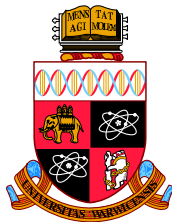


# Unbinned model-independent measurements with quantum-correlated $D^0$ decays

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# Introduction

- Model-independent approach to describe multibody  $D$  decays can be (and is) used in various measurements
    - CKM angle  $\gamma$  from  $B \rightarrow DK, DK\pi$
    - CKM angle  $\beta$  from  $B^0 \rightarrow Dh^0, Dh h$
    - Charm mixing and CP violation in charm
  - Uses the fact that we can obtain both the magnitude and phase difference between  $D^0$  and  $\bar{D}^0$  from data (using quantum-correlated  $D^0\bar{D}^0$  pairs from CLEO/BESIII)
  - Uses **bins** (piecewise uniform function) to approximate varying amplitude; constructed such that even though approximation is rough, physics observables are **unbiased**.
- 
- Here I will show that binned approximation is not the only one possible.
  - Use  $\gamma$  measurement in  $B \rightarrow DK, D \rightarrow K_S^0 \pi^+ \pi^-$  as an example, but technique could be extended to multibody  $B$  decay fits ( $B \rightarrow DK\pi$ ) and time-dependent fits ( $\alpha$ , charm mixing).
  - Refer to [\[arXiv:1712.08326\]](https://arxiv.org/abs/1712.08326) for details

Reminder:  $\gamma$  from  $B \rightarrow DK$ ,  $D \rightarrow K_S^0 \pi^+ \pi^-$

[GGSZ, 2003; Bondar, 2002]

Information on  $\gamma$  from Dalitz plot analysis of  $D \rightarrow K_S^0 \pi^+ \pi^-$  from  $B \rightarrow DK$ .

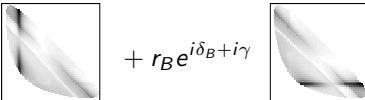
Dalitz plot density:  $d\sigma(m_+^2, m_-^2) \sim |A|^2 dm_+^2 dm_-^2$ , where  $m_\pm^2 = m_{K_S \pi^\pm}^2$

Flavor  $D$  amplitude:  $A_D(m_+^2, m_-^2) \equiv A_D(\mathbf{z})$

$CP$ -conservation in  $D \rightarrow K_S^0 \pi^+ \pi^-$  decays:  $\bar{A}_D(m_+^2, m_-^2) = A_D(m_-^2, m_+^2)$

Amplitude of  $D \rightarrow K_S^0 \pi^+ \pi^-$  from  $B^+ \rightarrow DK^+$ :

$$A_B(m_+^2, m_-^2) = A_D(m_+^2, m_-^2) + r_B e^{i\delta_B + i\gamma} A_D(m_-^2, m_+^2)$$

$$= \text{[Dalitz Plot 1]} + r_B e^{i\delta_B + i\gamma} \text{[Dalitz Plot 2]}$$


Need to know  $A_D(m_+^2, m_-^2)$ , both amplitude and phase (or, more precisely, phase difference between  $(m_+^2, m_-^2)$  and  $(m_-^2, m_+^2)$ ).

**Model-dependent:** obtain  $A_D$  from  $D \rightarrow K_S^0 \pi^+ \pi^-$  fit to the isobar model  $\Rightarrow$  model uncertainty

**Model-independent:** obtain phase difference info from  $e^+ e^- \rightarrow D^0 \bar{D}^0$  decays.

# Reminder: binned model-independent technique

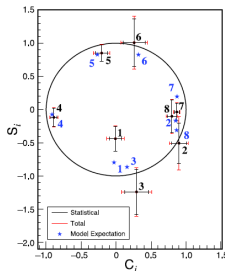
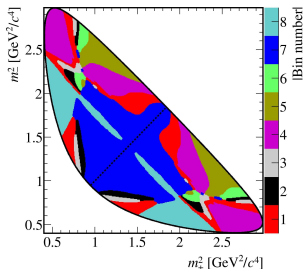
**Model-independent:** use binned Dalitz plot, deal with bin yields.  
Use symmetric binning,  $m_+ > m_-$  for  $i > 0$ ,  $m_+ < m_-$  for  $i < 0$  bins.  
Relation between bin yields for  $B^+ \rightarrow DK^+$  and flavour-specific  $D$ .

$$N_{\pm i}(B^+) = h_{B^+} [K_i + r_B^2 K_{-i} + 2\sqrt{K_i K_{-i}}(x_+ c_i + y_+ s_i)]$$

(+c.c., which is mostly omitted in this presentation).

