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Machine Learning Applied to $b \to s\ell^+\ell^-$

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Outline

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Outline

Motivation

Angular observables in $B \to K^* \mu^+ \mu^-$

Tension: $\sim 2\sigma$

Long distance (LD) effects

Hard to compute

Solution

Neural Network

Outline

Effective Hamiltonian

$$\mathcal{H}_{\text{eff}} = \frac{4G_F}{\sqrt{2}} V_{tb} V_{ts}^* \sum_i C_i O_i \,,$$

$$O_9 = \frac{e^2}{16\pi^2}(\bar{s}\gamma_\nu P_L b)(\bar{\mu}\gamma^\nu \mu)\,, \quad O_{10} = \frac{e^2}{16\pi^2}(\bar{s}\gamma_\nu P_L b)(\bar{\mu}\gamma^\nu \gamma_5 \mu)\,.$$

$\bar{B}^0 \to \bar{K}^{*0}(\to K^-\pi^+)\mu^+\mu^-$

Differential decay rate

$$\frac{d^4\Gamma}{dq^2\, d\cos\theta_l\, d\cos\theta_{K^*}\, d\phi} = \sum_i a_i J_i$$

Angular coefficients

$J_i = J_i(C_i, FFs, LD, ..)$

Issue

Dependence on LD effects

Optimized observables

Descotes-Genon/Hurth/Matias/Virto: 1303.5794

P_i

Linear combinations of J_i

Example

$P_{5'} = (J_5 + \bar{J}_5)/2\mathcal{N}'$

Advantage

small dependence on FFs

Goal

Find optimized observables

Small dependence on LD effects

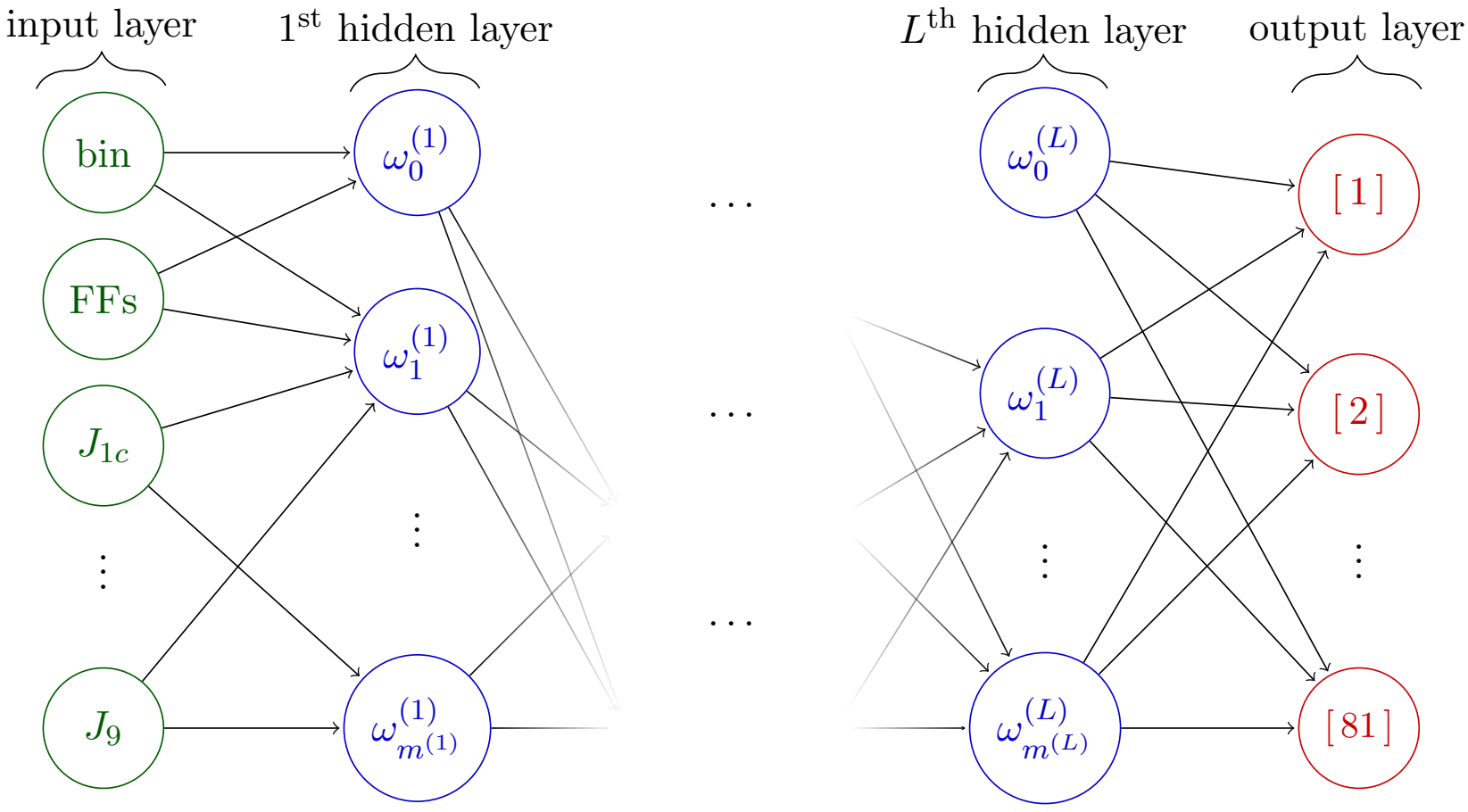
Form

Lin. comb. of J's

Parameter inference

Find C_9, C_{10}, divided into classes

Neural Network



Outline

Training data

WCs

$C_9^{NP} \in [-C_9^{SM}, C_9^{SM}], \quad C_{10}^{NP} \in [-C_{10}^{SM}, C_{10}^{SM}]$

