indications of a rare Higgs boson process

The ATLAS and CMS experiments at CERN have announced new results which show that the Higgs boson decays into two muons

3 AUGUST, 2020

Part 3: ATLAS Higgs coupling measurements with combination of various channels

(ATLAS Run 2, up to 139 fb^{-1})

Signal strength & production cross-section measurements

	ggF	VBF	VH	ttH+tH
H→γγ	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})
H→ZZ	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (36-139 fb^{-1})
H→WW	✔ (139 fb^{-1})	✔ (139 fb^{-1})		
H→ττ	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})	
H→bb		✔ (126 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})
H→μμ	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})
H→Zγ	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})	✔ (139 fb^{-1})

✔: channel included in the combination

Inclusive signal strength

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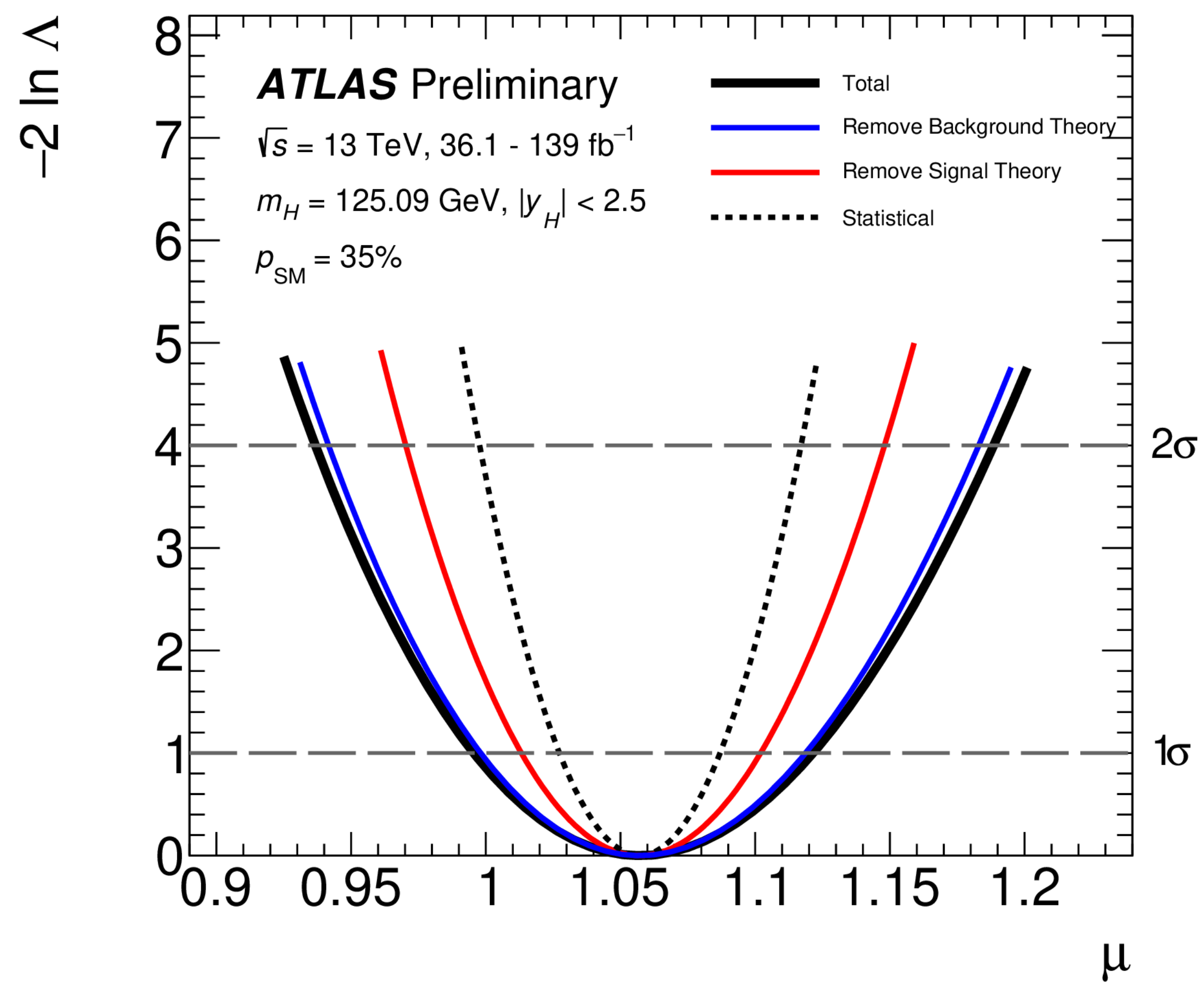

- Inclusive signal strength, defined as the measured Higgs boson signal yield normalized to its SM prediction, is determined to be

$$\mu = 1.06^{+0.06}_{-0.06} = 1.06 \pm 0.03(\text{stat.})^{+0.03}_{-0.03}(\text{exp.})^{+0.04}_{-0.04}(\text{sig. th.})^{+0.02}_{-0.02}(\text{bkg. th.})$$

- This measurement is systematically limited

Production mode cross sections (assuming the SM decays)

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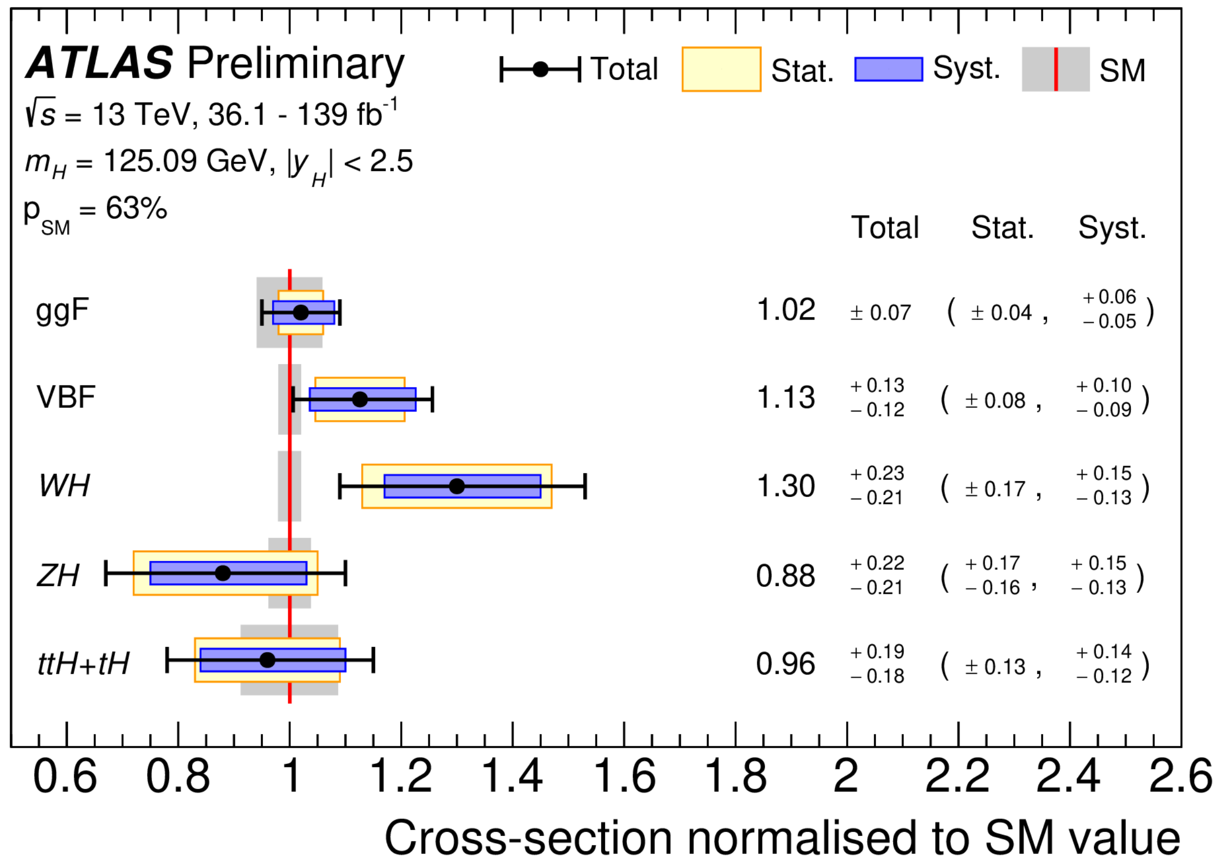

- ggF cross section is now measured with 7% precision
  - Precision of N3LO cross section prediction: 5%
- All major production modes (ggF, VBF, WH, ZH, ttH) are observed
  - Measurements consistent with SM predictions

Simplified template cross section (STXS) measurements

<table>
<tr><th></th><th>ggF</th><th>VBF</th><th>VH</th><th>ttH+tH</th></tr>
<tr><td>$H\to\gamma\gamma$</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
<tr><td>$H\to ZZ$</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td rowspan="3">✔ (36-139 fb^{-1})</td></tr>
<tr><td>$H\to WW$</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td></td></tr>
<tr><td>$H\to\tau\tau$</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
<tr><td>$H\to bb$</td><td></td><td>✔ (126 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
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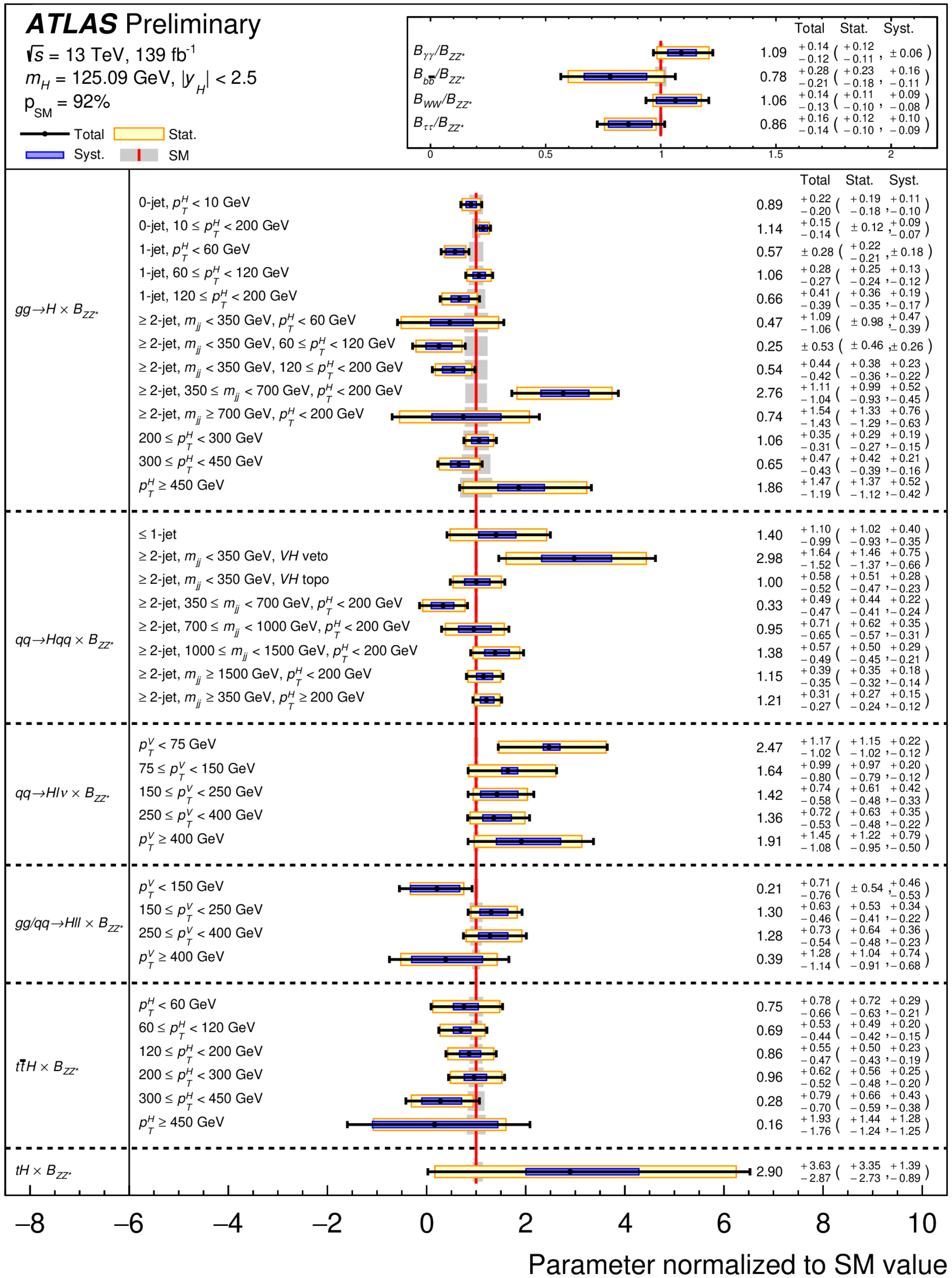
✔: channel included in the combination

