Application of Machine Learning techniques to the discovery of new physics

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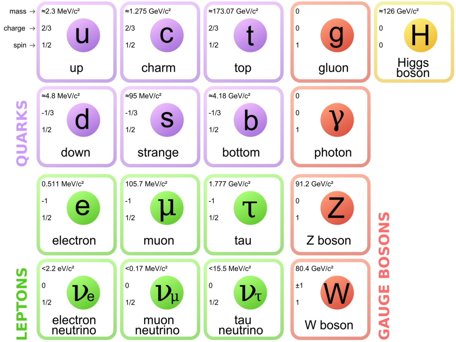
Outline

1. Problem description
2. Machine Learning techniques
3. Results
4. Conclusions

Flavor-changing neutral currents FCNC

- $B \to K^* \mu\mu$
- $\Delta S = \Delta Q = \pm 1$.
- $\Delta S = 2$ and FCNC only at second order in SM.
- Very suppressed processes by GIM mechanism.
- Candidates to search for new physics.



GIM mechanism

- Put forth by Sheldon Lee Glashow, John Iliopoulos and Luciano Maiani.
- Required the introduction of a new quark.
- mass-squared difference of the different virtual quarks exchanged in the box diagram.

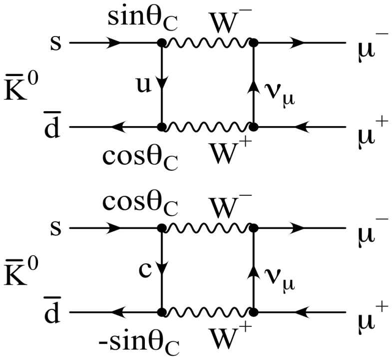


Figure:

Neutral Kaon decay [17]

Experimental data

- In 2013, the LHCb collaboration announced the measurement of angular observables describing the decay $B \to K\mu\mu$.
- Two observables, P_2 and P_5' were in significant disagreement with the SM expectations.
- $RK = Br(B \to K\mu\mu)/Br(B \to Kee)$ measurement $\neq 1$. Could indicate Lepton Flavor Universality Violation (LFUV).

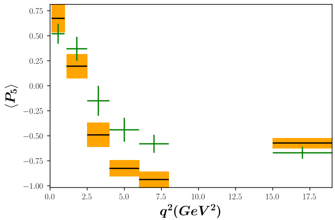


Figure: Observable P_5.

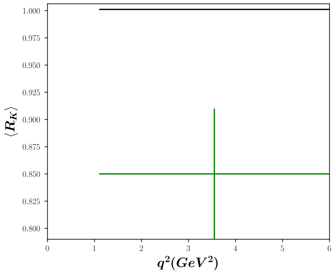


Figure: $R_K = Br(B \to K\mu\mu)/Br(B \to Kee)$.

Searching for New Physics

- Effective field theory framework (EFT)

$$\mathcal{H}_{eff} = -\frac{4G_F}{\sqrt{2}} V_{tb} V_{ts}^* \sum_i \mathcal{C}_i \mathcal{O}_i.$$

- Heavy degrees of freedom (the top quark, the W and Z bosons, the Higgs and any heavy new particle) are integrated out in short-distance Wilson coefficients $\mathcal{C}_i$, leaving only a set of operators $\mathcal{O}_i$ describing the physics at long distances.
- In the SM, the Hamiltonian contains 10 main operators with specific chiralities due to the V - A structure of the weak interactions.
- We reduce such set to the two dominant operators:

$$\mathcal{O}_9 = \frac{e}{16\pi^2} m_b (\bar{s}\gamma_\mu P_L b)(\bar{\ell}\gamma^\mu \ell),$$

$$\mathcal{O}_{10} = \frac{e}{16\pi^2} m_b (\bar{s}\gamma_\mu P_L b)(\bar{\ell}\gamma^\mu \gamma_5 \ell).$$

Searching for New Physics

- Current analysis of anomalies in flavor physics are based on a linear regression of a χ^2 function.
- The observables measured by the experimental collaborations can be written in terms of the C_i Wilson coefficients.
- It is common to split the Wilson coefficients in two pieces: the SM contributions and the NP contributions:

$$C_9 = C_9^{SM} + C_9^{NP}$$

$$C_{10} = C_{10}^{SM} + C_{10}^{NP}$$

Discriminative vs Generative

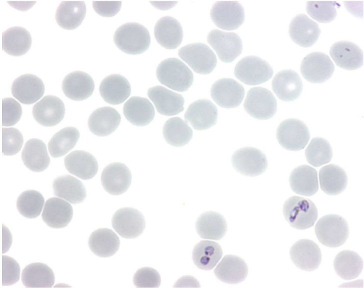
- Two distinct approaches to solving decision problems.
- Generative:
  - Determine the class-conditional densities $p(x|C_k)$ for each class individually and the prior class probabilities.
  - Use Bayes theorem to find the posterior:

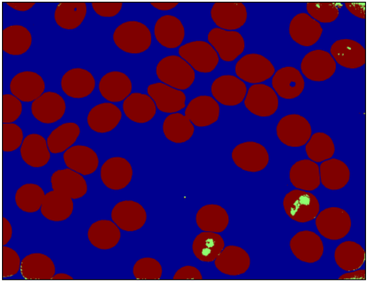
$$p(C_k|x) = \frac{p(x|C_k)p(C_k)}{p(x)}$$

  - We have a model of our data. We can sample from it.
  - E.g.: Naive Bayes, Mixture Models, Generative Adversarial Networks.
- Discriminative:
  - We have labeled data.
  - Directly determine the posterior class probabilities $p(C_k|x)$.
  - E.g.: Neural Networks.

Generative models

- $p(x|\mu, \Sigma, \pi) = \sum_{i=1}^{k} \pi_i p(x|\mu_i, \Sigma_i)$.
- Model the probability distribution of the data.
- Fit model parameters using Maximum Likelihood.
- Use Bayes theorem to classify new data point.





Generative Adversarial Networks (GANs)

- First described in the 2014 paper by Ian Goodfellow [16].
- **What are they?** $\rightarrow$ Model architecture for training a generative model.
- Implicitly learn rich distributions hard to model with an explicit likelihood.

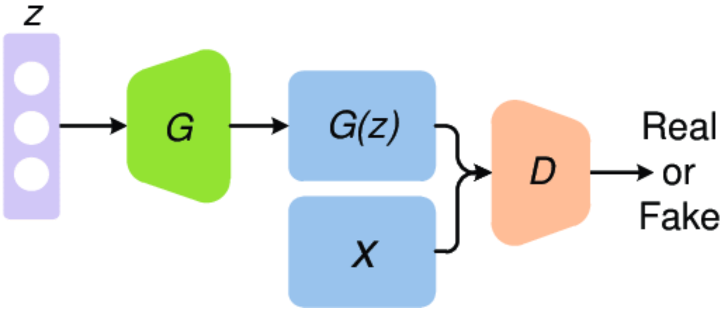


Figure: **GAN architecture**, from Recent Progress on Generative Adversarial Networks (GANs): A Survey [15]

GAN training problems

- **Vanishing gradients** $\rightarrow$ optimal discriminator doesn't provide enough information for the generator to make progress.
- **Mode collapse** $\rightarrow$ if a generator produces an especially plausible output, the generator may learn to produce only that output.
- **Failure to converge** $\rightarrow$ If the generator succeeds perfectly, then the discriminator has a 50% accuracy and the discriminator feedback gets less meaningful over time.

Results. Dataset

- 8 observables.
- 37 bin values.
- 10000 samples.
- 10×10 $C_9 \in [-2, 0]$, $C_{10} \in [-1, 1]$.
- 100 $a_0, a_1, a_2 \in [-0.01, 0.01]$.

$C_9 = -1.33$, $C_{10} = -0.44$ $\chi^2 = 23.33$	a_0	a_1	a_2
P_1	-0.093	0.001	0
P_2	-0.093	0.001	0
P_4	-0.093	0.001	0
P_5	-0.093	0.001	0
BrK^{0*}	-0.093	0.001	0
BrK^{0}	-0.093	0.001	0
R_K	-0.093	0.001	0
R_{K^*}	-0.093	0.001	0

Figure: Coefficients of sample in training set with lowest χ^2 value.

Results. Neural networks

$C_9 = -0.79,\ C_{10} = -0.07,\ \chi^2 = 29.5$	a_0	a_1	a_2
P_1	0	0	0
P_2	0	0	0
P_4	0.03	0	0
P_5	0.02	0	0
BrK^{0*}	-0.01	0	0
BrK^0	-0.01	0	0
R_K	-0.01	0	0
R_{K^*}	-0.01	0	0

Figure: Coefficients predicted by the NN after training

Results. GAN

$C_9 = -0.74,\ C_{10} = -0.62\ ,\ \chi^2 = 373.48$	a_0	a_1	a_2
P_1	0.012	0.016	0.0008
P_2	-0.017	0.030	-0.002
P_4	-0.010	0.010	-0.001
P_5	0.001	0.008	0.0003
BrK^{0*}	-0.026	0.023	0.001
BrK^{0}	-0.008	0.014	0.005
R_K	-0.019	0.012	-0.004
R_{K^*}	-0.013	0.011	-0.006

Figure: Coefficients with lowest χ^2 sampled from GAN.

Conclusions

- The parametrization of the observables

Thank you

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