New developments in partial-wave analysis with light hadrons

Boris Grube

Institute for Hadronic Structure and Fundamental Symmetries Technische Universität München Garching, Germany

> PWA10/ATHOS5 IHEP Beijing, 17. July 2018







Era of High-Precision Data Sets

- E.g. from BESIII, COMPASS, GlueX, VES, ...
- Interesting excited light-meson states often decay into multi-body final states
 - Requires modelling of decay amplitudes
 - Often isobar model is used
- Partial-wave analyses (PWA) limited by systematic uncertainties due to model dependence
- Estimation of model dependence often difficult

Systematic uncertainties of the isobar model: (some) challenges

- How to determine the wave set?
- How to verify and improve the isobar parametrizations?

This talk

- Discuss ideas to study or reduce model dependence
- Use as an example PWA of $\pi^-\pi^-\pi^+$ data from COMPASS

Era of High-Precision Data Sets

- E.g. from BESIII, COMPASS, GlueX, VES, ...
- Interesting excited light-meson states often decay into multi-body final states
 - Requires modelling of decay amplitudes
 - Often isobar model is used
- Partial-wave analyses (PWA) limited by systematic uncertainties due to model dependence
- Estimation of model dependence often difficult

Systematic uncertainties of the isobar model: (some) challenges

- How to determine the wave set?
- Item to verify and improve the isobar parametrizations?

This talk

- Discuss ideas to study or reduce model dependence
- Use as an example PWA of $\pi^-\pi^-\pi^+$ data from COMPASS

Era of High-Precision Data Sets

- E.g. from BESIII, COMPASS, GlueX, VES, ...
- Interesting excited light-meson states often decay into multi-body final states
 - Requires modelling of decay amplitudes
 - Often isobar model is used
- Partial-wave analyses (PWA) limited by systematic uncertainties due to model dependence
- Estimation of model dependence often difficult

Systematic uncertainties of the isobar model: (some) challenges

- How to determine the wave set?
- Item to verify and improve the isobar parametrizations?

This talk

- Discuss ideas to study or reduce model dependence
- Use as an example PWA of $\pi^-\pi^-\pi^+$ data from COMPASS



- 191 GeV / c pion beam
- Exclusive measurement
 - Clean data sample
- $46 \times 10^{\circ} \pi^{-} \pi^{-} \pi^{+}$ events
- Squared four-momentum transfer 0.1 < t' < 1.0 (GeV/c)²
- Well-known 3π resonances appear in m_{3π} spectrum





C. Adolph et al., PRD 95 (2017) 032004



C. Adolph et al., PRD 95 (2017) 032004



Decay of *X* via intermediate $\pi^-\pi^+$ resonances = "isobars"

C. Adolph et al., PRD 95 (2017) 032004



Decay of *X* via intermediate $\pi^-\pi^+$ resonances = "isobars"

Boris Grube, TU München New developments in partial-wave analysis with light hadrons









C. Adolph et al., PRD 95 (2017) 032004

PWA fit in give $n(m_{3\pi}, t')$ bin

• Neglect $m_{3\pi}$ and t' dependence within bin

$$\mathrm{d}\sigma \propto \underbrace{\left|\sum_{i}^{\mathrm{waves}} \mathcal{T}_{i} \Psi_{i}(\tau)\right|^{2}}_{\equiv \mathcal{I}(\tau; \{\mathcal{T}_{i}\})} \mathrm{dLIPS}_{3}(\tau)$$

• Model for measured τ distribution: intensity $\mathcal{I}(\tau; \{\mathcal{T}_i\})$



C. Adolph et al., PRD 95 (2017) 032004

PWA fit in given $(m_{3\pi}, t')$ bin

• Neglect $m_{3\pi}$ and t' dependence within bin

$$\mathrm{d}\sigma \propto \underbrace{\left|\sum_{i}^{\mathrm{waves}} \mathcal{T}_{i} \Psi_{i}(\tau)\right|^{2}}_{\equiv \mathcal{I}(\tau; \{\mathcal{T}_{i}\})} \mathrm{dLIPS}_{3}(\tau)$$