$x_{\pm} = r_B \cos(\delta_B \pm \gamma)$ ,  $y_{\pm} = r_B \sin(\delta_B \pm \gamma)$  are free parameters.

To reach optimal precision, need bins where phase difference is  $\sim$  constant, so the amplitudes add up coherently across bin area.



Model-inspired binning used by CLEO ( $8 \times 2$  bins). [CLEO, PRD82 (2010)]

# Phase coefficients $c_i, s_i$

$c_i = \langle \cos \Delta\delta_D \rangle$ ,  $s_i = \langle \sin \Delta\delta_D \rangle$  measured by CLEO (BESIII) in  $e^+e^- \rightarrow D^0\bar{D}^0$ .  
Density of correlated  $D \rightarrow K_S^0\pi^+\pi^-$  Dalitz plots:

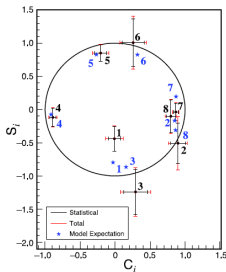
$$p_{DD}(m_+^2, m_-^2, m_+^{\prime 2}, m_-^{\prime 2}) \propto |f_D \bar{f}_D' - \bar{f}_D f_D'|^2 \propto$$

$$p_D \bar{p}_D' + p_D' \bar{p}_D - 2\sqrt{p_D \bar{p}_D' p_D' \bar{p}_D}(cc' + ss')$$

After binning:

$$M_{ij} \propto K_i K_{-j} + K_{-i} K_j - 2\sqrt{K_i K_{-j} K_{-i} K_j}(c_i c_j + s_i s_j)$$

which gives  $c_i, s_i$  in the fit.



$c_i, s_i$  are aligned around a circle, and their values are well consistent with the calculations from the  $D \rightarrow K_S^0\pi^+\pi^-$  model.

**Do we really need 16 independent parameters to describe an (almost) circle in the phase?**

Not really, but then need to go beyond simple binned approximation.

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# Model-independent formalism with weighted integrals

## Charm data observables:

$$p_D(\mathbf{z}) = |A_D(\mathbf{z})|^2, \quad \bar{p}_D(\mathbf{z}) = |\bar{A}_D(\mathbf{z})|^2$$

## $B^\pm \rightarrow DK^\pm$ data observables:

$$\bar{p}_B(\mathbf{z}) \propto p_D(\mathbf{z}) + r_B^2 \bar{p}_D(\mathbf{z}) + 2[x_+ C(\mathbf{z}) - y_+ S(\mathbf{z})]$$

$$p_B(\mathbf{z}) \propto \bar{p}_D(\mathbf{z}) + r_B^2 p_D(\mathbf{z}) + 2[x_+ C(\mathbf{z}) + y_+ S(\mathbf{z})]$$

## Quantum-correlated $D^0 \bar{D}^0$ data observables:

$$p_{DD}(\mathbf{z}_1, \mathbf{z}_2) \propto p_D(\mathbf{z}_1) \bar{p}_D(\mathbf{z}_2) + p_D(\mathbf{z}_2) \bar{p}_D(\mathbf{z}_1) - 2[C(\mathbf{z}_1)C(\mathbf{z}_2) + S(\mathbf{z}_1)S(\mathbf{z}_2)]$$

## Unknowns:

$$C(\mathbf{z}) = \text{Re} [A_D^*(\mathbf{z}) \bar{A}_D(\mathbf{z})], \quad S(\mathbf{z}) = \text{Im} [A_D^*(\mathbf{z}) \bar{A}_D(\mathbf{z})].$$

We want to relate  $p_D(\mathbf{z})$ ,  $\bar{p}_B(\mathbf{z})$  and  $p_{DD}(\mathbf{z}_1, \mathbf{z}_2)$  and eliminate  $C(\mathbf{z}), S(\mathbf{z})$ .

We need a way to do it with scattered experimental data.