STXS results (w/o assuming the SM decays)



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- STXS are measured granularly in this combination: 41 regions are probed
  - VBF, ggF+2jets: more granular in mass(jj)
  - VH: reach high pT(V)
  - ttH: reach high pT(H)
- The upper limit on the tH cross section is 9.3 times the SM prediction
- All regions are statistically limited; in some regions (e.g. ggF 0-jet) systematics are not negligible
- Good compatibility with the SM prediction

Coupling modifier (“kappa”) interpretation

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<tr><td>H→γγ</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
<tr><td>H→ZZ</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td rowspan="3">✔ (36-139 fb^{-1})</td></tr>
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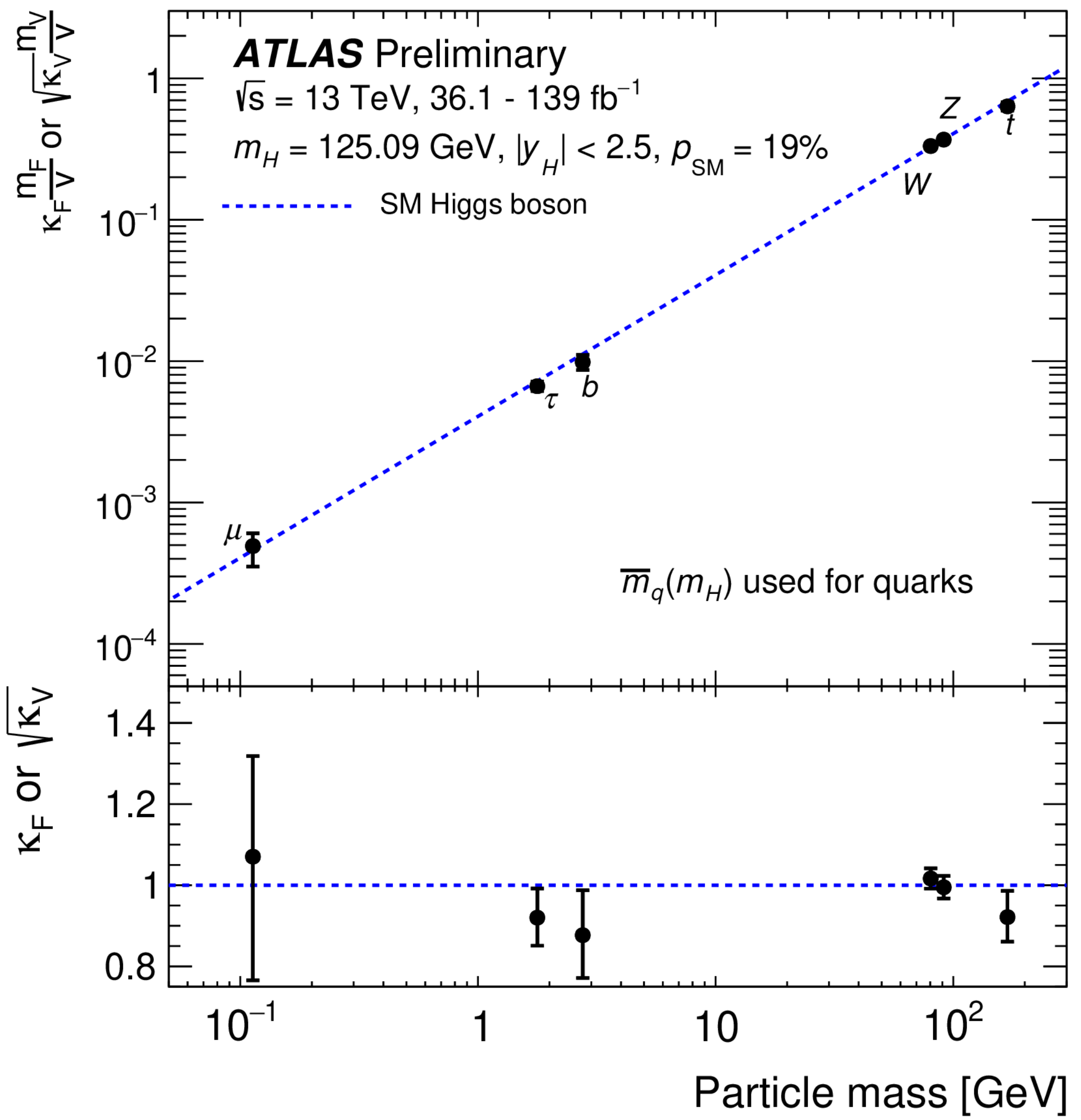
<tr><td>H→bb</td><td></td><td>✔ (126 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
<tr><td>H→μμ</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
<tr><td>H→Zγ</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td><td>✔ (139 fb^{-1})</td></tr>
</table>

✔: channel included in the combination

Analysis of H→invisible (139 fb^{-1}) is also included in relevant studies

Coupling modifier vs. particle mass

- "Kappa" framework: assign coupling modifier to each interaction vertex (e.g. κ_W, κ_t…)
- Here assume no BSM contribution in loop-induced processes (ggF, H→γγ etc.) or total width
  - κ_t is related to part 1 of this talk, κ_μ is related to part 2 of this talk
- Good agreement with the SM across 3 orders of magnitude of particle mass!



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Interpretation of STXS measurements with Effective Field Theory (EFT)

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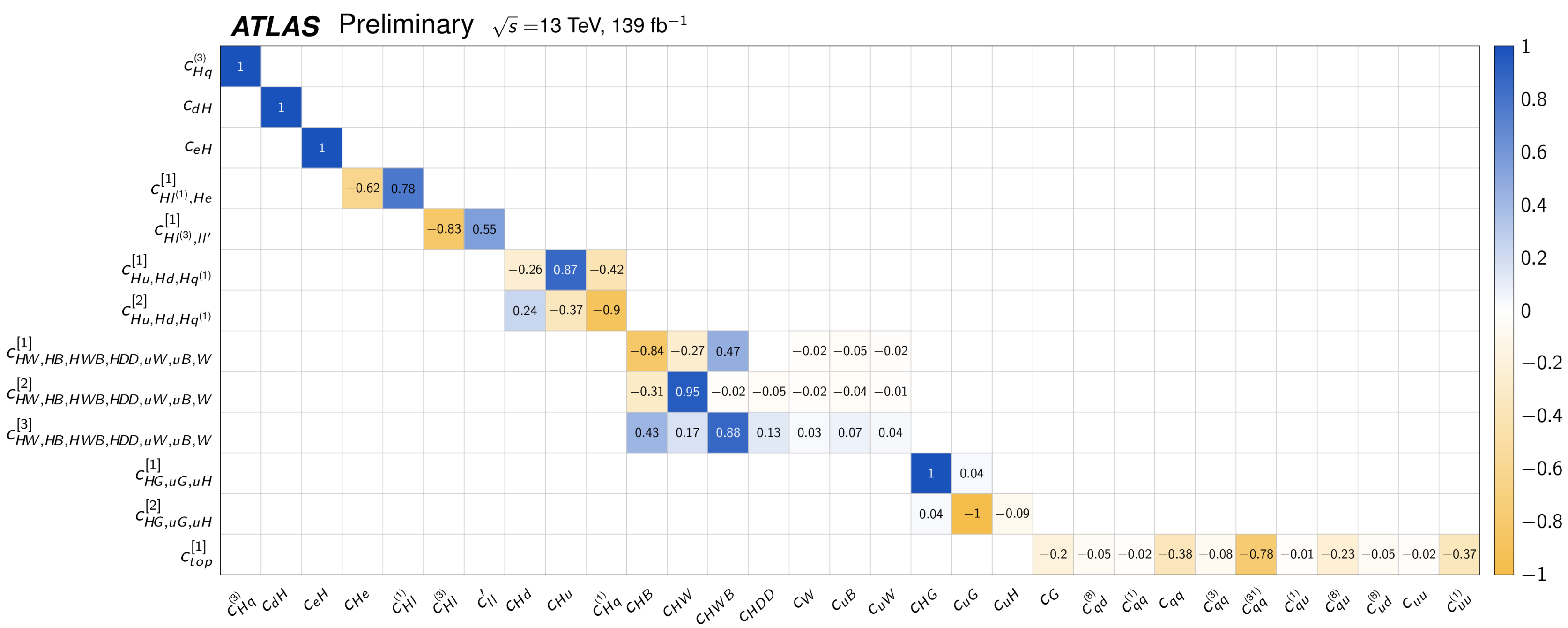
✔: channel included in the combination

Interpretation of STXS with EFT

$$\mathcal{L}_{\mathrm{SMEFT}} = \mathcal{L}_{\mathrm{SM}} + \sum_{i}^{N_{d6}} \frac{c_i}{\Lambda^2} \mathcal{O}_i^{(6)} + \sum_{j}^{N_{d8}} \frac{b_j}{\Lambda^4} \mathcal{O}_j^{(8)} + \ldots$$