- Model for measured τ distribution: intensity $\mathcal{I}(\tau; \{\mathcal{T}_i\})$
- Extended likelihood function

$$\mathcal{L}_{\text{ext}}(\{\mathcal{T}_i\}) = \underbrace{\frac{\overline{N}^N e^{-\overline{N}}}{N!}}_{\text{Poisson}} \prod_{k=1}^N \underbrace{\frac{\mathcal{I}(\tau_k; \{\mathcal{T}_i\})}{\int \text{dLIPS}_3(\tau) \eta(\tau) \mathcal{I}(\tau; \{\mathcal{T}_i\})}}_{\text{Probability density}}$$

• Estimate $\{\mathcal{T}_i\}$ by maximizing $\ln \mathcal{L}_{ext}$

C. Adolph et al., PRD 95 (2017) 032004

- Maximum likelihood fit performed independently in narrow m_{3π} and t' bins
- PWA makes no assumptions about contributing 3π resonances



Partial-wave notation: $J^{PC} M^{\epsilon} \xi \pi L$

C. Adolph et al., PRD 95 (2017) 032004

- Maximum likelihood fit performed independently in narrow m_{3π} and t' bins
- PWA makes no assumptions about contributing 3π resonances



Partial-wave notation: $J^{PC} M^{\varepsilon} \xi \pi L$

- Maximum likelihood fit performed independently in narrow $m_{3\pi}$ and t' bins
- PWA makes no assumptions about contributing 3π resonances



PWA of $\pi^-\pi^-\pi^+$ Final State: Major Waves



PWA of $\pi^-\pi^-\pi^+$ Final State: Major Waves



PWA of $\pi^-\pi^-\pi^+$ Final State: Major Waves





Up to now, wave sets constructed "by hand"

- Often stepwise trial-and-error procedure
- Remove or add single waves and look at change of ln L_{ext} or intensity of wave



● But only finite data sample ⇒ have to select wave set

Up to now, wave sets constructed "by hand"

- Often stepwise trial-and-error procedure
- Remove or add single waves and look at change of ln L_{ext} or intensity of wave



C. Adolph et al., PRD 95 (2017) 032004



Fit model

- Included isobar resonances:
 - $[\pi\pi]_S \qquad J^{PC} = 0^{++}$
 - $\rho(770)$ 1⁻⁻ • $f_{0}(980)$ 0⁺⁺
 - $f_0(980)$ 0⁺⁺ • $f_2(1270)$ 2⁺⁺
 - $f_0(1500)$ 0⁺⁺

3

- ρ₃(1690)
- Requires precise knowledge of isobar $\rightarrow \pi^{-}\pi^{+}$ amplitudes

- *J* and *L* up to 6
- 87 partial waves
- Additional incoherent isotropic background wave
- Derived from 128 wave set by removing waves with relative intensities $\lesssim 10^{-4}$

Construction "by hand"

- Not a well-defined procedure
- Difficult to document and reproduce
- Danger of introducing observer bias
- Very time consuming procedure
- Stepwise procedures are known to be suboptimal

A. Miller, Subset Selection in Regression, Chapman and Hall/CRC, London (2002)

Alternative approach: add regularization terms to log-likelihood function

Guegan et al., JINST 10 (2015) 09002; K. Bicker, PhD thesis, TUM (2016); O. Drotleff, Master thesis,

TUM (2015); F. Kaspar, Master thesis, TUM (2017)

$$\ln \mathcal{L}(\{\mathcal{T}_i\}) = \ln \mathcal{L}_{ext}(\{\mathcal{T}_i\}) + \ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$$

- Choose $\mathcal{L}_{reg}(\{\mathcal{T}_i\})$ such that
 - Jeaves waves with large intensities unchanged
- Use systematically constructed set of allowed partial waves up to cut-off criterion = "wave pool"

Construction "by hand"

- Not a well-defined procedure
- Difficult to document and reproduce
- Danger of introducing observer bias
- Very time consuming procedure
- Stepwise procedures are known to be suboptimal

