Universität Münster

Encoding off-shell effects in top pair production in direct diffusion networks

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Motivation

- Basis of every LHC analysis: Fast and precise predictions of event kinematics from first principles
- Two main challenges:
  - **Conceptual problems to overcome: e.g. dealing with loop diagrams with many scales**
  - **Technical problems: increased precision comes with higher computational cost**
- In this talk (and the corresponding paper) we focus on off-shell effects
  - **Given the precision targets of the upcoming LHC runs, approximate decay modelling is not justified**
  - **High computational cost of exact calculation**
  - **Can a neural network encode the exact calculation of full off-shellness with the purpose to make it easier to use, more efficient, to store and publish results etc.**

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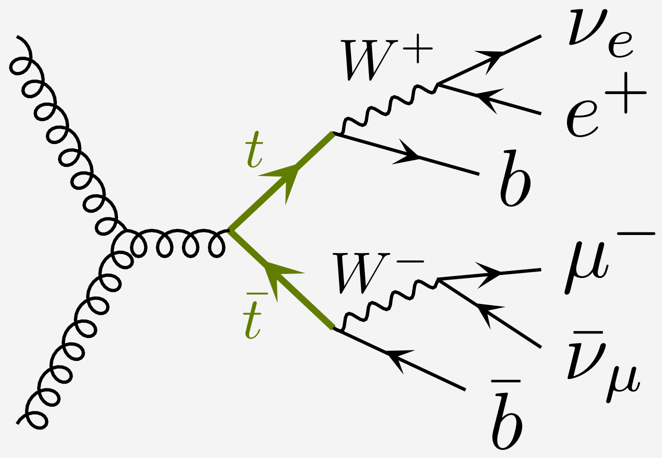
Off-shell effects in MC event generation

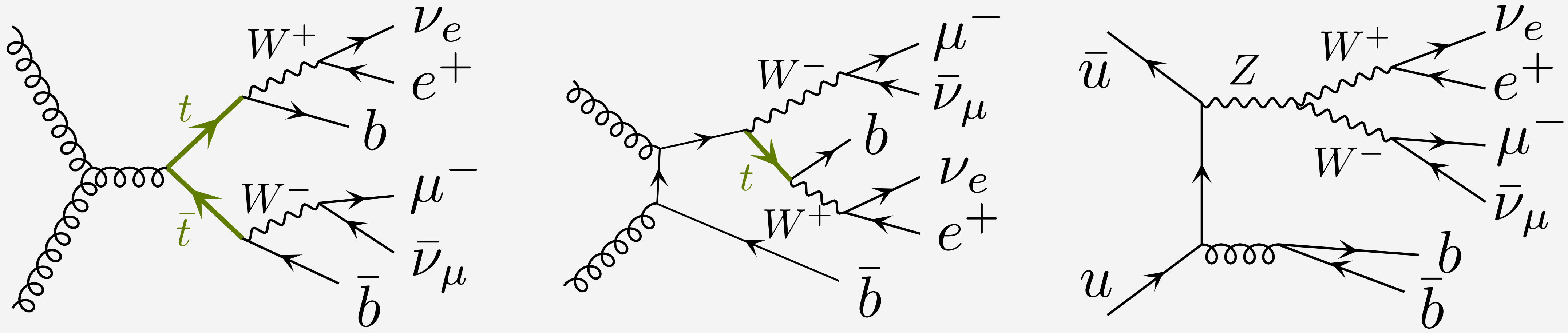
- Proof of concept: top pair production and dileptonic decay (LO in QCD)



- Generated data for training a transformation of “on-shell” to off-shell events:
  - **hvq data includes only approx. off-shell effects using finite top width**