- Parameterize the signal strengths, $(XS*BR)_{meas}/(XS*BR)_{SM}$, directly with Wilson coefficients of d=6 SMEFT operators
- Rotate the SMEFT basis cj to eigenvector cj' and fit 13 sensitive eigenvectors simultaneously



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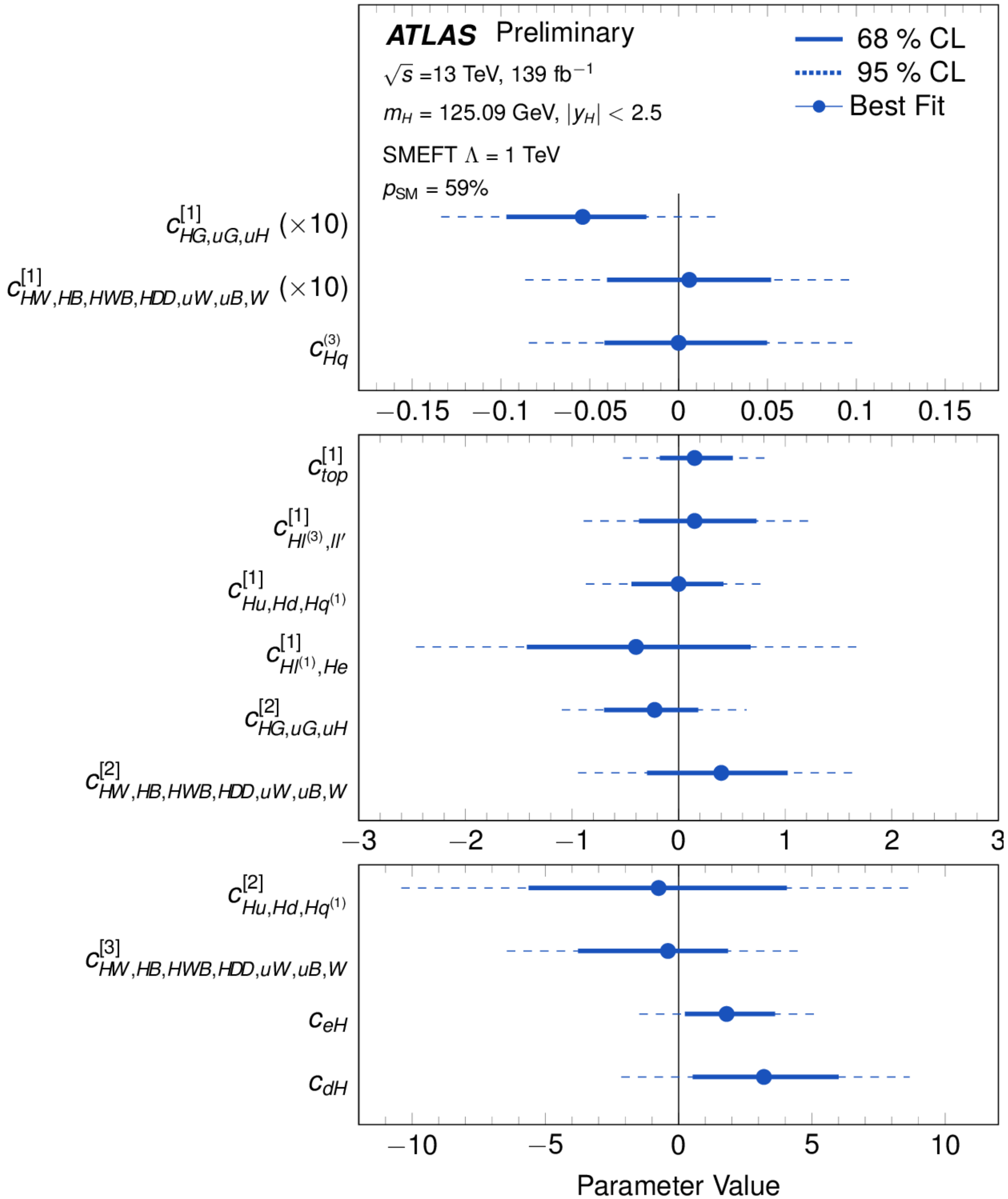
Interpretation of STXS with EFT

- All measured parameters are consistent with the SM expectation within their uncertainties
- Where the sensitivity to the 3 better constraint parameters are coming from:
  - $c_{HG,uG,uH}^{[1]}$ → mainly the EFT modifications to **ggH**
  - $c_{HW,HB,HWB,HDD,uW,uB,W}^{[1]}$ → comes from **H→γγ**
  - $c_{Hq}^{[3]}$ → well constrained from **VH** when splitting in different pTV bins (better measured in H→bb)

From a simultaneous fit



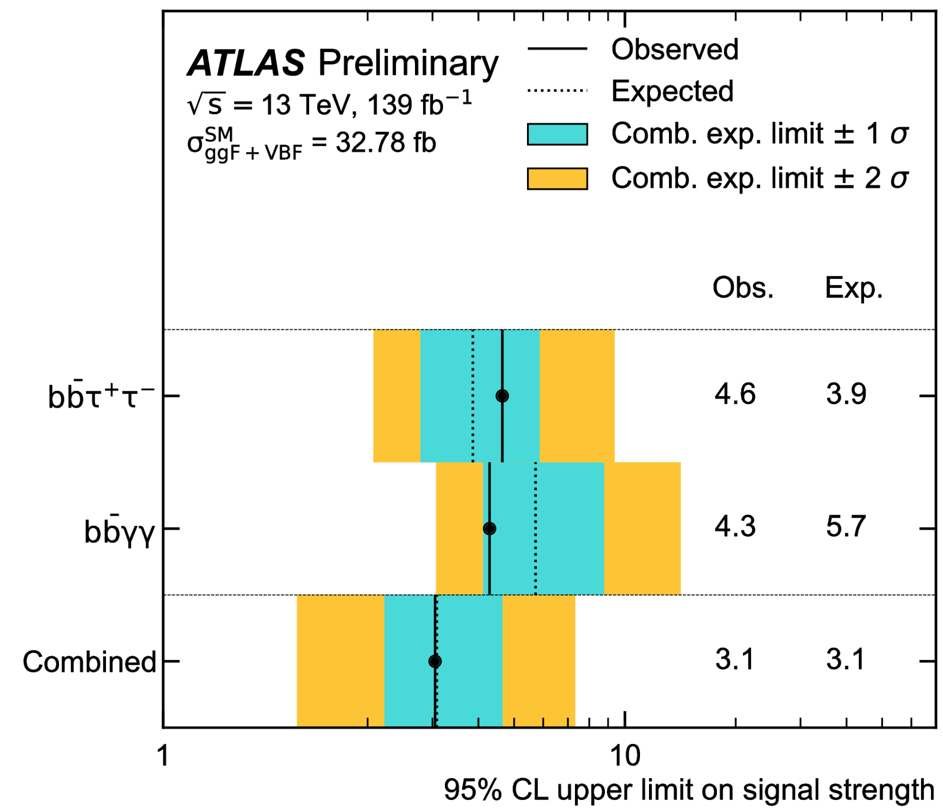
ATLAS-CONF-2021-053

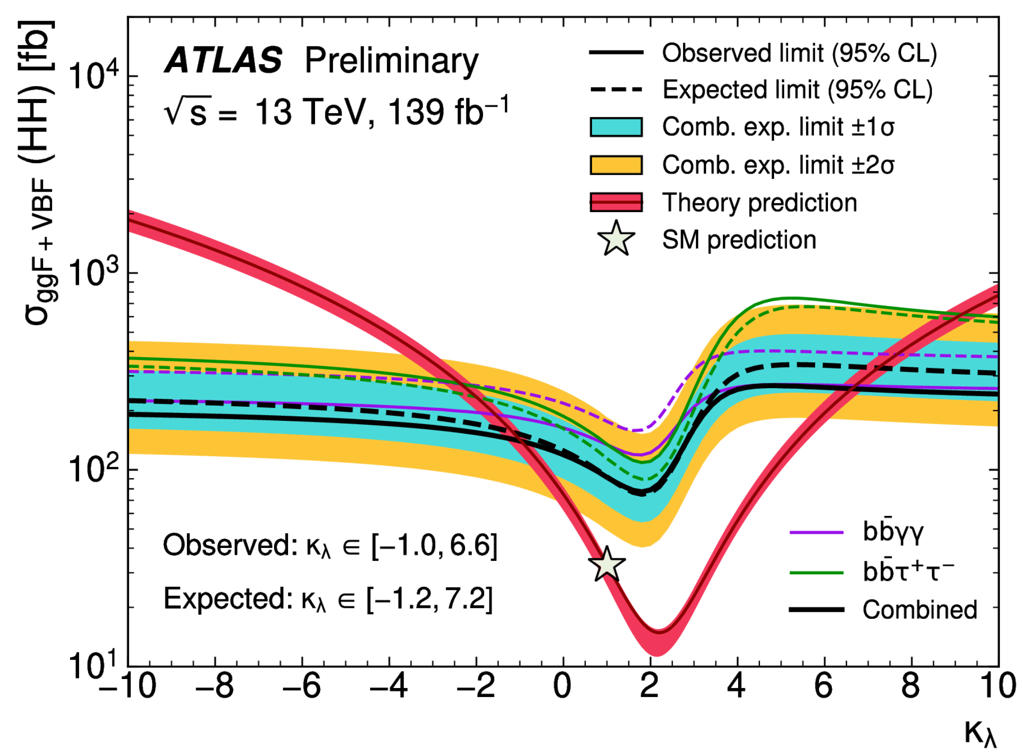
Part 3: ATLAS Higgs self-coupling study with combination of $HH \to bb\gamma\gamma$ and $HH \to bb\tau\tau$*

(ATLAS Run 2, up to 139 fb^{-1})

HH combination analysis result

- Observed (expected) limit of double Higgs cross section: 3.1 (3.1) times SM prediction
- Observed (expected) constrain on self-coupling strength: $-1.0<\kappa_\lambda<6.6$ ($-1.2<\kappa_\lambda<7.2$)
- Both are currently the world's best constraints
- Towards establishing Higgs self-coupling