# Model-independent formalism with weighted integrals

**Trick:** replace all functions  $f(\mathbf{z}) \rightarrow \int_{\mathcal{D}} f(\mathbf{z}) w_n(\mathbf{z}) d\mathbf{z}$

where  $f(\mathbf{z}) = p_D(\mathbf{z}), \bar{p}_B(\mathbf{z}), C(\mathbf{z}), S(\mathbf{z})$ .

$w_n(\mathbf{z}), 1 \leq n \leq N$  is a family of certain weight functions.

Similarly,  $p_{DD}(\mathbf{z}_1, \mathbf{z}_2) \rightarrow \int_{\mathcal{D}} p_{DD}(\mathbf{z}_1, \mathbf{z}_2) w_m(\mathbf{z}_1) w_n(\mathbf{z}_2) d\mathbf{z}_1 d\mathbf{z}_2$

All the equations will still hold, for any  $w_n(\mathbf{z})$ .

For scattered data, replace integrals by sums over individual events.

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**Binned approach** is a particular case with

$$w_n(\mathbf{z}) = \begin{cases} 1 & \text{if } \mathbf{z} \in \mathcal{D}_n \\ 0 & \text{otherwise} \end{cases} \quad \text{for bins defined by } \mathcal{D}_n.$$

Alternative approach: **Fourier analysis of the modelled phase difference**

$$w_{2n}(\mathbf{z}) = \sin n\Phi(\mathbf{z}), \quad w_{2n+1} = \cos n\Phi(\mathbf{z})$$

where

$$\Phi(\mathbf{z}) = \arg A_D^{(\text{model})}(\mathbf{z}) - \arg \bar{A}_D^{(\text{model})}(\mathbf{z})$$



# Fourier analysis approach

Let's see why Fourier analysis approach is more optimal

We already use model to define optimal binning, the first step is just a continuous generalisation: instead of bins in  $\Delta\phi$  we use a continuous variable  $\phi$ . E.g. for  $D \rightarrow K_S^0 \pi^+ \pi^-$  Dalitz plot, define

$$\Phi(m_+^2, m_-^2) = \arg A_D^{(\text{model})}(m_+^2, m_-^2) - \arg A_D^{(\text{model})}(m_-^2, m_+^2)$$

Instead of binning in  $\Phi(\mathbf{z})$ , deal with continuous 1D distribution:

$$p_D(\phi) = \int_{\Phi(\mathcal{D})=\phi} p_D(\mathcal{D}) d\mathcal{D}$$

It is just a PDFs of the  $\phi = \Phi(\mathcal{D})$  variable for the flavour  $D$  sample ( $\mathcal{D} \equiv (m_+^2, m_-^2)$ ).

Define all functions of  $\phi$  similarly ( $\bar{p}_B(\phi)$ ,  $p_{DD}(\phi_1, \phi_2)$ ,  $C(\phi)$ ,  $S(\phi)$ )

- $C(\phi)$  is even,  $S(\phi)$  is odd by construction

# Fourier analysis approach

Now we have relation between 1D  $p_D(\phi)$  distributions for flavour  $D$  and 2D  $p_{DD}(\phi_1, \phi_2)$  distributions for correlated  $D^0 \bar{D}^0$ :

$$p_{DD}(\phi_1, \phi_2) \propto p_D(\phi_1)\bar{p}_D(\phi_2) + \bar{p}_D(\phi_1)p_D(\phi_2) - 2[C(\phi_1)C(\phi_2) + S(\phi_1)S(\phi_2)]$$

This constrains  $S(\phi)$  and  $C(\phi)$ , which we can apply to  $B^+ \rightarrow DK^+$ :

$$\bar{p}_B(\phi) \propto p_D(\phi) + r_B^2 \bar{p}_D(\phi) + 2[x_+ C(\phi) - y_+ S(\phi)],$$

and extract  $x$  and  $y$  (and thus  $\gamma$ , after adding  $B^-$ ).

We still need a way to parametrise functions  $C(\phi)$  and  $S(\phi)$  to deal with scattered data.

These functions are continuous, periodic, and *resemble*  $\cos \phi$  and  $\sin \phi$ , so Fourier series is a natural parametrisation.

- Calculating Fourier transformation of scattered data is easy.
- Most of the information will already be contained in the leading Fourier term!