A. Miller, Subset Selection in Regression, Chapman and Hall/CRC, London (2002)

Alternative approach: add regularization terms to log-likelihood function

Guegan et al., JINST 10 (2015) 09002; K. Bicker, PhD thesis, TUM (2016); O. Drotleff, Master thesis,

TUM (2015); F. Kaspar, Master thesis, TUM (2017)

$$\ln \mathcal{L}(\{\mathcal{T}_i\}) = \ln \mathcal{L}_{ext}(\{\mathcal{T}_i\}) + \ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$$

- Choose $\mathcal{L}_{reg}(\{\mathcal{T}_i\})$ such that
 - ullet it suppresses waves with small intensities $|\mathcal{T}_i|^2$
 - leaves waves with large intensities unchanged
- Use systematically constructed set of allowed partial waves up to cut-off criterion = "wave pool"

Construction "by hand"

- Not a well-defined procedure
- Difficult to document and reproduce
- Danger of introducing observer bias
- Very time consuming procedure
- Stepwise procedures are known to be suboptimal

A. Miller, Subset Selection in Regression, Chapman and Hall/CRC, London (2002)

Alternative approach: add regularization terms to log-likelihood function

Guegan et al., JINST 10 (2015) 09002; K. Bicker, PhD thesis, TUM (2016); O. Drotleff, Master thesis,

TUM (2015); F. Kaspar, Master thesis, TUM (2017)

$$\ln \mathcal{L}(\{\mathcal{T}_i\}) = \ln \mathcal{L}_{ext}(\{\mathcal{T}_i\}) + \ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$$

- Choose $\mathcal{L}_{reg}(\{\mathcal{T}_i\})$ such that
 - it suppresses waves with small intensities $|\mathcal{T}_i|^2$
 - leaves waves with large intensities unchanged
- Use systematically constructed set of allowed partial waves up to cut-off criterion = "wave pool"

"Cauchy" Regularization Term

$$\mathcal{L}_{\text{reg}}(\{\mathcal{T}_i\}) = \prod_{i}^{\text{waves}} \frac{1}{1 + |\mathcal{T}_i|^2 / \Gamma^2}$$
$$\ln \mathcal{L}_{\text{Cauchy}} = \ln \mathcal{L}_{\text{ext}} - \sum_{i}^{\text{waves}} \ln \left[1 + \frac{|\mathcal{T}_i|^2}{\Gamma^2}\right]$$

- \mathcal{L}_{reg} has Cauchy form in $|\mathcal{T}_i|$
- "Heavy tailed" distribution
- Pulls intensities of small waves toward zero
- Small bias for large waves

 $\ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$ in \mathcal{T}_i plane



"Cauchy" Regularization Term

$$\mathcal{L}_{\text{reg}}(\{\mathcal{T}_i\}) = \prod_i^{\text{waves}} \frac{1}{1 + |\mathcal{T}_i|^2 / \Gamma^2}$$
$$\ln \mathcal{L}_{\text{Cauchy}} = \ln \mathcal{L}_{\text{ext}} - \sum_i^{\text{waves}} \ln \left[1 + \frac{|\mathcal{T}_i|^2}{\Gamma^2}\right]$$

- \mathcal{L}_{reg} has Cauchy form in $|\mathcal{T}_i|$
- "Heavy tailed" distribution
- Pulls intensities of small waves toward zero
- Small bias for large waves

 $\ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$ in \mathcal{T}_i plane



"Cauchy" Prior



Monte Carlo data generated using 88-wave fit result from real data

- Black: 235 waves in wave pool ordered by intensity
- Red: waves from fit with 88-wave input model
- Clear drop in intensities \Rightarrow clear place where to cut
 - Selected waves have intensities similar to fit with input model
 - Wrongly deselected waves that are actually in input model are small (< 10 events)