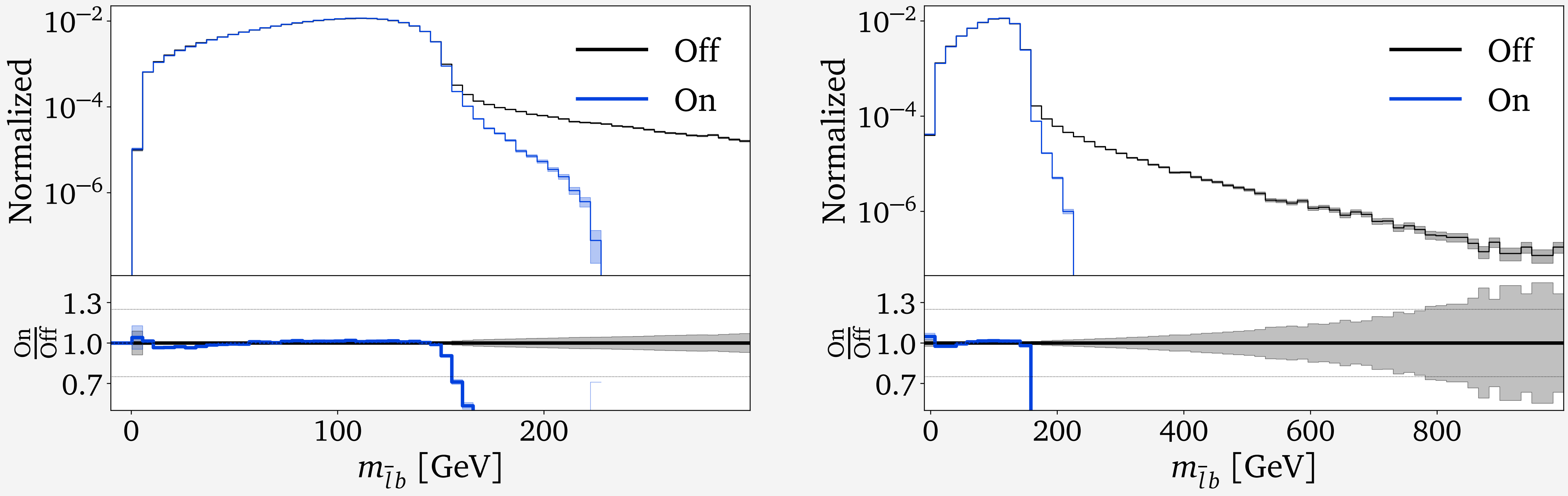
Off-shell effects in MC event generation

- Proof of concept: top pair production and dileptonic decay (LO in QCD)



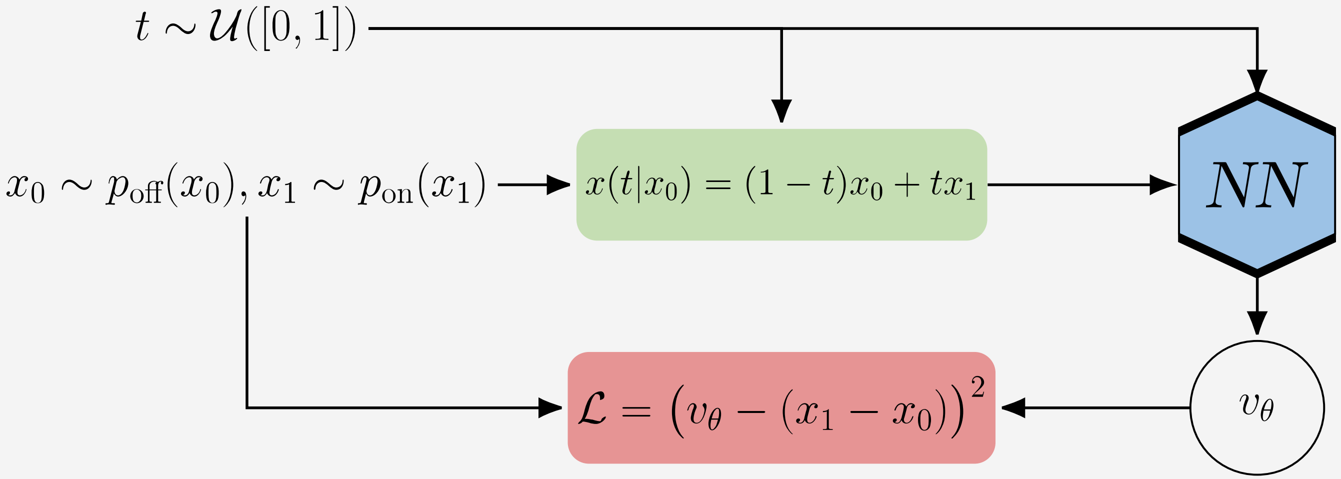
- Generated data for training a transformation of “on-shell” to off-shell events:
  - **hvq data includes only approx. off-shell effects using finite top width**
  - **bb4l data includes full off-shell effects (including e.g non-resonant effects)**