# Equations for coefficients of Fourier series

So,  $p_D(\phi)$  will be parametrised by Fourier series:

$$p_D(\phi) = \frac{a_0^D}{2} + \sum_{n=1}^M [a_n^D \cos(n\phi) + b_n^D \sin(n\phi)],$$

similarly for  $\bar{p}_B(\phi)$  (coeffs  $a_n^B$ ,  $b_n^B$ ),

$C(\phi)$  (coeffs  $a_n^C$ , only cosine terms),

$S(\phi)$  (coeffs  $b_n^S$ , only sine terms)

$p_{DD}(\phi_1, \phi_2)$  (coeffs  $a_{nm}^{DD}$ ,  $b_{nm}^{DD}$ ,  $c_{nm}^{DD}$ , and  $d_{nm}^{DD}$ )

They will be related as

$$a_{mn}^{DD} = 2h_{DD} (a_m^D a_n^D - a_m^C a_n^C),$$

$$b_{mn}^{DD} = c_{mn}^{DD} = 0, \quad \text{for } D^0 \bar{D}^0 \text{ data}$$

$$d_{mn}^{DD} = -2h_{DD} (b_m^D b_n^D + b_m^S b_n^S).$$

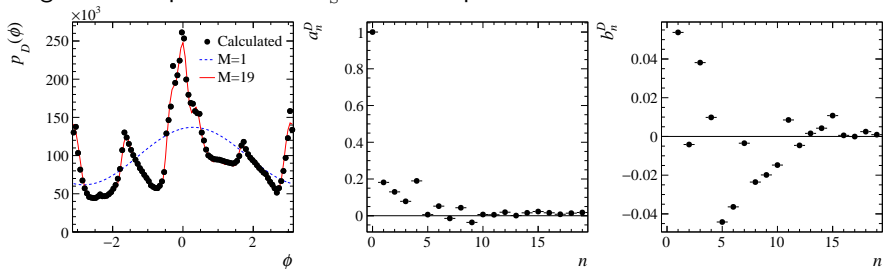
and

$$a_n^B = h_B [(1 + r_B^2) a_n^D + 2x_- a_n^C],$$

$$b_n^B = h_B [(1 - r_B^2) b_n^D + 2y_- b_n^S]. \quad \text{for } B \rightarrow DK \text{ data}$$

System of equations, can be solved for any  $M \geq 1$  with maximum likelihood fit

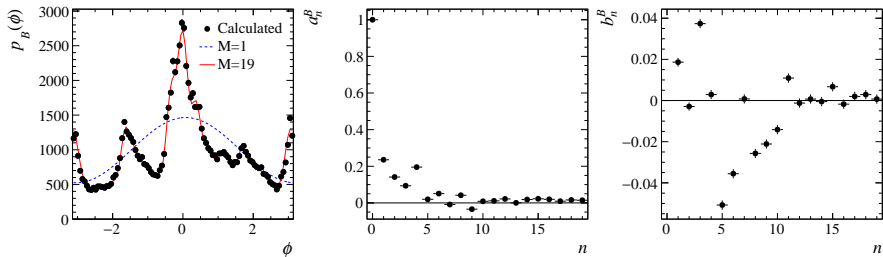
Large flavour-specific  $D \rightarrow K_s^0 \pi^+ \pi^-$  sample:  $10^7$  events



$p_D(\phi)$  density and its spectral coefficients.

Blue line is expansion up to  $M = 1$  (first term in Fourier series)

Large  $B^+ \rightarrow DK^+$  sample:  $10^5$  events

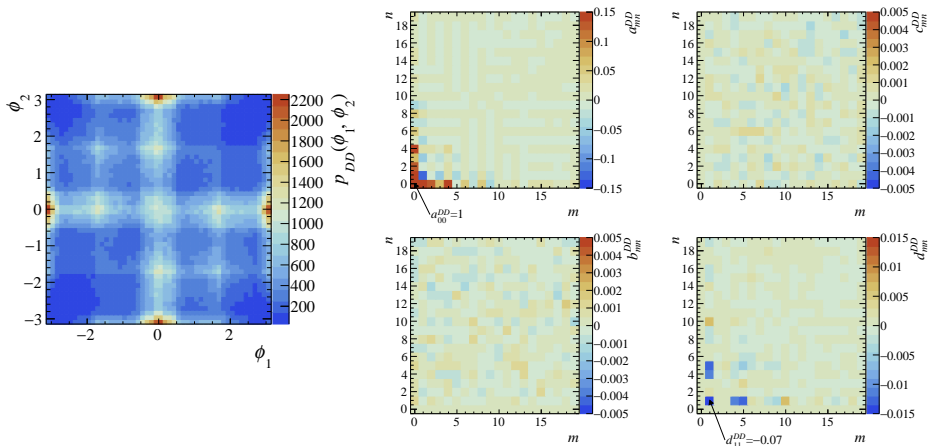


$\bar{p}_B(\phi)$  density and its spectral coefficients.