"Cauchy" Prior



Monte Carlo data generated using 88-wave fit result from real data

- Black: 235 waves in wave pool ordered by intensity
- Red: waves from fit with 88-wave input model
- Clear drop in intensities ⇒ clear place where to cut
 - Selected waves have intensities similar to fit with input model
 - Wrongly deselected waves that are actually in input model are small (< 10 events)

"Least Absolute Shrinkage and Selection Operator" Tibshirani, J. Royal Stat. Soc. B **58** (1996) 267

$$\mathcal{L}_{\mathrm{reg}}(\{\mathcal{T}_i\}) = \prod_{i}^{\mathrm{waves}} e^{-\lambda |\mathcal{T}_i|}$$

$$\ln \mathcal{L}_{\text{LASSO}} = \ln \mathcal{L}_{\text{ext}} - \lambda \sum_{i}^{\text{waves}} |\mathcal{T}_{i}|$$

- \mathcal{L}_{LASSO} has Laplacian form in $|\mathcal{T}_i|$
- Suppresses waves with small intensities effectively
- Penalizes also waves with large intensities ⇒ potential bias

 $\ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$ in \mathcal{T}_i plane



"Least Absolute Shrinkage and Selection Operator" Tibshirani, J. Royal Stat. Soc. B **58** (1996) 267

$$\mathcal{L}_{\mathrm{reg}}(\{\mathcal{T}_i\}) = \prod_i^{\mathrm{waves}} e^{-\lambda |\mathcal{T}_i|}$$

$$\ln \mathcal{L}_{\text{LASSO}} = \ln \mathcal{L}_{\text{ext}} - \lambda \sum_{i}^{\text{waves}} |\mathcal{T}_{i}|$$

- \mathcal{L}_{LASSO} has Laplacian form in $|\mathcal{T}_i|$
- Suppresses waves with small intensities effectively
- Penalizes also waves with large intensities ⇒ potential bias

 $\ln \mathcal{L}_{reg}(\{\mathcal{T}_i\})$ in \mathcal{T}_i plane



Regularization of likelihood function

Promising approach

- Method makes wave-set selection reproducible and bias explicit
- Choice of regularization terms is subjective
 - Applying different regularization terms ⇒ study wave-set dependence of PWA result
- Allows to systematically study dependence of PWA result on
 - Set of isobars
 - Isobar parametrizations
 - Inclusion of higher partial waves
 - ...

• Studies with Monte Carlo and real data still work in progress
Regularization of likelihood function

Promising approach

- Method makes wave-set selection reproducible and bias explicit
- Choice of regularization terms is subjective
 - Applying different regularization terms ⇒ study wave-set dependence of PWA result
- Allows to systematically study dependence of PWA result on
 - Set of isobars
 - Isobar parametrizations
 - Inclusion of higher partial waves
 - ...

• Studies with Monte Carlo and real data still work in progress

Regularization of likelihood function

Promising approach

- Method makes wave-set selection reproducible and bias explicit
- Choice of regularization terms is subjective
 - Applying different regularization terms ⇒ study wave-set dependence of PWA result
- Allows to systematically study dependence of PWA result on
 - Set of isobars
 - Isobar parametrizations
 - Inclusion of higher partial waves
 - ...

• Studies with Monte Carlo and real data still work in progress

Regularization of likelihood function

Promising approach

- Method makes wave-set selection reproducible and bias explicit
- Choice of regularization terms is subjective
 - Applying different regularization terms ⇒ study wave-set dependence of PWA result
- Allows to systematically study dependence of PWA result on
 - Set of isobars
 - Isobar parametrizations
 - Inclusion of higher partial waves
 - ...

• Studies with Monte Carlo and real data still work in progress

Regularization of likelihood function

- Regularization terms make likelihood function multimodal
- Cauchy and LASSO are two extreme cases of a continuum of regularization terms
 - Cauchy prior: heavy-tailed \Rightarrow low bias
 - LASSO: light-tailed \Rightarrow higher bias
 - Regularization term with tunable bias?
- Model-selection problem is ill-posed at low $m_{3\pi}$
 - Small phase space \Rightarrow only low-mass tails of isobars contribute
 - E.g. cannot distinguish between $f_0(980)$ and $f_0(1500)$ waves
 - Currently solved by imposing thresholds on waves ⇒ caveat: model and hence result discontinuous in *m*
 - Binary decision (include/not include wave) not optimal
 - Smooth turning-on of waves via individual regularization terms?
- Reduce bias on selected waves such that fit with regularization term gives final result?