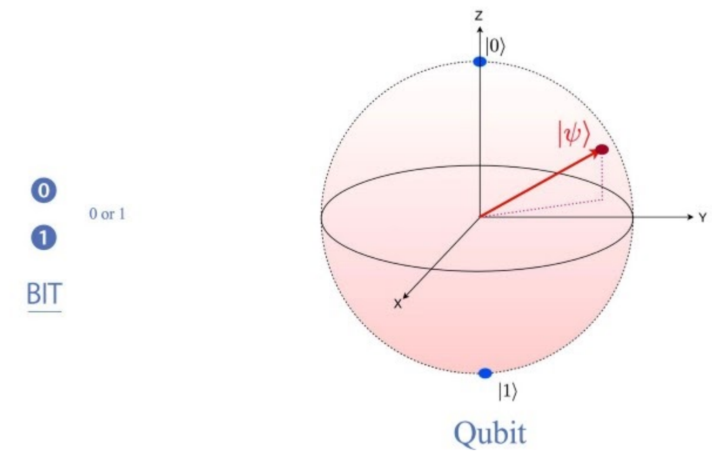




ATLAS-CONF-2021-052

Part 4: Application of quantum machine learning to LHC Higgs physics analyses

Quantum machine learning



- Quantum computing
  - Perform computation using the quantum state of qubits
  - A way of parallel execution of multiple processes
  - Can speed up certain types of problems effectively

- Quantum machine learning
  - Intersection between machine learning and quantum computing
  - May lead to more powerful solutions and offer a computational "speed up", by exploiting the high dimensional quantum state space through the action of superposition, entanglement, etc
  - Quantum machine learning could possibly become a valuable alternative to classical machine learning for HEP data analysis

Quantum machine learning for HEP

- I have been working with an interdisciplinary collaboration to perform High Energy Physics flagship analyses with Quantum Machine Learning methods (Variational Quantum Classifier, Quantum SVM Kernel Method, Quantum Neural Network) on gate-model quantum computer systems (from IBM, Google, Amazon)

- Goal: to demonstrate that the potential of quantum computers can be a new computational paradigm for big data analysis in HEP, as a proof of principle

Example 1: Employing Variational Quantum Classifier for ttH ($H \to \gamma\gamma$) and $H \to \mu\mu$ analyses

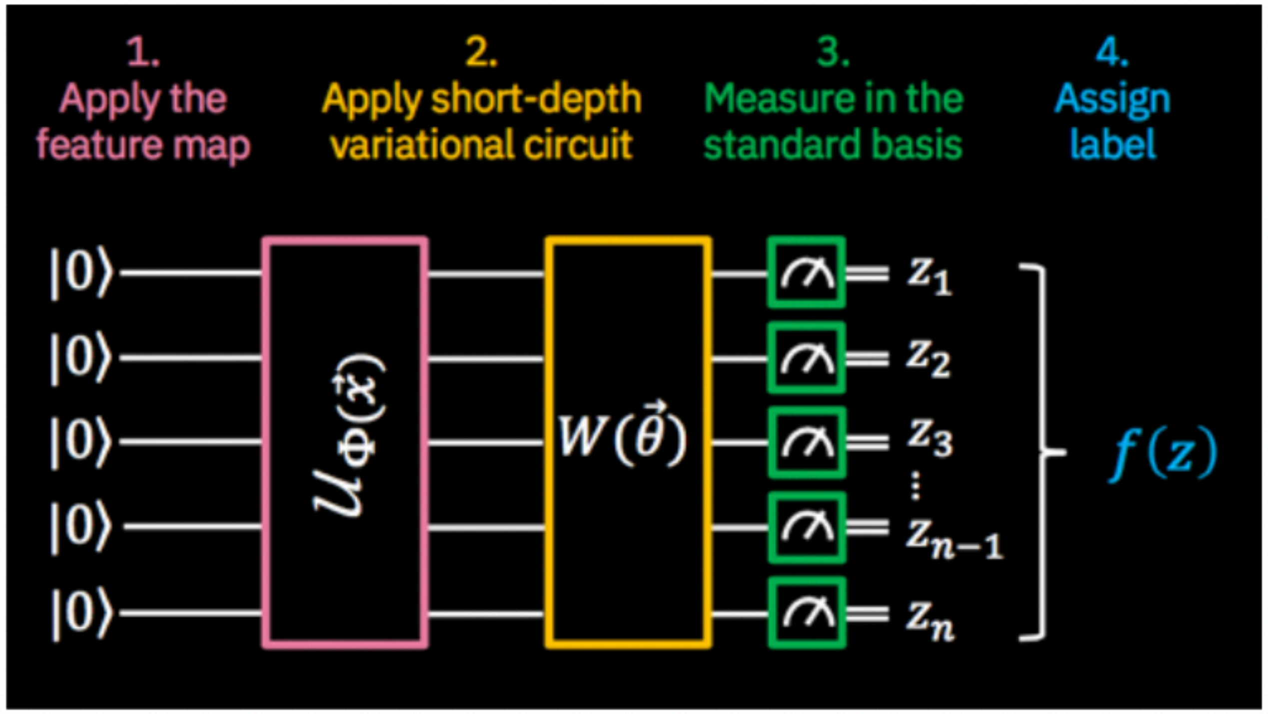
(accepted by ***J. Phys. G: Nucl. Part. Phys.*** **https://doi.org/10.1088/1361-6471/ac1391)**

Variational Quantum Classifier

- **In 2018, a Variational Quantum Classifier method was introduced by IBM, published in Nature 567 (2019) 209.**
- **The Variational Quantum Classifier method can be summarized in four steps.**

Variational Quantum Classifier

- **1. Apply feature map circuit $U_{\Phi(\vec{x})}$ to encode input data $\vec{x}$ into quantum state $|\Phi(\vec{x})\rangle$**
- **2. Apply short-depth quantum variational circuit W(θ) which is parameterized by gate angles θ**
- **3. Measure the qubit state in the standard basis (standard basis: $|0\rangle$, $|1\rangle$ for 1 qubit; $|00\rangle$, $|01\rangle$, $|10\rangle$, $|11\rangle$ for 2 qubits; ...)**
- **4. Assign the label ("signal" or "background") to the event through the action of a diagonal operator f in the standard basis**



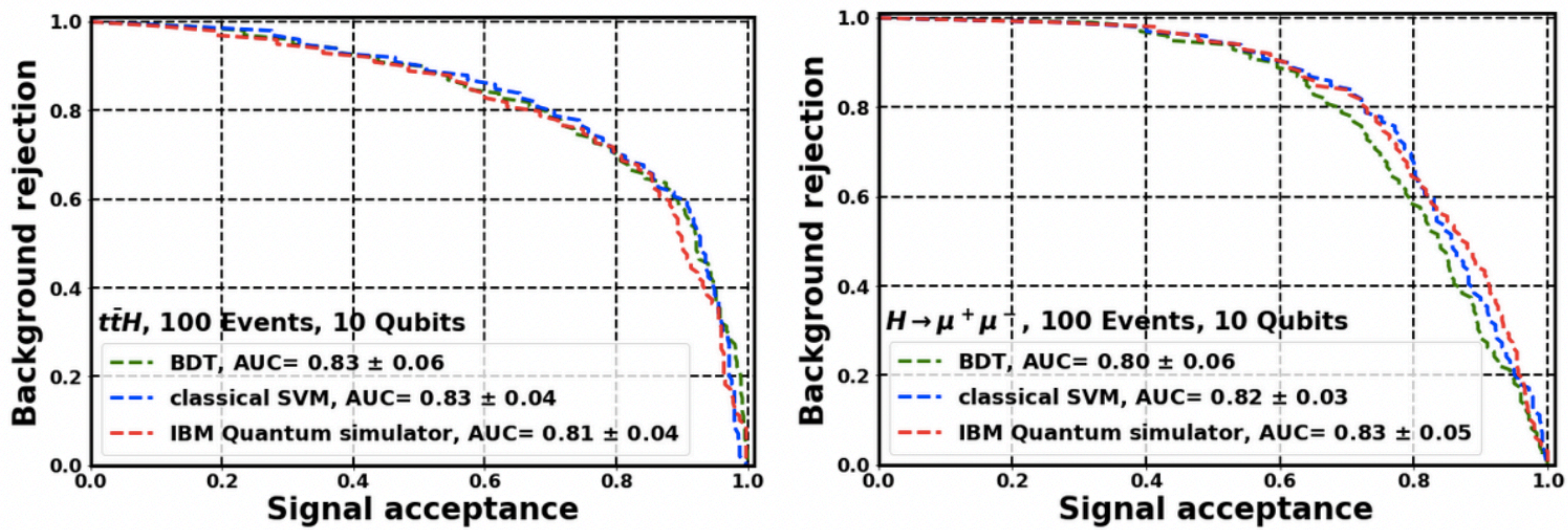
- **During the training phase, a set of events are used to train the circuit W(θ) to reproduce correct classification**
- **Using the optimized W(θ), an independent set of events are used for evaluation and testing**

Employing Variational Quantum Classifier with quantum simulator

Using 10 qubits, we successfully finished training and testing 100 events with IBM Qiskit QASM simulator (where '100' events means 100 training events and 100 test events).

- **Q simulator (Quantum circuits simulator): here IBM Qiskit QASM simulator is used. This simulation incorporates the hardware noise**
- **Quantum circuits are optimized to best fit the constraints imposed by hardware (e.g. qubit connectivity, hardware noise) and the nature of data**

Employing Variational Quantum Classifier with quantum simulator



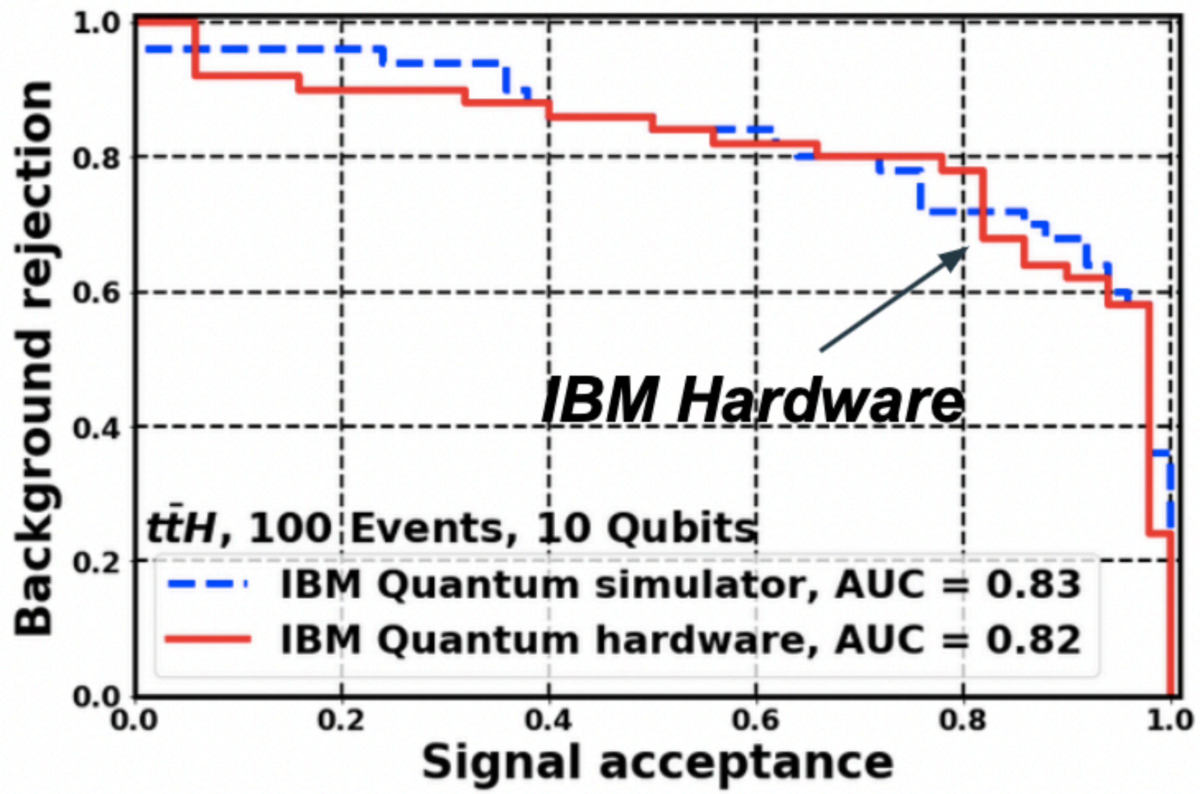
For 10 qubits, using ttH analysis dataset (100 events) and H → $\mu\mu$ analysis dataset (100 events), Variational Quantum Classifier on IBM simulator (red) performs similarly with classical BDT (green) and classical SVM (blue).