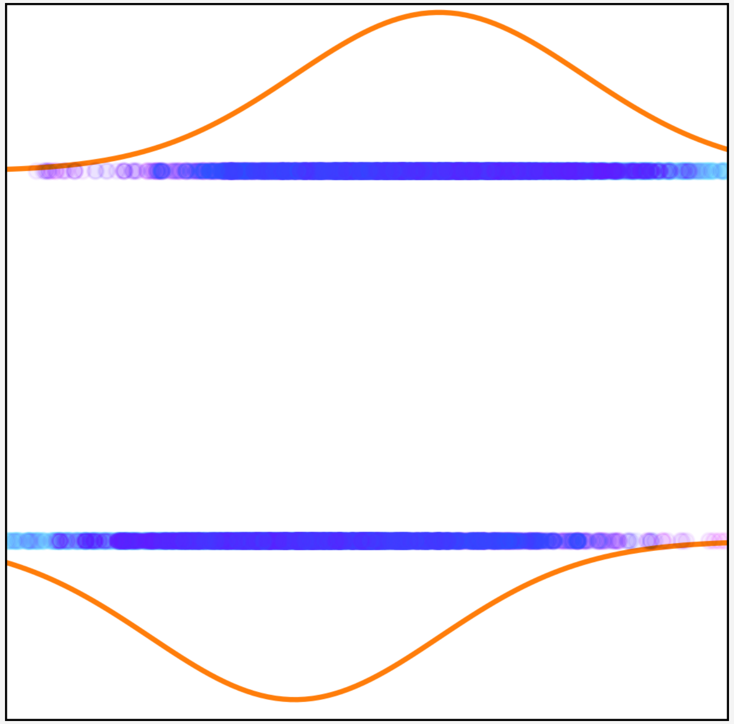
The deviation between approx. and full off-shell calculation



The Direct Diffusion network

- Off-Shell event $x_{off}(t=0)=x_0$, on-shell events $x_{on}(t=1)=x_1$ respectively





[arXiv:2209.15571, arXiv:2210.02747, arXiv:2209.03003, arXiv:2305.10475v2]

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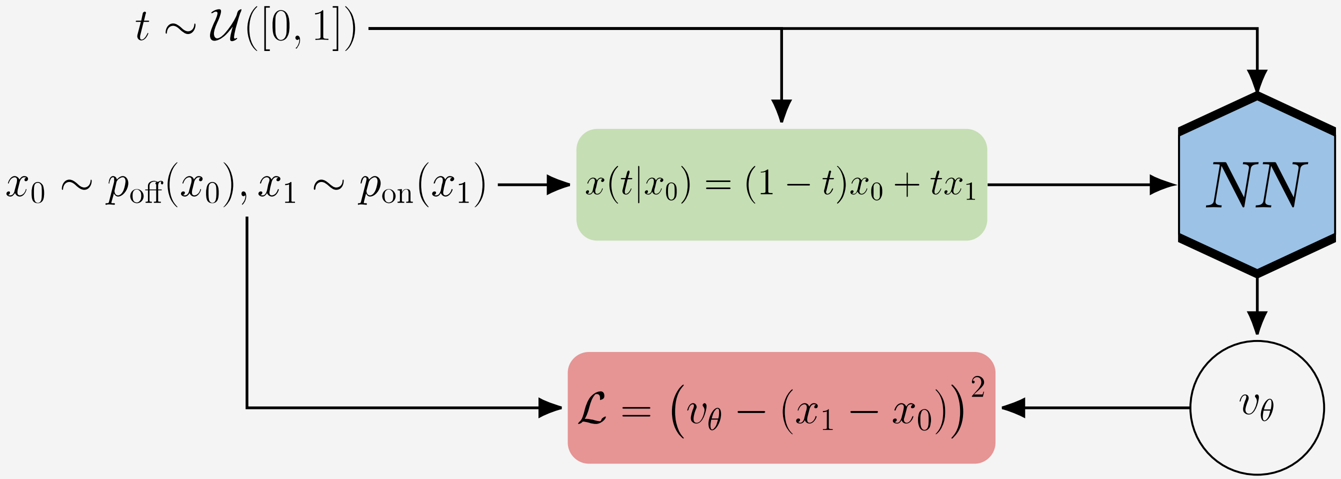