Regularization of likelihood function

- Regularization terms make likelihood function multimodal
- Cauchy and LASSO are two extreme cases of a continuum of regularization terms
 - Cauchy prior: heavy-tailed ⇒ low bias
 - LASSO: light-tailed \Rightarrow higher bias
 - Regularization term with tunable bias?
- Model-selection problem is ill-posed at low $m_{3\pi}$
 - Small phase space \Rightarrow only low-mass tails of isobars contribute
 - E.g. cannot distinguish between $f_0(980)$ and $f_0(1500)$ waves
 - Currently solved by imposing thresholds on waves ⇒ caveat: model and hence result discontinuous in *m*
 - Binary decision (include/not include wave) not optimal
 - Smooth turning-on of waves via individual regularization terms?
- Reduce bias on selected waves such that fit with regularization term gives final result?

Regularization of likelihood function

- Regularization terms make likelihood function multimodal
- Cauchy and LASSO are two extreme cases of a continuum of regularization terms
 - Cauchy prior: heavy-tailed ⇒ low bias
 - LASSO: light-tailed \Rightarrow higher bias
 - Regularization term with tunable bias?
- Model-selection problem is ill-posed at low $m_{3\pi}$
 - Small phase space \Rightarrow only low-mass tails of isobars contribute
 - E.g. cannot distinguish between $f_0(980)$ and $f_0(1500)$ waves
 - Currently solved by imposing thresholds on waves \Rightarrow caveat: model and hence result discontinuous in $m_{3\pi}$
 - Binary decision (include/not include wave) not optimal
 - Smooth turning-on of waves via individual regularization terms?
- Reduce bias on selected waves such that fit with regularization term gives final result?

Regularization of likelihood function

- Regularization terms make likelihood function multimodal
- Cauchy and LASSO are two extreme cases of a continuum of regularization terms
 - Cauchy prior: heavy-tailed ⇒ low bias
 - LASSO: light-tailed \Rightarrow higher bias
 - Regularization term with tunable bias?
- Model-selection problem is ill-posed at low $m_{3\pi}$
 - Small phase space \Rightarrow only low-mass tails of isobars contribute
 - E.g. cannot distinguish between $f_0(980)$ and $f_0(1500)$ waves
 - Currently solved by imposing thresholds on waves \Rightarrow caveat: model and hence result discontinuous in $m_{3\pi}$
 - Binary decision (include/not include wave) not optimal
 - Smooth turning-on of waves via individual regularization terms?
- Reduce bias on selected waves such that fit with regularization term gives final result?





Novel analysis method inspired by (Q)MIPWA

E791, PRD 73 (2006) 032204

- Replace fixed $J^{PC} = 0^{++}$ isobar parametrizations by piece-wise constant amplitudes in $m_{\pi^-\pi^+}$ bins for 3π waves with $J^{PC} = 0^{-+}$, 1^{++} , and 2^{-+}
- Extract $m_{3\pi}$ dependence of total $J^{PC} = 0^{++}$ isobar amplitude from data
 - Advantage: reduction of model bias
 - Caveats: significant increase in number of fit parameters



nen New developments in partial-wave analysis with light hadrons

Novel analysis method inspired by (Q)MIPWA

E791, PRD 73 (2006) 032204

- Replace fixed $J^{PC} = 0^{++}$ isobar parametrizations by piece-wise constant amplitudes in $m_{\pi^-\pi^+}$ bins for 3π waves with $J^{PC} = 0^{-+}$, 1^{++} , and 2^{-+}
- Extract $m_{3\pi}$ dependence of total $J^{PC} = 0^{++}$ isobar amplitude from data
 - Advantage: reduction of model bias
 - Caveats: significant increase in number of fit parameters