	AUC (ttH)	AUC (H → $\mu\mu$)
VQC	0.81	0.83
BDT	0.83	0.80
SVM	0.83	0.82

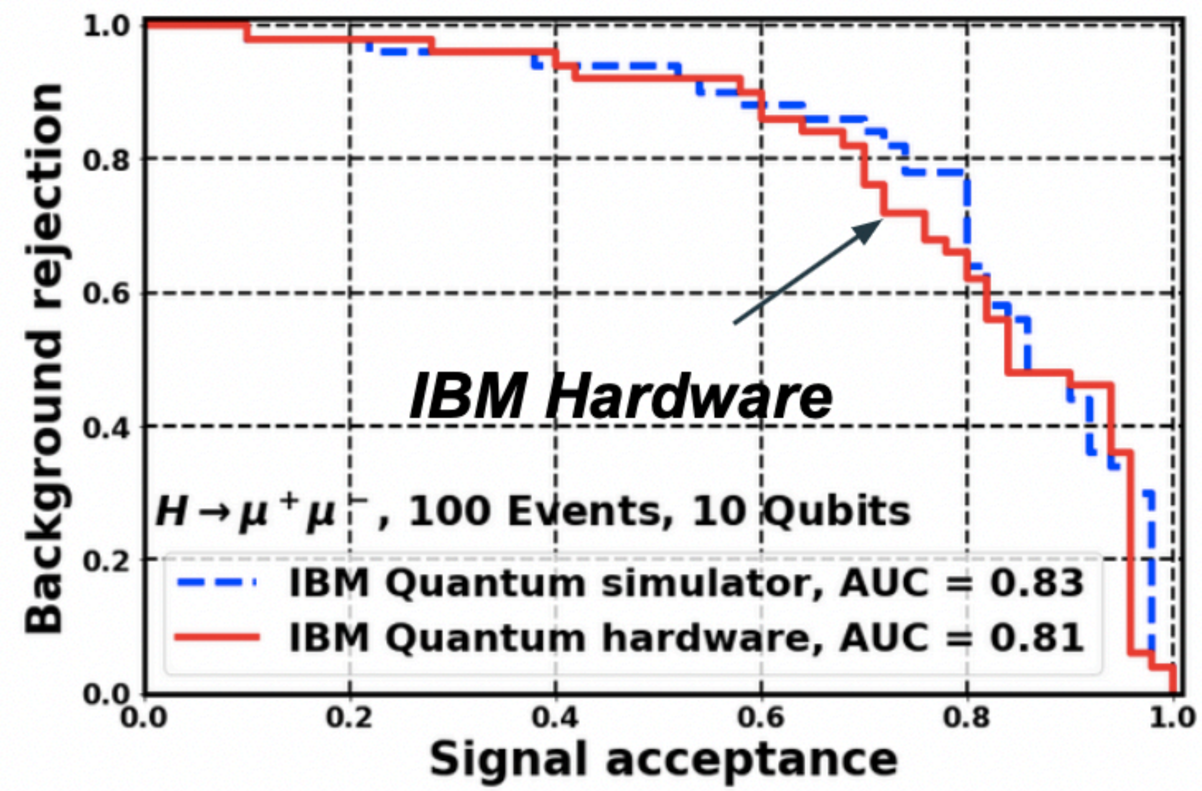
Employing Variational Quantum Classifier with quantum hardware

- With the help of IBM Research Zurich, Fermilab and BNL, we have carried out a number of jobs on the IBM superconducting quantum computers (ibmq_boeblingen, a 20-qubit machine and ibmq_paris, a 27-qubit machine). In each job, 10 qubits of the quantum computer are used to study 100 training events and 100 test events.
- For each analysis, due to current limitation of hardware access time, we apply the Variational Quantum Classifier method to one dataset on quantum hardware (rather than ten datasets on quantum simulator)

Employing Variational Quantum Classifier with quantum hardware



hardware AUC = 0.82, simulator AUC = 0.83



hardware AUC = 0.81, simulator AUC = 0.83

- For 10 qubits, using ttH analysis dataset (100 events) and H $\to \mu\mu$ analysis dataset (100 events), the result of Variational Quantum Classifier from IBM Quantum Hardware and result from Quantum Simulator are in good agreement.
- The hardware running time for 100 events is 200 hours

Example 2: Employing Quantum Support Vector Machine (QSVM) Kernel for ttH ($H \rightarrow \gamma\gamma$) analysis

<u>Phys. Rev. Research 3, 033221 (2021)</u>

Quantum SVM Kernel method

- ***Quantum SVM Kernel method** (introduced by IBM, published in Nature 567 (2019) 209):*
  - *map classical data $\vec{x}$ to a quantum state $|\Phi(\vec{x})\rangle$ using a Quantum Feature Map function;*
  - *calculate the similarity between any two data events ("kernel entry") as $K(\vec{x}_1,\vec{x}_2)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_2)\rangle|^2$ using a quantum computer;*
  - *then using the kernel entries to find a separating hyperplane that separates signal from background.*

map classical data

$\vec{x}_1 \rightarrow |\Phi(\vec{x}_1)\rangle$

$\vec{x}_2 \rightarrow |\Phi(\vec{x}_2)\rangle$

$\vec{x}_3 \rightarrow |\Phi(\vec{x}_3)\rangle$

...

calculate kernel entries

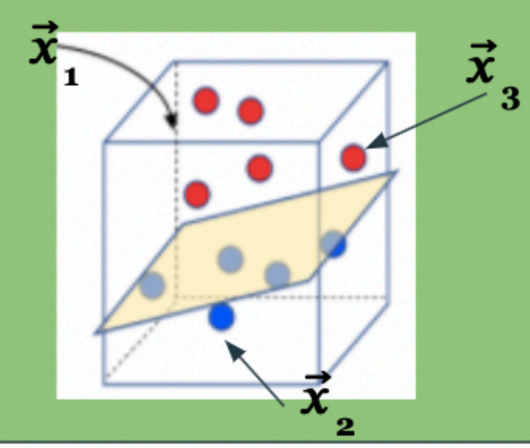
$K(\vec{x}_1,\vec{x}_2)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_2)\rangle|^2$

$K(\vec{x}_1,\vec{x}_3)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_3)\rangle|^2$

$K(\vec{x}_2,\vec{x}_3)=|\langle\Phi(\vec{x}_2)|\Phi(\vec{x}_3)\rangle|^2$

...