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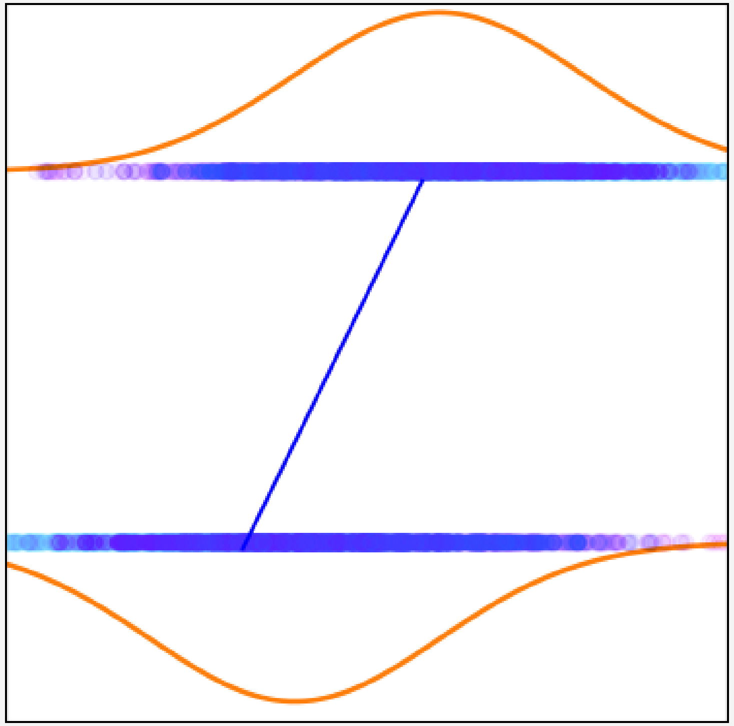

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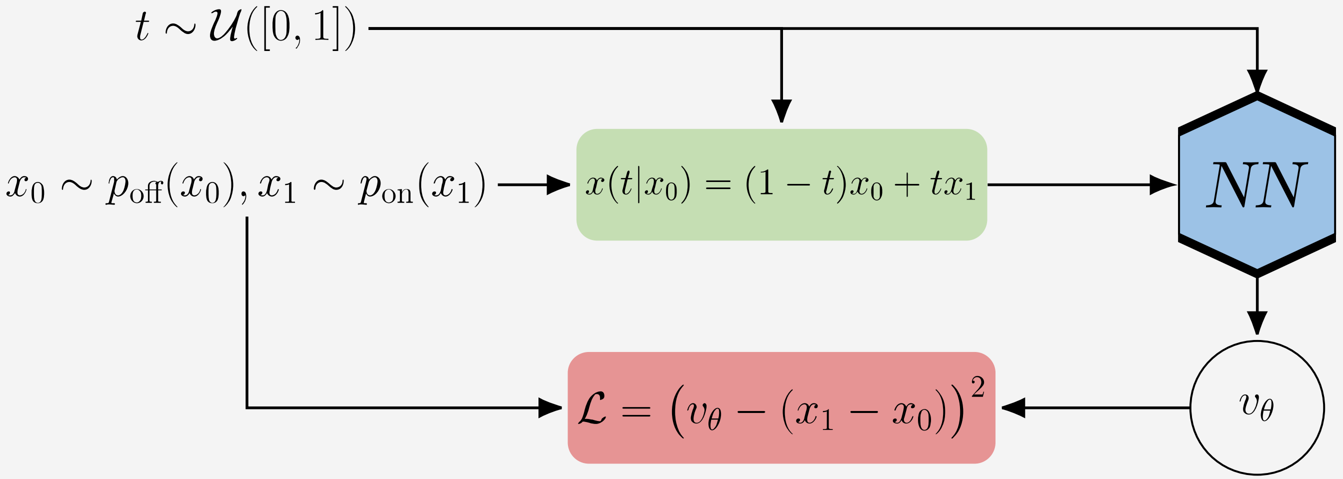