FFs

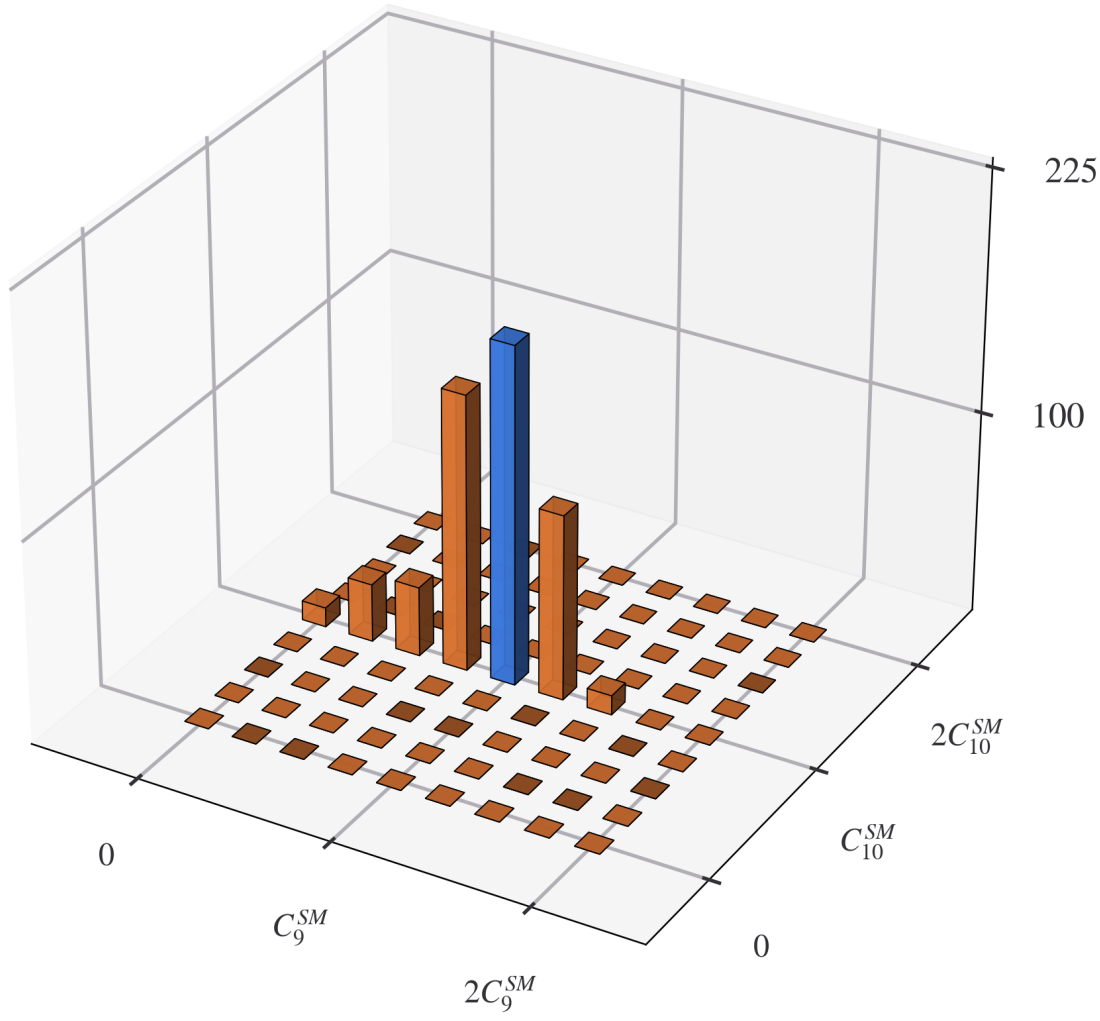
Bharucha/Straub/Zwicky: 1503.05534

SSE parameters

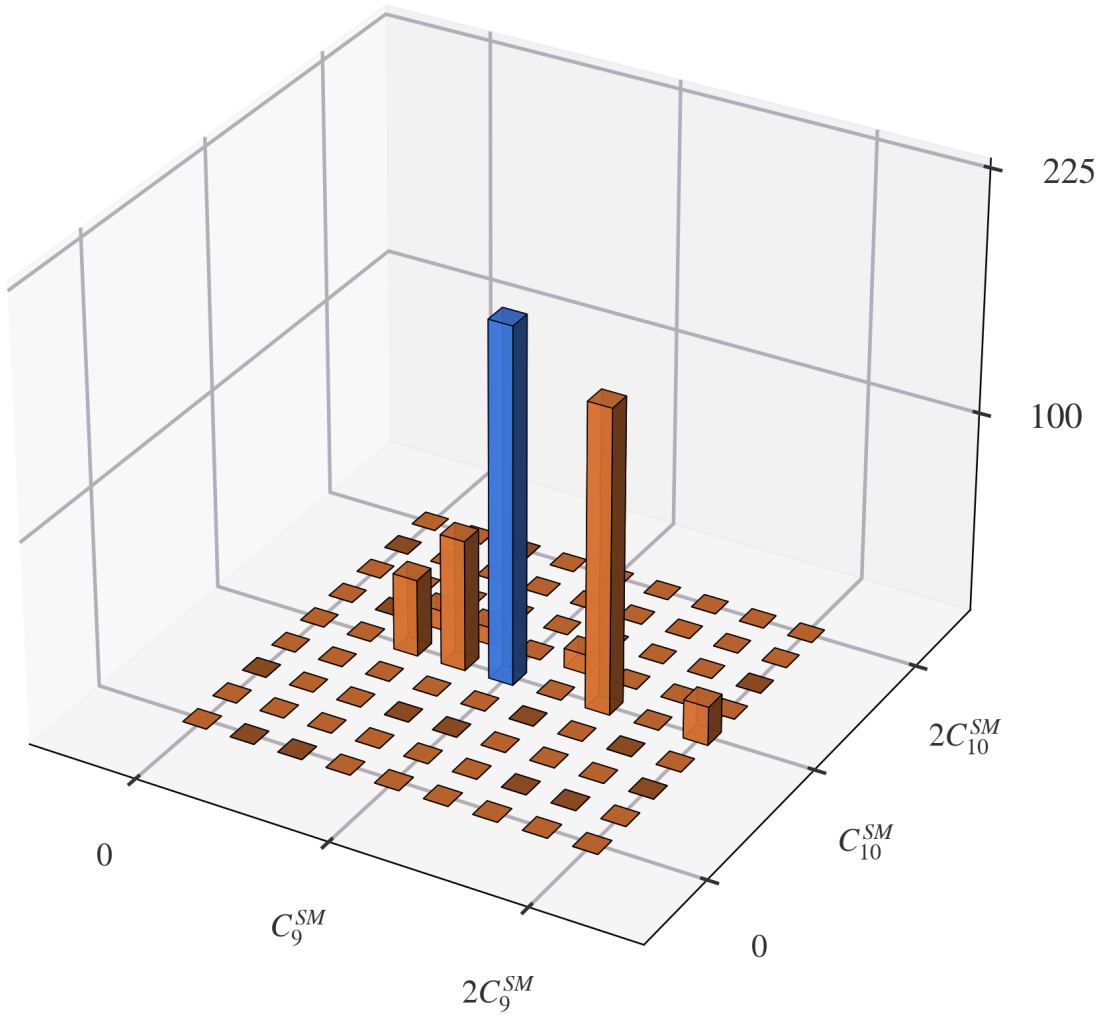
LD

$C_9 \to C_9 + \Delta C_9^{LD}$

Result: Small LD



Result: large LD



Outline

Summary

Angular observables for $B \to K^* \mu^+ \mu^-$

Depend on LD contributions

ML techniques

NN that minimizes dependence on LD

Parameter inference

comparable results