find separating hyperplane



Quantum SVM Kernel method

- ***Quantum SVM Kernel method*** ***(introduced by IBM, published in Nature 567 (2019) 209):***
  - *map classical data $\vec{x}$ to a quantum state $|\Phi(\vec{x})\rangle$ using a Quantum Feature Map function;*
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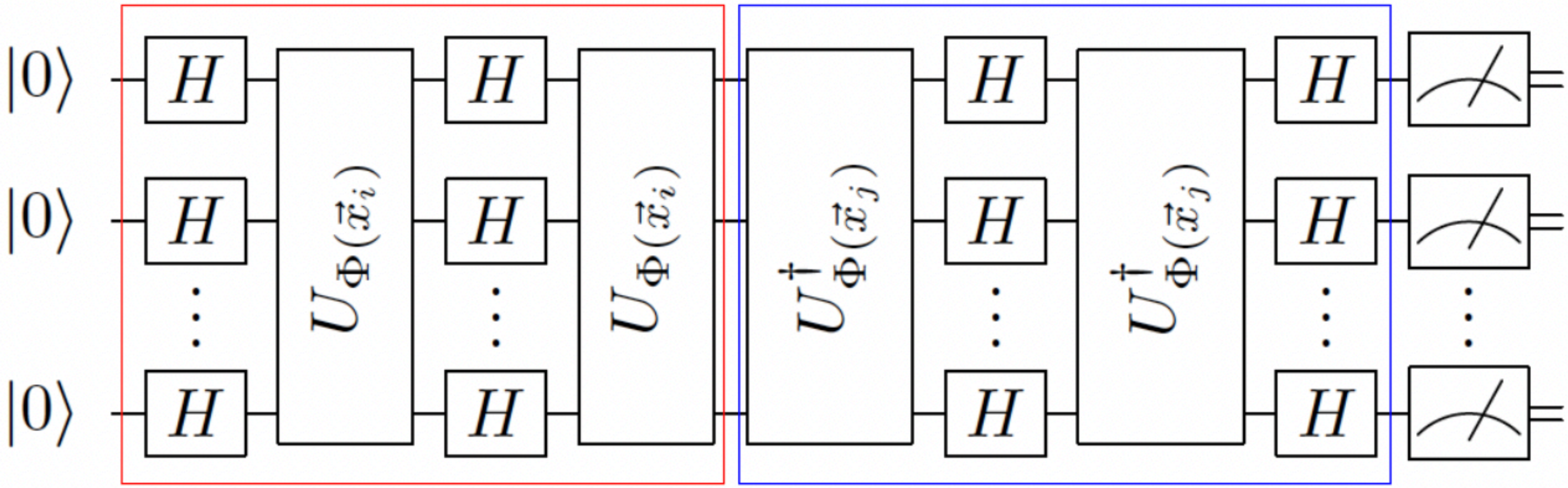
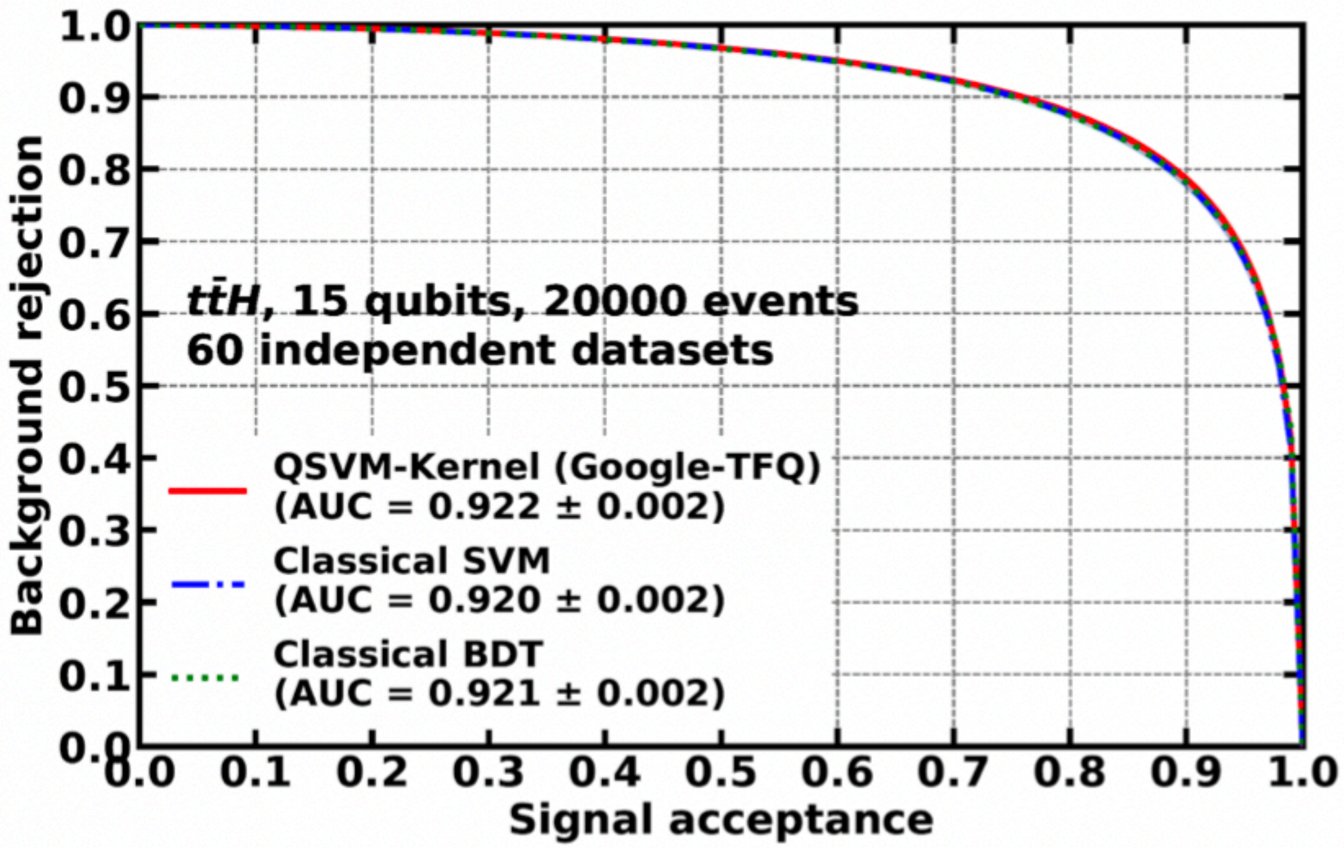
  - *then using the kernel entries to find a separating hyperplane that separates signal from background.*



Employing Quantum SVM Kernel method with quantum simulator

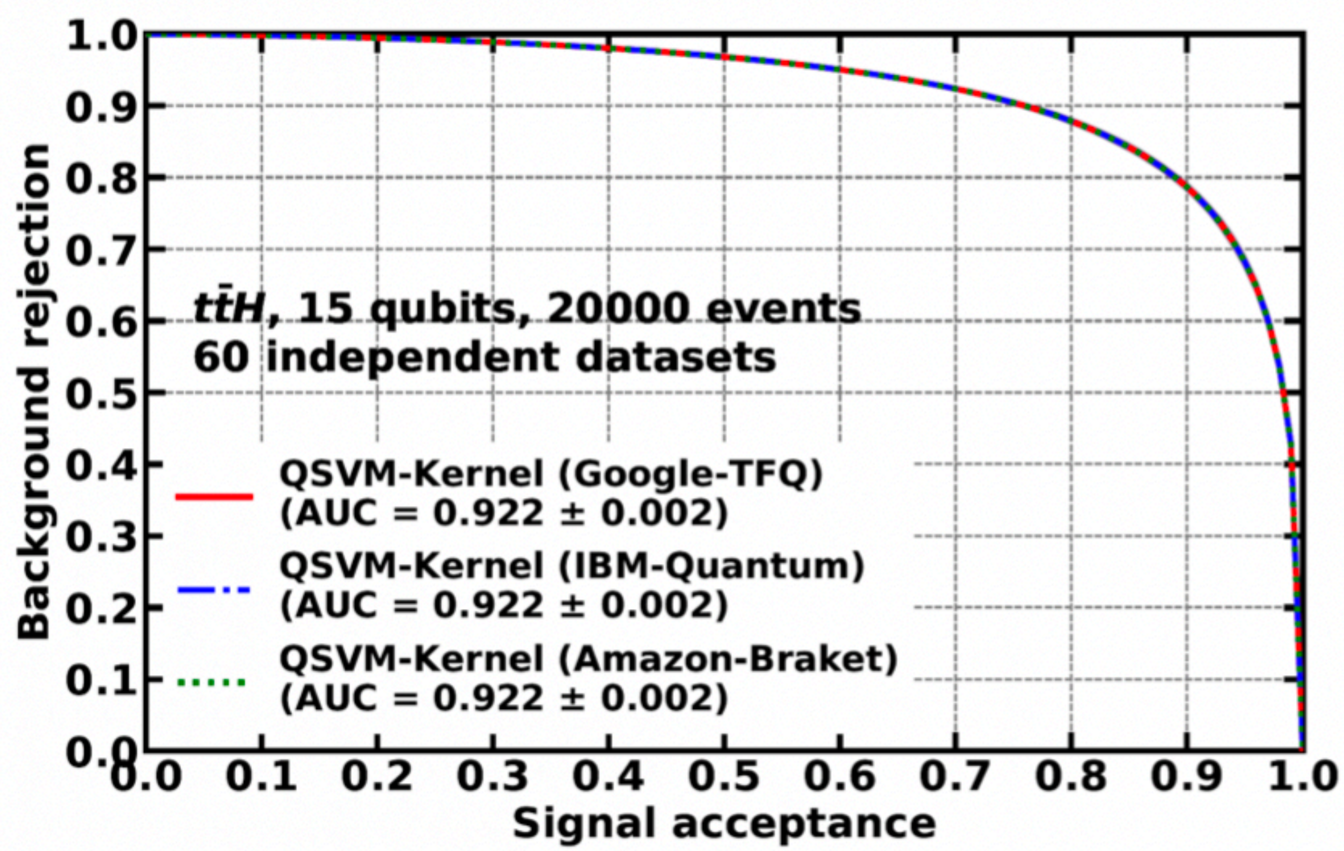
- ***We have implemented the QSVM Kernel algorithm using the qsim Simulator from the Google TensorFlow Quantum framework, the Statevector Simulator from the IBM Qiskit framework and the Local Simulator from the Amazon Braket framework***
  - ***These simulators represent the ideal quantum hardware that performs infinite measurement shots and experiences no hardware device noise***
  - ***We have overcome the challenges of heavy computing resources in the use of up to 20 qubits and up to 50000 events on the quantum computer simulators***

Employing Quantum SVM Kernel method with quantum simulator



- For 15 qubits, using ttH analysis dataset (20000 events), QSVM Kernel on simulator (red) achieves similar performances with classical SVM (blue) and classical BDT (green).

Employing Quantum SVM Kernel method with quantum simulator

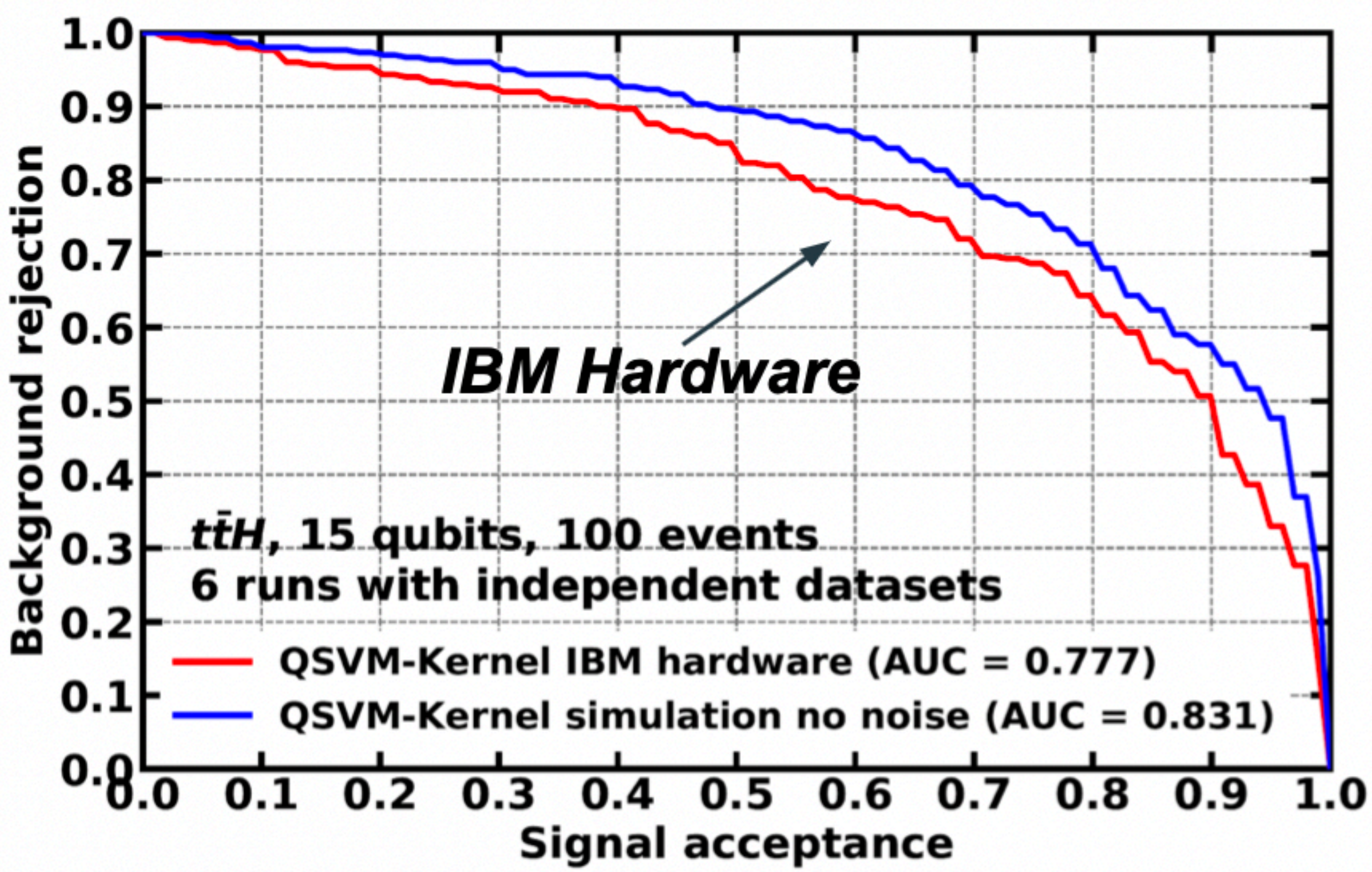


- For 15 qubits, using ttH analysis dataset (20000 events), Google qsim simulator (red), IBM statevector simulator (blue), and Amazon local simulator (green) provide identical performances for QSVM Kernel method