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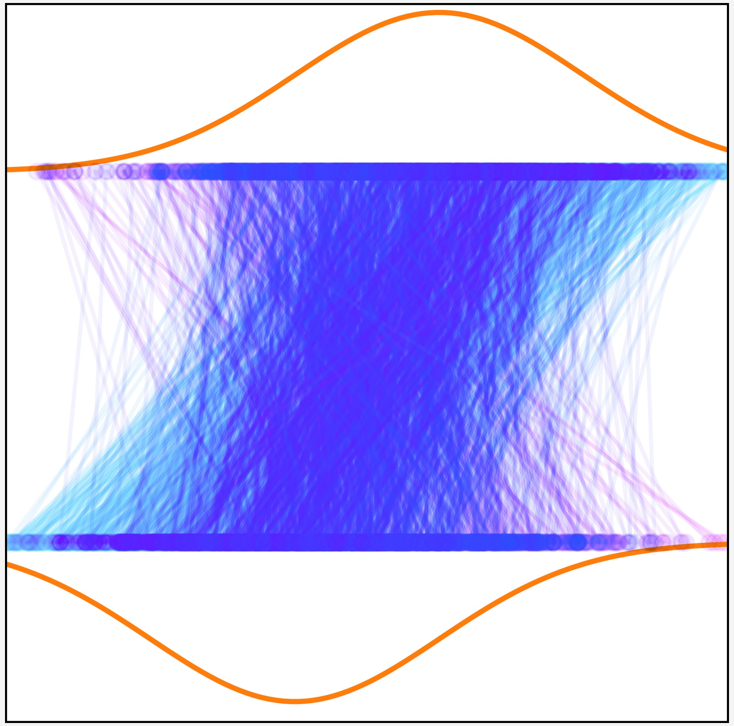

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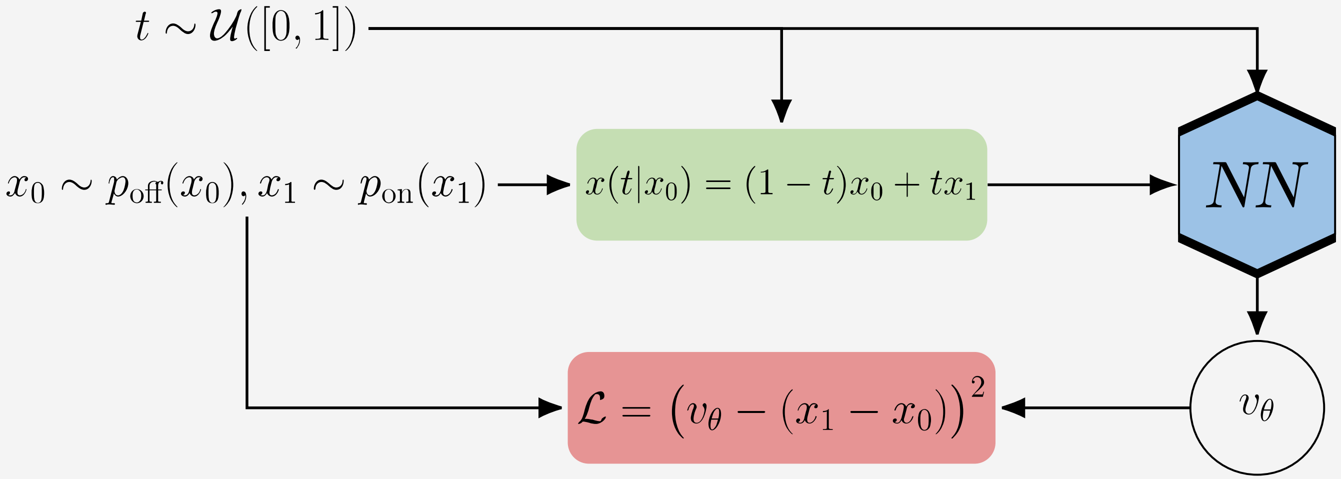

