# The role of Padé approximants as fitting functions in the context of the MuonE experiment

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## Introduction



#### **Problem**

Finding a reliable method to fit the data + good **extrapolation** outside data region





- Already applied in similar contexts:
  - Masjuan, Peris (2009) arXiv:0903.0294 [hep-ph]
  - Golterman, Maltman, Peris (2014) arXiv:1405.2389 [hep-lat]

arXiv:1512.07555 [hep-lat]

- Chakraborty, Davies, de Oliveira, Koponen, Lepage, van de Water (2016)
- Aubin, Blum, Chau, Golterman, Peris, Tu (2017) arXiv:1601.03071 [hep-lat]
- Masjuan, Sanchez-Puertas (2017) arXiv:1701.05829 [hep-ph]

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#### **Advantages of PAs**

- Systematic and model-independent method
- Partial reconstruction of analytical (physical) properties
- Efficient approximation
- Possible to provide a convergence error

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#### **Padé's Theory**

#### **Stieltjes function**



- There are convergence theorems for PAs to Stieltjes functions
- Some convergence properties:

\* poles of 
$$P_N^{N+J}$$
,  $J \ge -1$ , are real and simple;

- \* Padé sequences  $P_N^{N+J}$ ,  $J \ge -1$ , uniformity converge to the original function;
- \* Padés act as bounds of the function

$$\lim_{N \to \infty} P_N^N(t) \ge \bar{\Pi}(t) \ge \lim_{N \to \infty} P_N^{N+1}(t)$$

### **Padé's Theory**



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Method

#### **Data Generation**



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#### Model of Greynat and de Rafael

$$\operatorname{Im}\Pi_{\text{had}}(s) = \alpha \left(1 - \frac{4m_{\pi}^2}{s}\right)^{3/2} \left[\frac{1}{12} |F(s)|^2 + \Theta(s) \sum_{\text{quarks}} q_f^2\right] \theta(s - 4m_{\pi}^2)$$

model used to generate toy data

Greynat, de Rafael (2022)

$$\begin{split} \Gamma(s) &= \frac{m_{\rho} s}{96\pi f_{\pi}^2} \left[ \left( 1 - \frac{4m_{\pi}^2}{s} \right)^{3/2} \theta(s - 4m_{\pi}^2) \\ &+ \frac{1}{2} \left( 1 - \frac{4m_{\pi}^2}{s} \right)^{3/2} \theta(s - 4m_{K}^2) \right] & (5) \\ |F(s)|^2 &= \frac{m_{\rho}^4}{(m_{\rho}^2 - s)^2 + m_{\rho}^2 \Gamma^2(s)} \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\arctan(\frac{s-s_c}{\Delta}) - \arctan(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})}{\operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{4m_{\pi}^2 - s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{2}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{s-s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{s-s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{s-s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{s-s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{\operatorname{arctan}(\frac{s-s_c}{\Delta}) - \operatorname{arctan}(\frac{s-s_c}{\Delta})}{\operatorname{arctan}(\frac{s-s_c}{\Delta})} \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \right] & (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \\ (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \\ (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \\ (5) \\ \Theta(s) &= \frac{1}{\pi} \left[ \frac{s-s_c}{\Delta} \right] \\ (5) \\ \Theta(s) &=$$

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## **Fitting Method**

• Padés as fitting functions

 $(\theta_{\mu}, R_{\text{had}})$  $0.16 \le \theta_{\mu}(\text{mrad}) \le 4.8$ 

30 equally spaced data points

 $(x, R_{\text{had}}^{\text{mod}})$  $0.214 \le x \le 0.932$ 

$$R_{\rm had}^{\rm mod} = (R_{\rm had} - 1) \times 10^5 \approx 10^5 \times 2\,\Delta\alpha_{\rm had}$$

$$\Delta \alpha_{\text{had}}(x) = \sum_{n=0}^{\infty} c_n \, x^n = c_2 \, x^2 + c_3 \, x^3 + \dots$$

- PA parameters:  $\chi^2$  minimization
- Error propagation: Monte Carlo

# Example

#### Toy data set

- Data points  $(x, \overline{\Pi}_{had})$  generated in the interval  $0.23 \le x \le 0.93$  in steps of 0.01
- Central value randomly chosen from a gaussian distribution with  $1\ \%$  error



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#### Toy data set



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## Padés to the model

#### **Canonical Padés**

- Canonical Padé  $P_N^M$ :
  - determination of the PA coefficients through matching
  - PA reproduces the first M + N + 1 Taylor series coefficients of the function



• Data without fluctuations or errors — estimate method uncertainty



- Data without fluctuations or errors estimate method uncertainty
- Padés as fitting functions imposing that  $c_0 = c_1 = 0$
- PAs used to calculate  $a_{\mu}$  in the whole region of  $x \in [0,1]$
- Better results for higher-order PAs
- Uncertainty from the method is small



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$$\Delta \alpha_{\text{model}}(t) = k \left\{ -\frac{5}{9} - \frac{4M}{3t} + \left(\frac{4M^2}{3t^2} + \frac{M}{3t} - \frac{1}{6}\right) \frac{2}{\sqrt{1 - \frac{4M}{t}}} \log \left| \frac{1 - \sqrt{1 - \frac{4M}{t}}}{1 + \sqrt{1 - \frac{4M}{t}}} \right| \right\}$$



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- 1000 toy data sets generated
- $(\theta_{\mu}, R_{had}) 30$  data points equally spaced in the interval  $0.16 \le \theta_{\mu}(mrad) \le 4.8$
- Central value randomly chosen from a gaussian distribution with  $0.001\,\%\,$  error precision of  $\mathcal{O}(10^{-5})$
- Selecting data sets whose relative error between its central value for  $a_{\mu}^{\rm partial}$  and the true one is lower than 1 %
- Monte Carlo analysis of the fits for each Padé approximant
- PAs used to calculate  $a_{\mu}$  in the whole x region

• 1000 toy data sets generated



• PAs used to calculate  $a_{\mu}$  in the whole x region

• 1000 toy data sets generated



• 1000 toy data sets generated







- Covariance between Padés predictions still needs to be computed
- Method uncertainty has to be added



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Dividing the error of the data points by 5

- No need for data points in larger values of x, but for lower errors
- Central value predicted by  $\Delta \alpha_{\rm model}$  is more distant from the real  $a_{\mu}$  than the Padés

# Conclusions and Outlooks



• Plots so far presented are based on a particular model

• Uncertainty due to the method can be estimated and is small

- Error of the model  $\Delta \alpha_{\rm model}$  is larger than the one coming from Padés method — has to be computed in final value

- Larger value of  $E_{\mu}$  is not needed but smaller errors of data points

#### Outlooks

- Results of Padés may be improved by employing:
  - partial Padés;
  - D-log Padés;
  - conformal mapping Padés also converge;
  - include the moments of the correlator;
  - \* impose  $c_2 = c_3$ ; model independent!



impose other constraints in PAs analysis

 Padés as fitting functions to data need more studies — no convergence theorems

# Thank you for your attention!