COMPASS, PRD 95 (2017) 032004



• Coupling of $\pi(1800)$ to $f_0(980)\pi$ and $f_0(1500)\pi$ decay modes

- Additional information about isobar amplitude
 - Verify/improve parametrizations of isobar amplitudes used in conventional analysis
 - Search for higher excited isobar resonances
 - Study distortions due to final-state interactions with bachelor pion

COMPASS, PRD 95 (2017) 032004



• Coupling of $\pi(1800)$ to $f_0(980)\pi$ and $f_0(1500)\pi$ decay modes

- Additional information about isobar amplitude
 - Verify/improve parametrizations of isobar amplitudes used in conventional analysis
 - Search for higher excited isobar resonances
 - Study distortions due to final-state interactions with bachelor pion

PWA model with more freed waves

- Based on 88-wave model from COMPASS, PRD 95 (2017) 032004
- Free isobar amplitudes of 11 largest + 3 "interesting" waves
- 69 waves with fixed isobar parametrizations remain

- Continuous mathematical ambiguities for some π⁻π⁺ amplitudes ("zero modes")
- Resolution requires additional constraints
 - See talk by D. Ryabchikov and F. Krinner et al., PRD 97 (2018) 114008
- Here: amplitudes after resolution of ambiguity

PWA model with more freed waves

- Based on 88-wave model from COMPASS, PRD 95 (2017) 032004
- Free isobar amplitudes of 11 largest + 3 "interesting" waves
- 69 waves with fixed isobar parametrizations remain

- Continuous mathematical ambiguities for some π⁻π⁺ amplitudes ("zero modes")
- Resolution requires additional constraints
 - See talk by D. Ryabchikov and F. Krinner et al., PRD 97 (2018) 114008
- Here: amplitudes after resolution of ambiguity



- 3π wave has spin-exotic quantum numbers
- Peak at $m_{3\pi} \approx 1.6 \,\text{GeV}/c^2$ correlated with $\rho(770)$
- Shape of $\rho(770)$ peak deviates slightly from Breit-Wigner



- 3π wave has spin-exotic quantum numbers
- Peak at $m_{3\pi} \approx 1.6 \,\text{GeV}/c^2$ correlated with $\rho(770)$
- Shape of $\rho(770)$ peak deviates slightly from Breit-Wigner



- 3π wave has spin-exotic quantum numbers
- Peak at $m_{3\pi} \approx 1.6 \,\text{GeV}/c^2$ correlated with $\rho(770)$
- Shape of $\rho(770)$ peak deviates slightly from Breit-Wigner



- 3π wave has spin-exotic quantum numbers
- Peak at $m_{3\pi} \approx 1.6 \,\text{GeV}/c^2$ correlated with $\rho(770)$
- Shape of $\rho(770)$ peak deviates slightly from Breit-Wigner

Freed-Isobar Partial-Wave Analysis

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^+\pi^+}$ dependence of amplitudes

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^+\pi^+}$ dependence of amplitudes

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes
 F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^+\pi^+}$ dependence of amplitudes

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^+\pi^+}$ dependence of amplitude

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^-\pi^+}$ dependence of amplitudes

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^-\pi^+}$ dependence of amplitudes

- Greatly reduces model bias in isobar analyses
- Detailed insight into 2π vs. 3π dynamics
 - Verify/learn isobar parametrizations from data
 - Search for higher excited isobar states
 - Study of final-state-interaction effects
- Ambiguities appear when many waves are freed
 - Can be identified and resolved
- Method directly applicable to heavy-meson decays
 - (Q)MIPWA is now a tool to extract physics not just to cross check single isobar amplitudes F. Krinner *et al.*, PRD **97** (2018) 114008

- Requires large data sets (several 10⁵ events)
- Modeling of extracted isobar amplitudes
 - Theory input needed
- *Final goal:* 2D fit of $m_{3\pi}$ and $m_{\pi^-\pi^+}$ dependence of amplitudes