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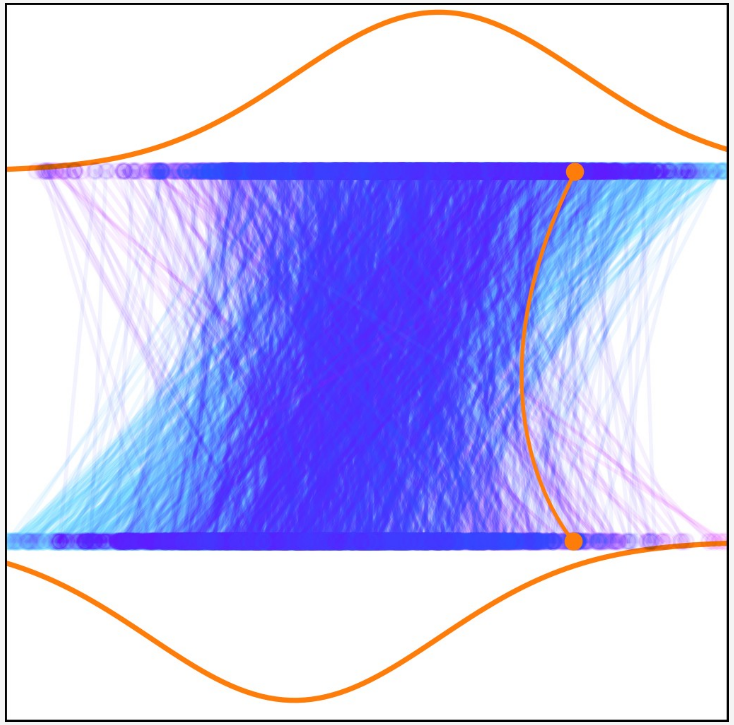
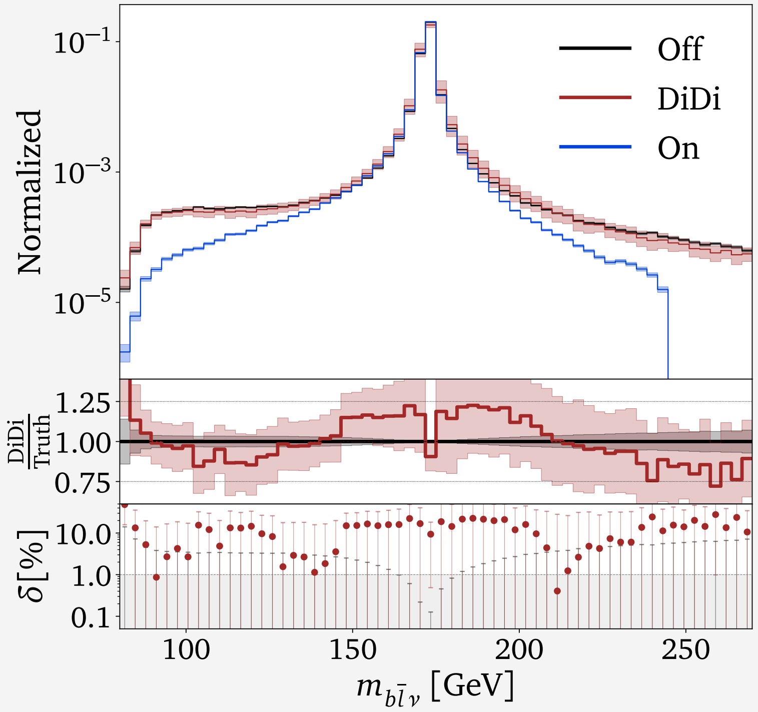
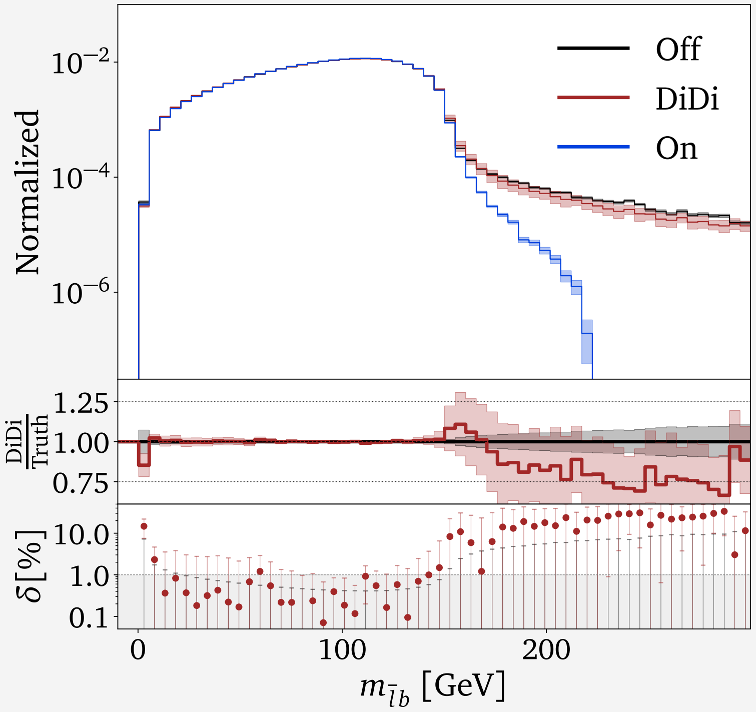