Employing Quantum SVM Kernel method with quantum hardware

- ***We have also been running the QSVM Kernel algorithm on quantum computer hardware provided by IBM (based on superconducting circuits)***
    - *to assess the quantum machine learning performances on today's noisy quantum computer hardware*
    - *due to current limitation of access time on imbq_paris, we only process six datasets of 100 training events and 100 test events*

Employing Quantum SVM Kernel method with quantum hardware



hardware AUC = 0.777

simulator AUC = 0.831

- Using ttH analysis dataset (100 events), the QSVM Kernel results on the IBM Quantum Hardware (15 qubits) are promising and approaching the QSVM Kernel results on Quantum Simulator (the difference is likely due to effect of hardware noise)

- *The average hardware running time is approximately 680 minutes per run*

Quantum machine learning for HEP

- **The results demonstrate quantum machine learning on the gate-model quantum computers has the ability to differentiate signal and background in realistic physics datasets**

- **Future developments:**
  - **Will investigate further and hopefully will see soon quantum machine learning outperforms classical machine learning, in particular, when more qubits and larger datasets are utilized**

  - **Furthermore, future quantum computers might offer speed-ups in quantum machine learning which could be critical for the HEP community**

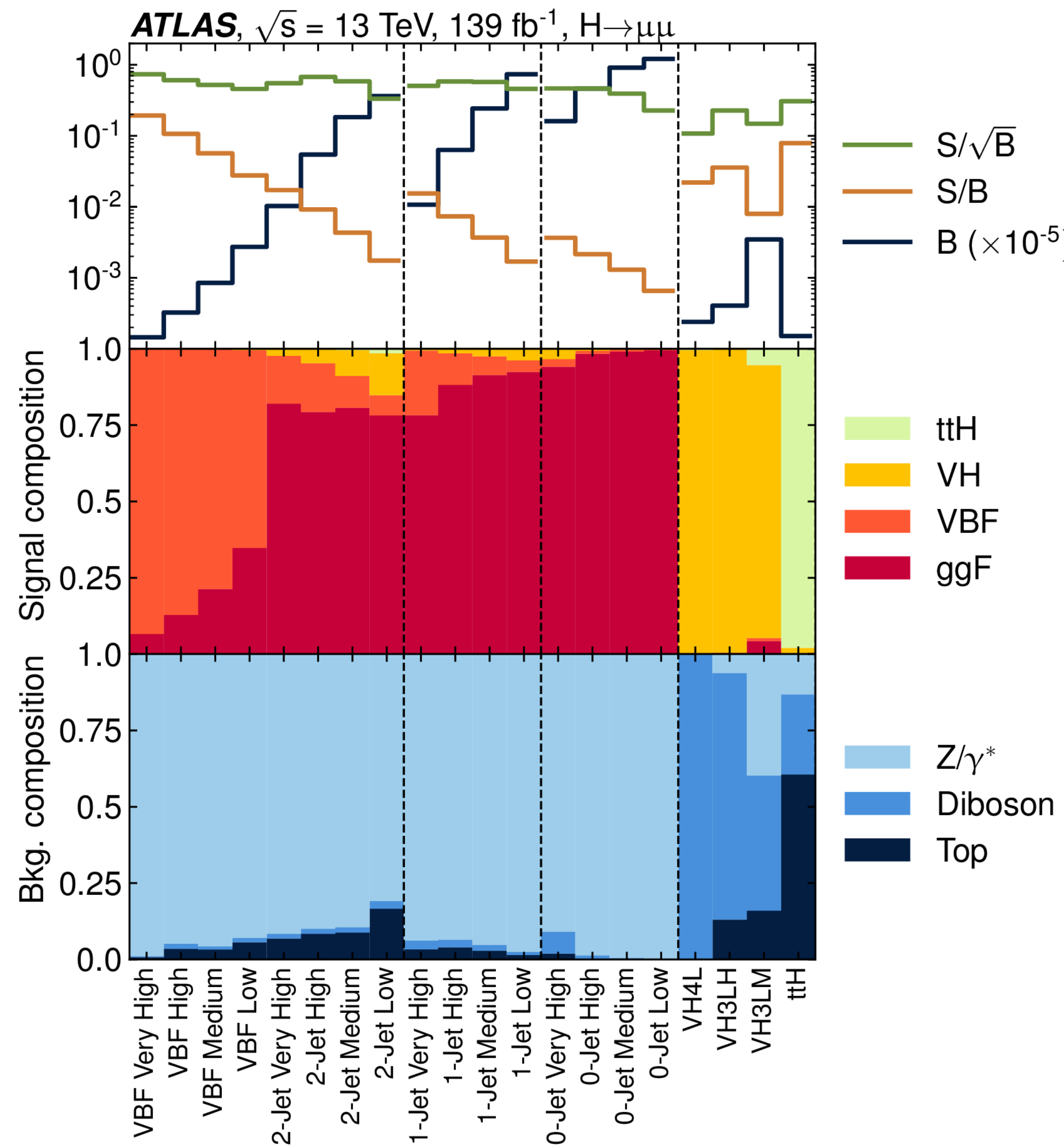
Summary

- I have been working on high-profile physics analyses, detector upgrade and quantum machine learning application
- ATLAS and CMS keep improving sensitivity for **Higgs coupling measurements** (including **Higgs self-couplings**)
  - In **H→γγ**, **H→μμ** and other decay channels
  - In **combination** of various channels
  - Results are currently in agreement with the SM predictions and can be interpreted using “kappa”, EFT and BSM models
- **Machine learning** greatly enhances our capability to identify rare signal in immense background
  - **Quantum machine learning** could possibly become another powerful tool for high energy physics
- I am enthusiastic to extend these studies at Peking University and also open to other topics

Backup slides

Event categorization

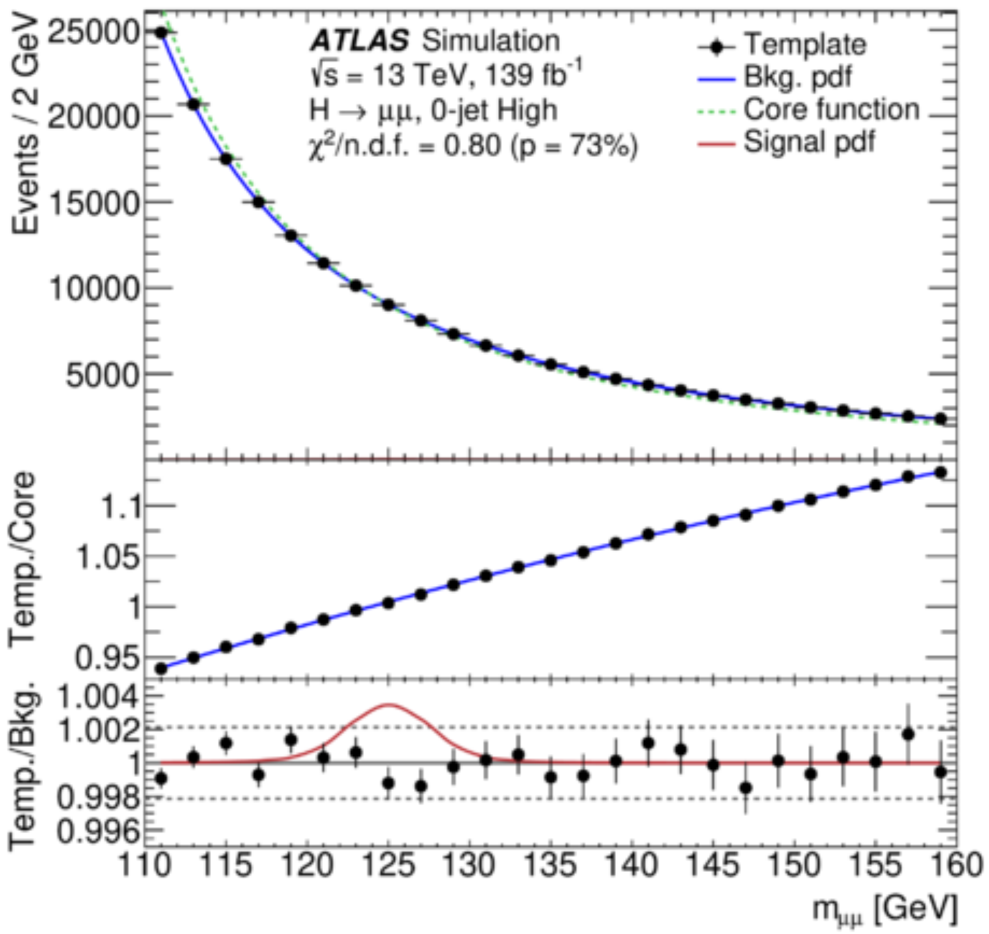
- Divide events into 0-jet, 1-jet and ≥2-jet channels
- In each channel, train a BDT with XGBoost to separate signal from background, create 4 ggF categories
  - In ≥2-jet channel, train an additional BDT to target VBF signal, create 4 VBF categories
- Also define 1 ttH category and 3 VH categories (which are less sensitive)
  - 20 categories in total
- The S/B ratios range from <0.1% (ggF 0-jet "low") to 18% (VBF "very high")
  - different Higgs production modes are well separated



Phys. Lett. B 812 (2021) 135980

Background modeling

- Background mass distribution modeled with Core x Empirical
- Core function:
  - LO Drell-Yan line-shape convoluted with detector resolution to describe mass shape inclusively
- Empirical function:
  - EpolyN or PowerN functions to correct for mass shape distortion due to selection+categorization, higher-order correction, etc.