Resonance-Model Fit of $\pi^-\pi^-\pi^+$ Data



Resonance-Model Fit of $\pi^-\pi^-\pi^+$ Data



LASSO Method



Mass bin at $m_{3\pi} = 1.8 \text{ GeV}/c^2$

- Also LASSO produces clear drop in intensity distribution
 - B. Guegan *et al.* used cut on relative intensity $> 10^{-3} \Rightarrow$ unnecessary
- Position depends strongly on value of $\lambda \Rightarrow$ dials wave-set size
- Increased bias in larger waves with increased λ
- Need criterion to tune λ

(MC Data)

LASSO Method



Mass bin at $m_{3\pi} = 1.8 \text{ GeV}/c^2$

- Also LASSO produces clear drop in intensity distribution
 - B. Guegan *et al.* used cut on relative intensity $> 10^{-3} \Rightarrow$ unnecessary
- Position depends strongly on value of $\lambda \Rightarrow$ dials wave-set size
- Increased bias in larger waves with increased λ
- Need criterion to tune λ

(MC Data)

LASSO Method



Mass bin at $m_{3\pi} = 1.8 \,\mathrm{GeV}/c^2$

- Also LASSO produces clear drop in intensity distribution
 - B. Guegan *et al.* used cut on relative intensity $> 10^{-3} \Rightarrow$ unnecessary
- Position depends strongly on value of $\lambda \Rightarrow$ dials wave-set size
- Increased bias in larger waves with increased λ
- Need criterion to tune λ

(MC Data)
B. Guegan et al. suggest to use information criteria (IC)

- IC are relative measure of model quality
 ⇒ tradeoff between goodness of fit and model complexity
- Akaike IC (AIC): choose value of λ that minimizes

 $2k-2\ln\hat{\mathcal{L}}$

k: number of selected parameters $\hat{\mathcal{L}}$: maximum likelihood value

• Bayesian IC (BIC): choose value of λ that minimizes

 $k\ln n - 2\ln \hat{\mathcal{L}}$

n: number of data points

- λ scans are work in progress
 - BIC seems to prefer λ round 5
 - AIC give typically larger waves sets than BIC

B. Guegan et al. suggest to use information criteria (IC)

- IC are relative measure of model quality
 ⇒ tradeoff between goodness of fit and model complexity
- Akaike IC (AIC): choose value of λ that minimizes

 $2k-2\ln \hat{\mathcal{L}}$

k: number of selected parameters $\hat{\mathcal{L}}$: maximum likelihood value

Bayesian IC (BIC): choose value of λ that minimizes

 $k\ln n - 2\ln \hat{\mathcal{L}}$

n: number of data points

• λ scans are work in progress

- BIC seems to prefer λ round 5
- AIC give typically larger waves sets than BIC

B. Guegan et al. suggest to use information criteria (IC)

- IC are relative measure of model quality
 ⇒ tradeoff between goodness of fit and model complexity
- Akaike IC (AIC): choose value of λ that minimizes

 $2k-2\ln \hat{\mathcal{L}}$

k: number of selected parameters $\hat{\mathcal{L}}$: maximum likelihood value

• Bayesian IC (BIC): choose value of λ that minimizes

 $k\ln n - 2\ln \hat{\mathcal{L}}$

n: number of data points

- λ scans are work in progress
 - BIC seems to prefer λ round 5
 - AIC give typically larger waves sets than BIC

B. Guegan et al. suggest to use information criteria (IC)

- IC are relative measure of model quality
 ⇒ tradeoff between goodness of fit and model complexity
- Akaike IC (AIC): choose value of λ that minimizes

 $2k-2\ln \hat{\mathcal{L}}$

k: number of selected parameters $\hat{\mathcal{L}}$: maximum likelihood value

• Bayesian IC (BIC): choose value of λ that minimizes

 $k\ln n - 2\ln \hat{\mathcal{L}}$

n: number of data points

- λ scans are work in progress
 - BIC seems to prefer λ round 5
 - AIC give typically larger waves sets than BIC