Results of the Direct Diffusion network





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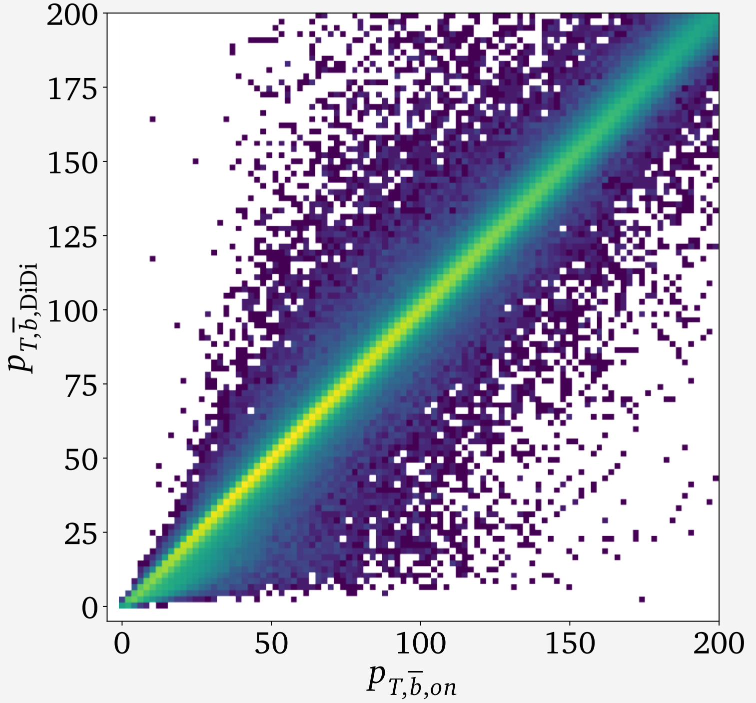
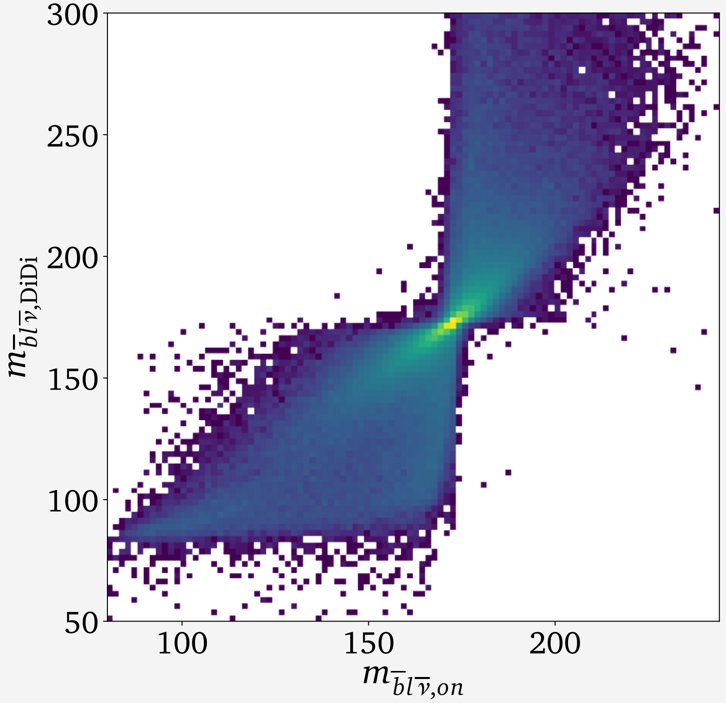
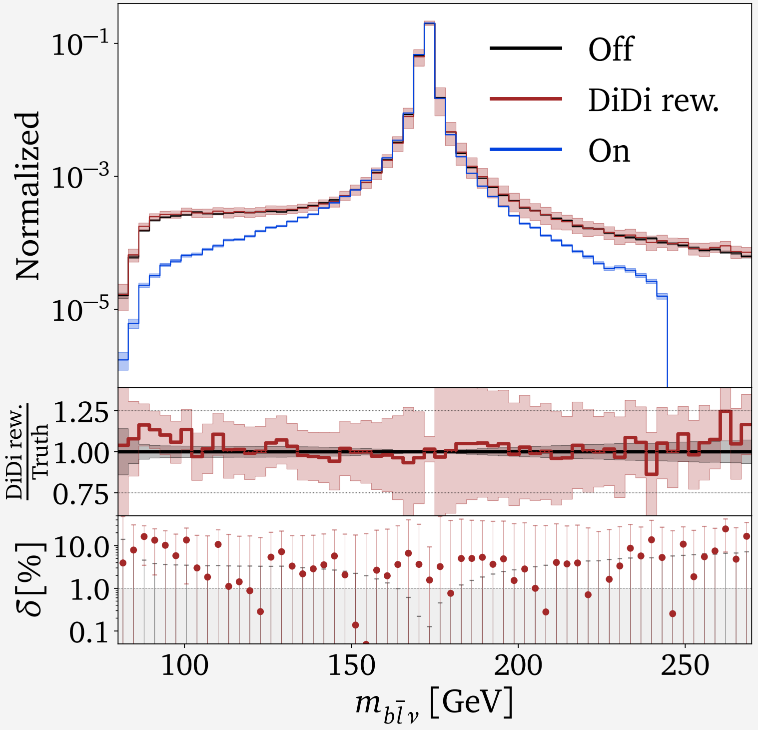
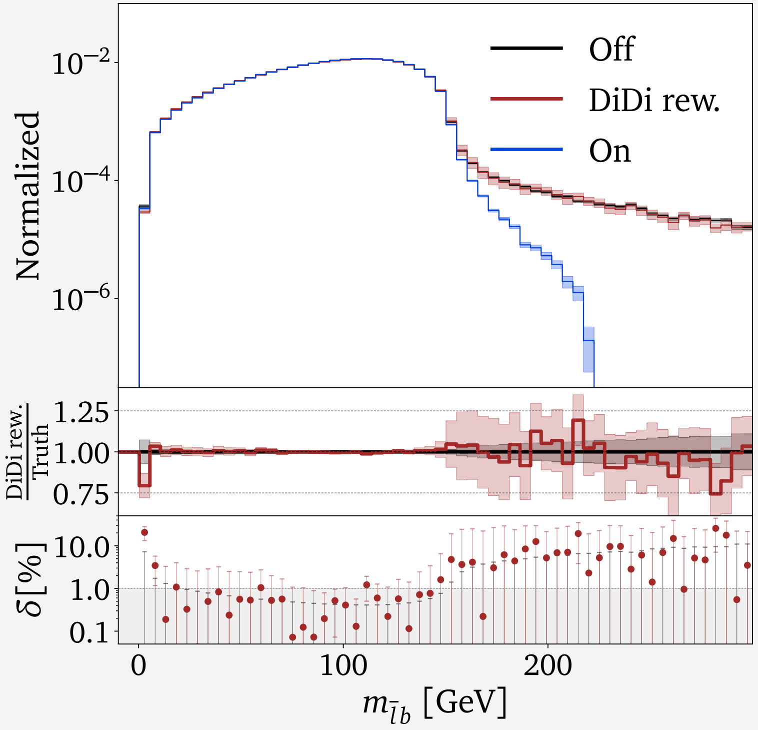




Results after an additional Reweighting





$$C(x) = \frac{p_{\text{off,data}}(x)}{p_{\text{off,data}}(x) + p_{\text{off,model}}(x)}$$

$$w(x) = \frac{p_{\text{off,data}}(x)}{p_{\text{off,model}}(x)} = \frac{C(x)}{1 - C(x)}$$

Conclusion & Outlook

- Small network with limited training effort can reproduce the target off-shell kinematics at the 10% level or better with only 5 million events
- Classifier reweighting improves its precision to the level of few percent even in challenging kinematic distributions
- Paper: Kicking it Off(-shell) with Direct Diffusion [arXiv:2311.17175]
- Advance to higher orders (paper in the making)
  - Increased dimensionality (DiDi scales well)
  - Contribution from single top (ongoing)
- Analyze impact on showering

Backup slides: NLO results

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