Function	Expression
PowerN	$m_{\mu\mu}^{(a_0+a_1 m_{\mu\mu}+a_2 m_{\mu\mu}^2+\ldots+a_N m_{\mu\mu}^N)}$
EpolyN	$\exp(a_1 m_{\mu\mu} + a_2 m_{\mu\mu}^2 + \ldots + a_N m_{\mu\mu}^N)$

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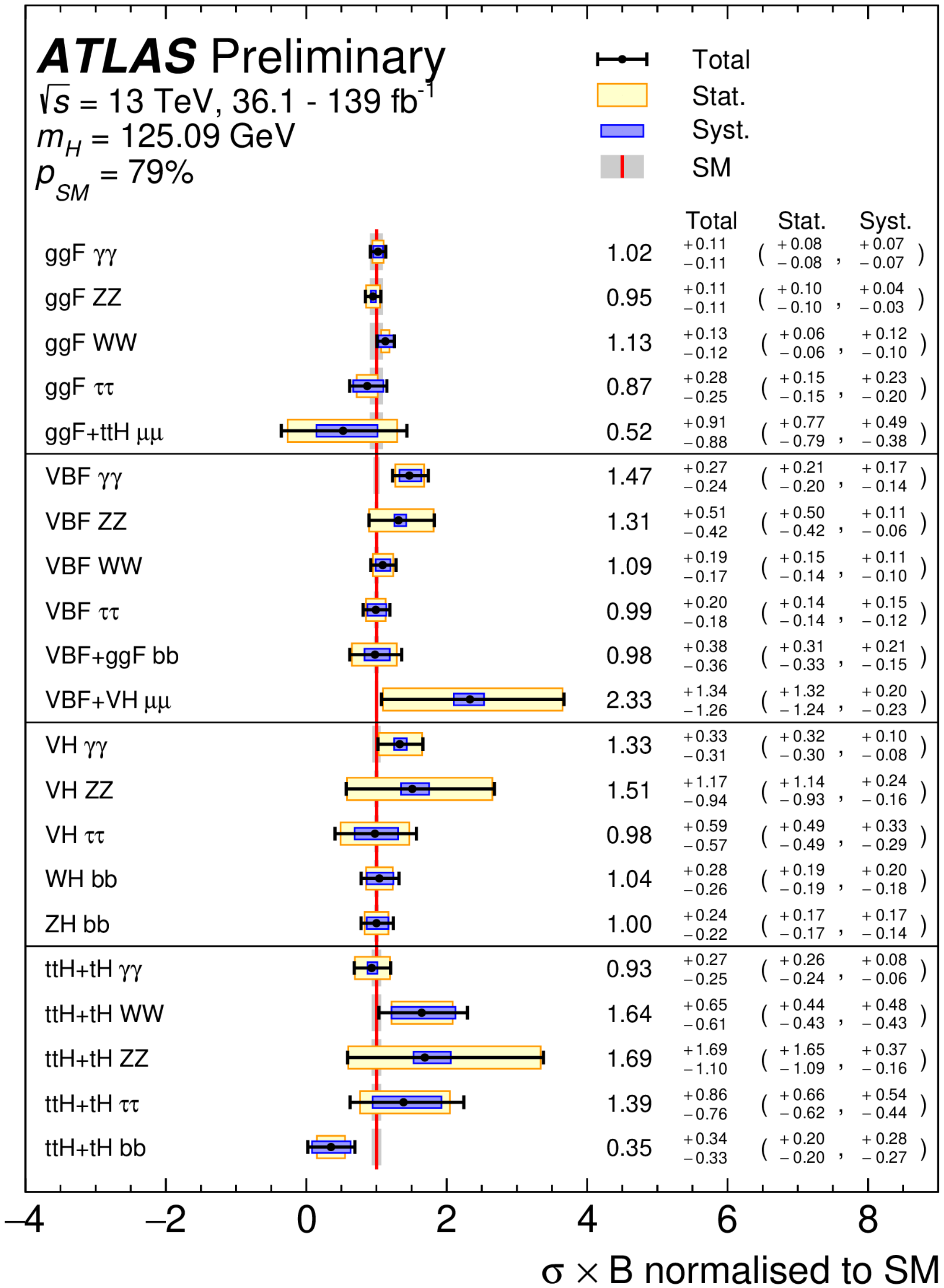
Production mode cross sections times decay branching ratios



- Most sensitive to ggF: H→γγ, H→ZZ, H→WW
- Most sensitive to VBF: H→WW, H→ττ, H→γγ
- Most sensitive to VH: H→bb, H→γγ
- Most sensitive to ttH and tH: H→γγ, H→bb
- Measurements consistent with SM predictions

ATLAS-CONF-2021-053

Coupling modifier ("kappa")

- Leading order motivated framework: assign coupling modifier to each (effective) interaction vertex (e.g. κ_W, κ_t…)
- In this framework, production cross section times decay branch fraction of i→H→f can be parameterized as

$$\sigma_i \times B_f = \frac{\sigma_i(\boldsymbol{\kappa}) \times \Gamma_f(\boldsymbol{\kappa})}{\Gamma_H},$$

  - (this allows for a consistent treatment of production and decay)
- Total width of Higgs boson can be expressed as

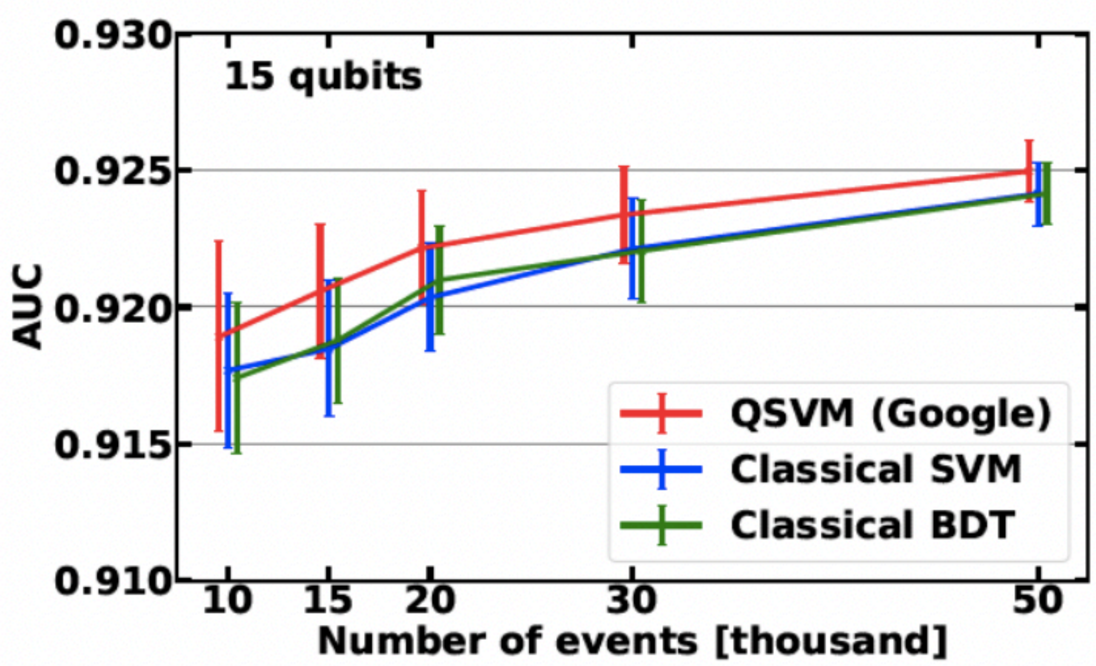
$$\Gamma_H(\boldsymbol{\kappa}, B_{\mathrm{i.}}, B_{\mathrm{u.}}) = \kappa_H^2(\boldsymbol{\kappa}, B_{\mathrm{i.}}, B_{\mathrm{u.}})\,\Gamma_H^{\mathrm{SM}}$$

$B_{i.}$= BSM contribution to BR of invisible decays

$B_{u.}$= BSM contribution to BR of undetected decays

Employing Quantum SVM Kernel method with quantum simulator

AUC vs number of events

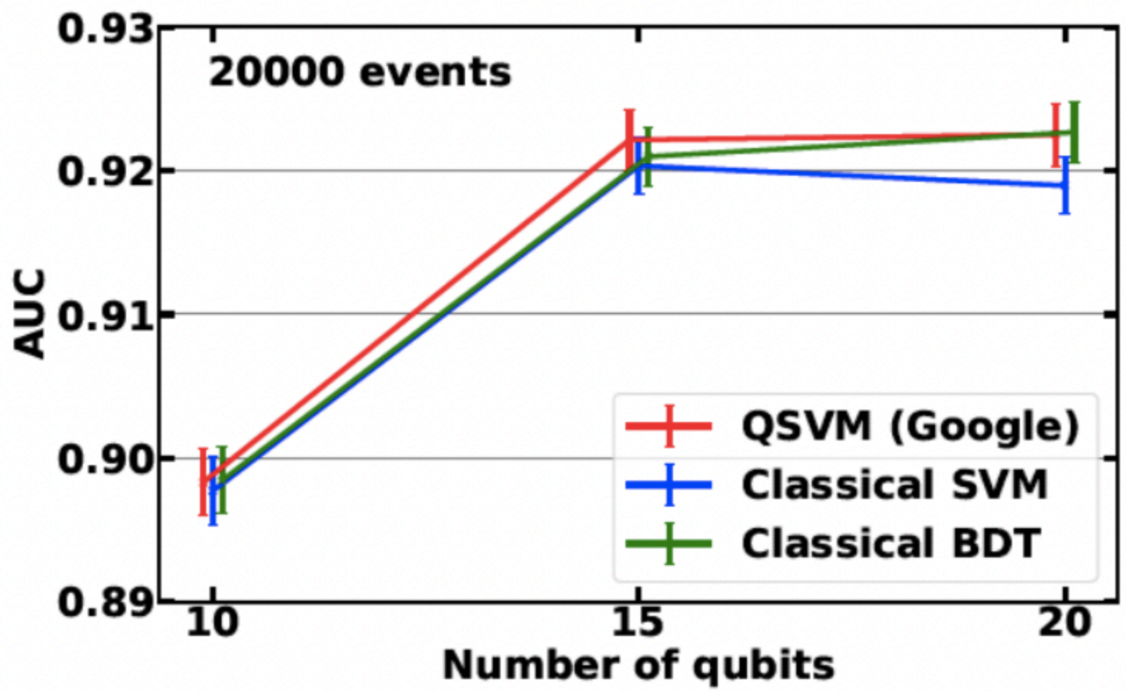


- **QSVM Kernel method and noiseless simulators enable us to work with a larger number of events.**

- **Using ttH analysis dataset (10000-50000 events, 15 variables), QSVM Kernel on simulator (red) achieves similar performances with classical BDT (blue) and classical SVM (green).**

Employing Quantum SVM Kernel method with quantum simulator

AUC vs number of qubits



- QSVM Kernel method and noiseless simulators also enable us to work with a larger number of qubits.

- Using ttH analysis dataset (20000 events, 10-20 variables), QSVM Kernel on simulator (red) achieves similar performances with classical BDT (blue) and classical SVM (green).