Blue line is expansion up to  $M = 1$  (first term in Fourier series)

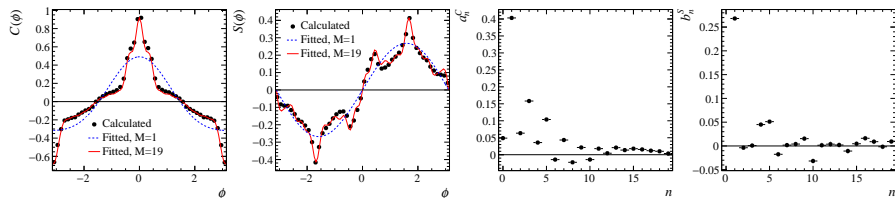
# Toy MC results

Large quantum-correlated  $D\bar{D}$  sample:  $10^6$  events



$p_{DD}(\phi_1, \phi_2)$  density and its (2D) spectral coefficients

This allows us to calculate  $(a, b)_n^{C,S}$  and reconstruct  $C(\phi)$  and  $S(\phi)$  (although to measure  $\gamma$  we don't need explicit functions, only coefficients)



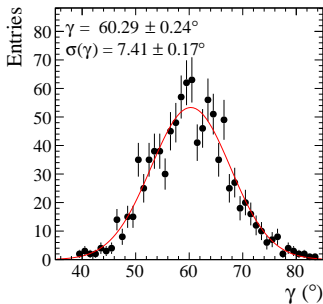
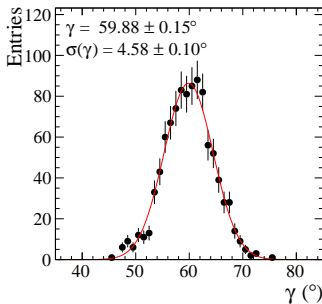
Spectral coefficients for  $C(\phi)$  and  $S(\phi)$  functions and reconstructed functions  
 As expected, largest “power” is in the 1st harmonics,  $\cos \phi$  term for  $C(\phi)$  and  $\sin \phi$  term for  $S(\phi)$

- With  $M = 1$ , only 3 free parameters of the  $D^0$  amplitude:  $a_0^C$ ,  $a_1^C$  and  $b_1^S$

# Toy MC results

Finally, perform  $\gamma$  fit.  $10^4 B^+ \rightarrow DK^+$  decays with  $\gamma = 60^\circ$ , 1000 toy samples.

Check that the method is  $\sim$ unbiased for any number of harmonics  $M$ , as well as if “wrong” model is used for phase variation  $\Phi(m_+^2, m_-^2)$ :



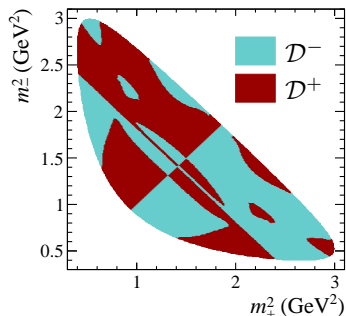
Reduced model: a simplified  $D \rightarrow K_S^0 \pi^+ \pi^-$  model with only  $K^*(892)$ ,  $\rho$ ,  $\omega$ ,  $f_0(980)$  + flat non-resonant term, used only for phase difference mapping (*i.e.* different from the generated one).



# Further improvement: split Dalitz plot

Using only phase difference information is not optimal, because regions with different  $|A_D|$  are treated equally. In the binned approach: “optimal” binning from stochastic optimisation of a certain FoM.

A straightforward solution for Fourier analysis: split Dalitz plot.



Split phase space into two regions, with  
 $|A_D^{(\text{model})}(\mathbf{z})| > |\bar{A}_D^{(\text{model})}(\mathbf{z})| \quad (\mathcal{D}^+)$

and

$|A_D^{(\text{model})}(\mathbf{z})| < |\bar{A}_D^{(\text{model})}(\mathbf{z})| \quad (\mathcal{D}^-)$

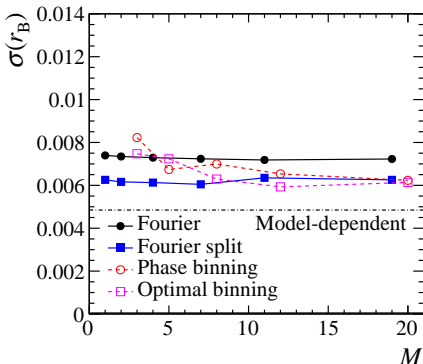
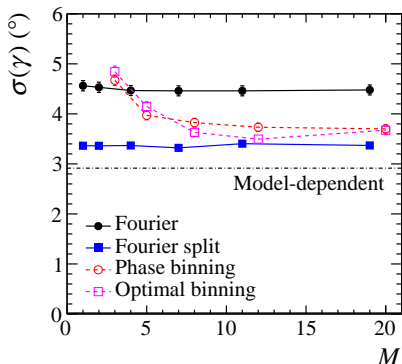
Perform Fourier analysis separately in the two regions

Can consider splitting into more regions.

More fitted parameters, but better follow  $|A|$ , needs optimisation.

# Toy MC results: $\gamma$ precision

$10^7 D \rightarrow K_S^0 \pi^+ \pi^-$ ,  $10^5 D \bar{D}$ ,  $10^4 B^+ \rightarrow DK^+$ , 1000 toy MC samples

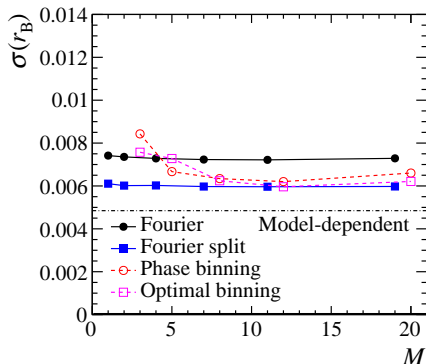
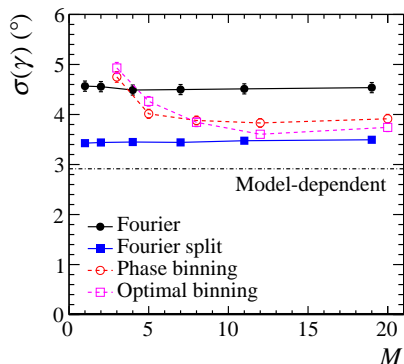


Very large sample of  $D \bar{D}$  events  $\Rightarrow$  precisely defined phase dependence.  
Weak dependence on number of harmonics, first one dominates.\*

\* Not guaranteed to be the case for any  $D$  decay, or if  $D$  model used for phase differs from true one

# Toy MC results: $\gamma$ precision

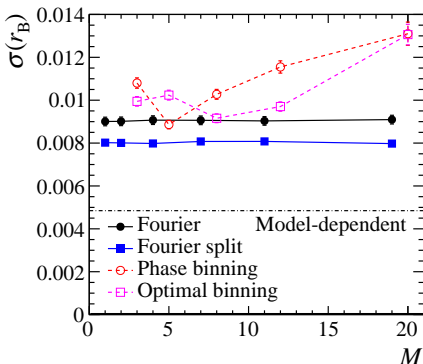
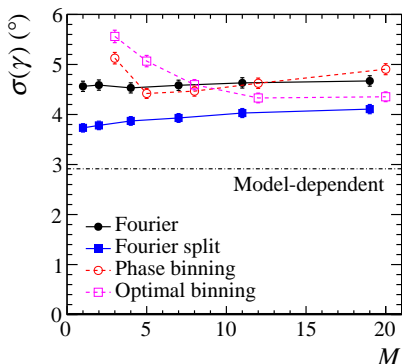
$10^7 D \rightarrow K_s^0 \pi^+ \pi^-$ ,  $10^4 D\bar{D}$ ,  $10^4 B^+ \rightarrow DK^+$ , 1000 toy MC samples



Equal samples of  $D\bar{D}$  and  $B$  events ( $\sim$  current situation for  $B \rightarrow DK$ ).  
 $D^0\bar{D}^0$  sample does not dominate in uncertainty

# Toy MC results: $\gamma$ precision

$10^7 D \rightarrow K_S^0 \pi^+ \pi^-$ , 1000  $D\bar{D}$ ,  $10^4 B^+ \rightarrow DK^+$ , 1000 toy MC samples



Very small sample of  $D\bar{D}$  events (1/10th of  $B$  sample).

Low number of free parameters of  $D^0$  amplitude is an advantage.

# Toy MC results: $\gamma$ precision

Sample size	$\gamma$ resolution, $^\circ$		
	Binned optimal	Fourier non-split	Fourier split
$2 \times 10^4 B^\pm \rightarrow DK^\pm, 10^3 D^0 \bar{D}^0$	$4.33 \pm 0.10$	$4.54 \pm 0.10$	$3.73 \pm 0.08$
$2 \times 10^4 B^\pm \rightarrow DK^\pm, 10^4 D^0 \bar{D}^0$	$3.60 \pm 0.08$	$4.51 \pm 0.10$	$3.43 \pm 0.08$
$2 \times 10^4 B^\pm \rightarrow DK^\pm, 10^5 D^0 \bar{D}^0$	$3.49 \pm 0.10$	$4.47 \pm 0.10$	$3.32 \pm 0.08$

For reference:

- Model-dependent approach:  $\sigma(\gamma) = 2.91 \pm 0.07^\circ$
- $B$  sample used here is roughly  $\times 10$  LHCb Run I sample
- CLEO: 470 events of  $D^0 \bar{D}^0 \rightarrow (K_S^0 \pi^+ \pi^-)^2$   
(+ other combinations, notably with  $K_L^0 \pi^+ \pi^-$ )

Fourier analysis is a good approximation to the optimum, but still not perfect:  $|A_D|$  information is either ignored (non-split) or taken very roughly (split approach).

How do we choose the set of weight functions  $w_n(\mathbf{z})$  such that  $\gamma$  precision is optimal?

Just a thought: can try to use machine learning technique:

- Choose generic  $w_n(\mathbf{z})$  parametrisations with e.g. NN or BDT.  
(or  $w_n(\phi, |A_D|, |\bar{A}_D|)$ )
- Apply  $w_n(\mathbf{z})$  to a set of toy MC samples, run  $\gamma$  fit.
- Use  $|\gamma_{\text{rec}} - \gamma_{\text{sim}}|^2$  as cost function, and apply ML to minimise cost.

The optimal solution will likely depend on  $B \rightarrow DK$  and  $D^0 \bar{D}^0$  samples, as well as on background levels.

- Quantum-correlated  $D^0\bar{D}^0$  data are **essential for many fundamental measurements**, including CKM  $\gamma$ ,  $\beta$  and charm mixing.
- These measurements have **extremely low theory uncertainties**, so any improvement in statistical treatment immediately pays off.
- Propose an approach alternative to conventional model-independent binned technique
  - Instead of performing model-independent fits in (limited number of) bins of the phase space, one works with **coefficients of Fourier series** of the phase difference spectrum.
  - Needs less parameters than binned technique: already the leading term in Fourier series contains most of the information.
    - Minimum: only 3 parameters to describe the phase variations.
  - More efficient use of QC data, could be useful when QC sample is limited, e.g.  $B \rightarrow DK$  with  $D \rightarrow 4h$  or  $B \rightarrow DK\pi$ ,  $D \rightarrow K_S^0\pi^+\pi^-$  double Dalitz.
- Further improvements possible, need more study.

Calculation of Fourier coefficients from scattered data  $\phi^{(i)}$ :

$$a_n = \frac{1}{\pi} \sum_{i=1}^N \cos(n\phi^{(i)}), \quad b_n = \frac{1}{\pi} \sum_{i=1}^N \sin(n\phi^{(i)}),$$

For ML fit, also need covariance matrix (uncertainties and correlations) coming from the limited sample size. It can be calculated by applying Poisson bootstrapping: each term entering the sum is multiplied by a Poisson-distributed random number with mean of 1.

E.g. dispersion is calculated from central limit theorem:

$$\sigma^2(a_n) = \frac{1}{\pi} \sum_{i=1}^N \cos^2(n\phi^{(i)}), \quad \sigma^2(b_n) = \frac{1}{\pi} \sum_{i=1}^N \sin^2(n\phi^{(i)}),$$

This is a certain approximation, but seems to work well for  $N > 100$  (pulls are compatible with 1).