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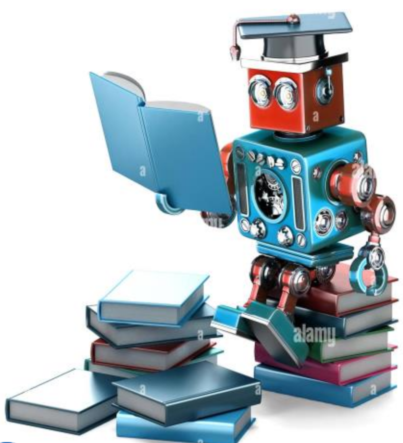
Transport properties of the QGP matter facilitated by Machine learning-based models



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29 September, 2023

2nd Workshop of the Network

NA7-HF-QGP

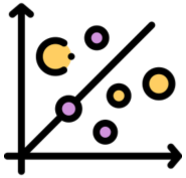
HFHF Theory Retreat 2023

CRC-TR 211
Strong-interaction matter under extreme conditions

STRONG 2020

Main objectives for a ML framework in theory

- Consistent framework (based on popular TensorFlow) for (on) off-shell model - simultaneously evaluate the EoS and transport coefficients of QGP to reduce model assumptions
- Create a faster framework to tune quasi-particle particle model parameters – can be easily adjusted for other models
- Check how strangeness is described within the quasi-particle models and its influence on transport coefficients
- Where can we gain knowledge from ML techniques (Unsupervised learning) for QGP phenomenology by the use of regression task not only classification?



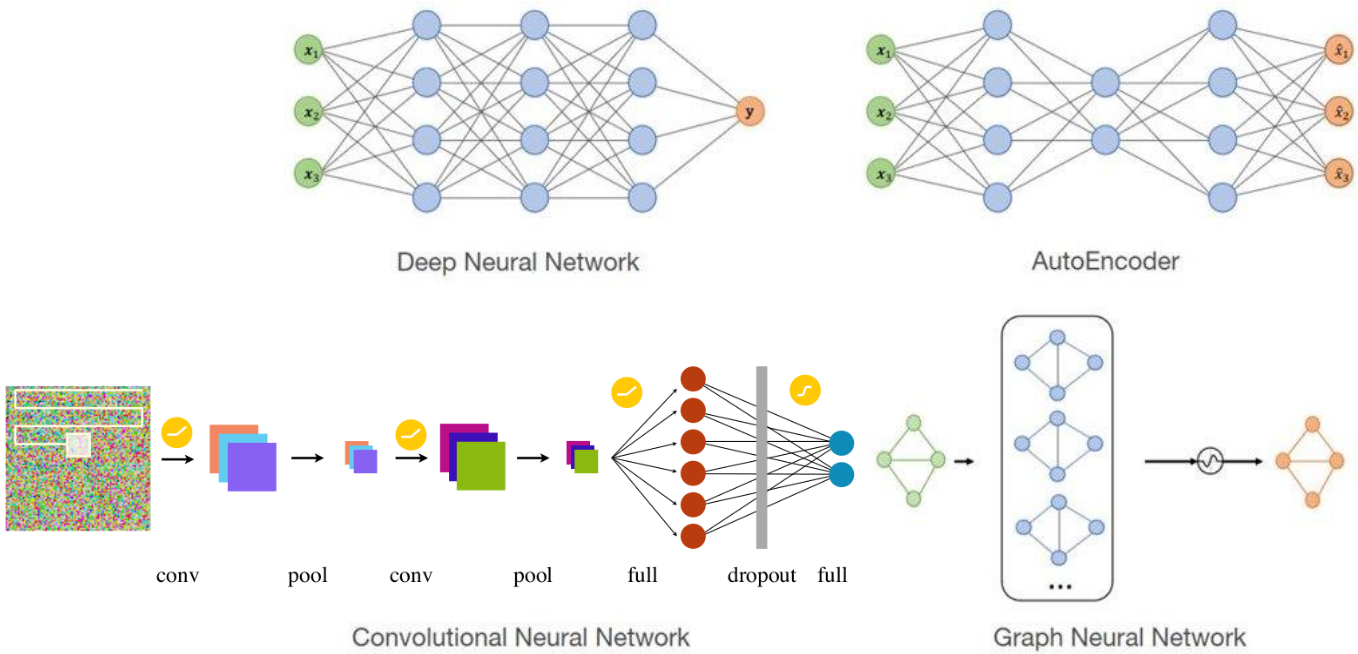
Unsupervised learning to explore the QGP

Popular types of NN used for phenomenology:

Regression/classification:

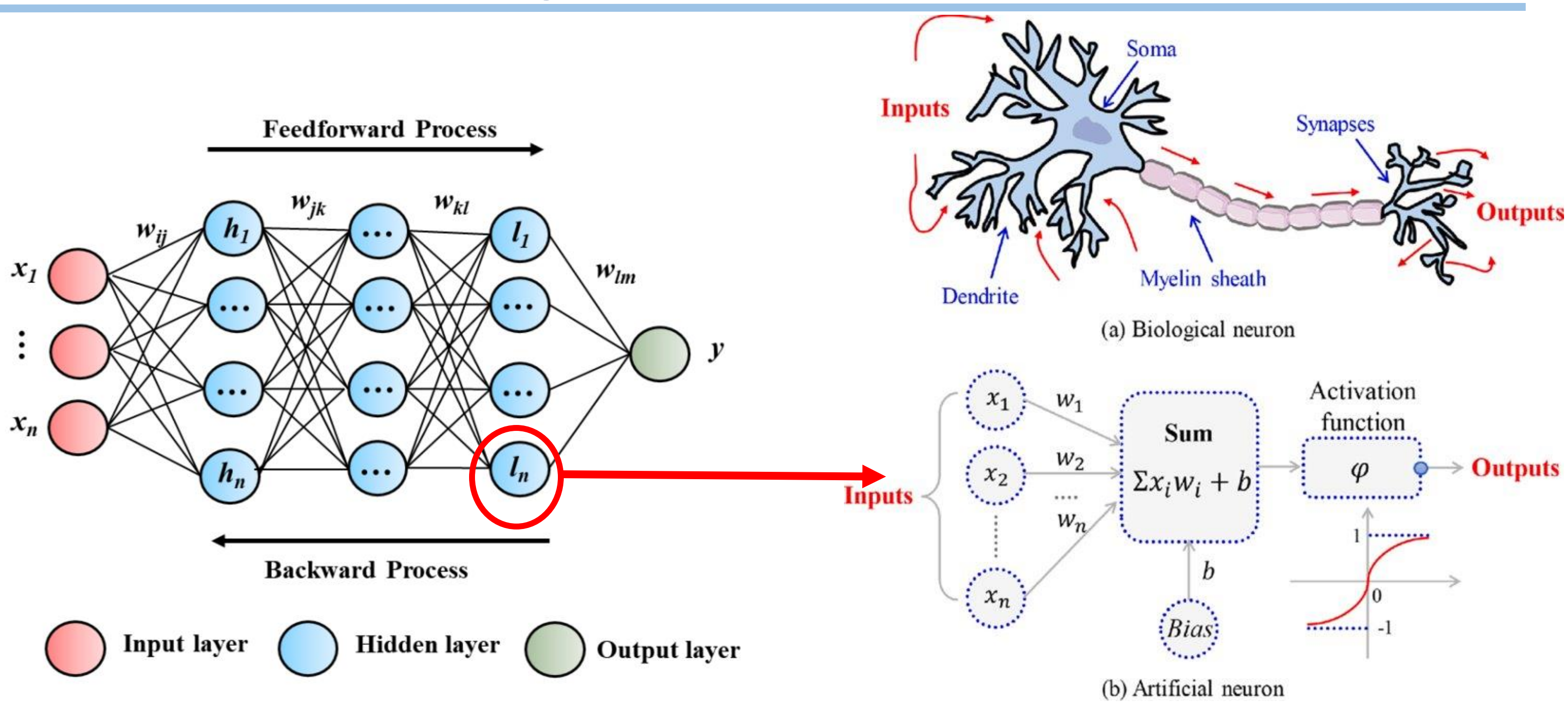
Classification:

Fast simulations:
CNN, new - GAN



- Unsupervised Learning is most promising/suitable for phenomenology / theory of nuclear physics
- Can we use Unsupervised Learning to learn about the dynamical properties of the QGP?
- Exploring QCD matter in extreme conditions with Machine Learning (recent review: https://arxiv.org/abs/2303.15136)

Machine Learning: Basic concepts



- **Forward propagation**: Transmission of input data resulting in an unsettled verdict
- **Loss estimation**: loss/cost function = discrepancy between predicted and actual values
- **Back propagation**: weights are iteratively refined to reduce the error
- **Optimization**: gradient descent (Adam) for correcting the weights

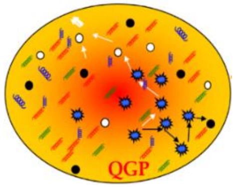
$$w \leftarrow w - \eta \frac{\partial l}{\partial w}$$

Objection: to minimize the loss of prediction on new data not used for trainings - we want to have some smooth loss function for optimization

- NN is a new tool for multidimensional optimization function which are more flexible and can encompass more features itself, and can be constructed in a more flexible manner then conventional optimization techniques

Can ML be useful for theory of the QGP?

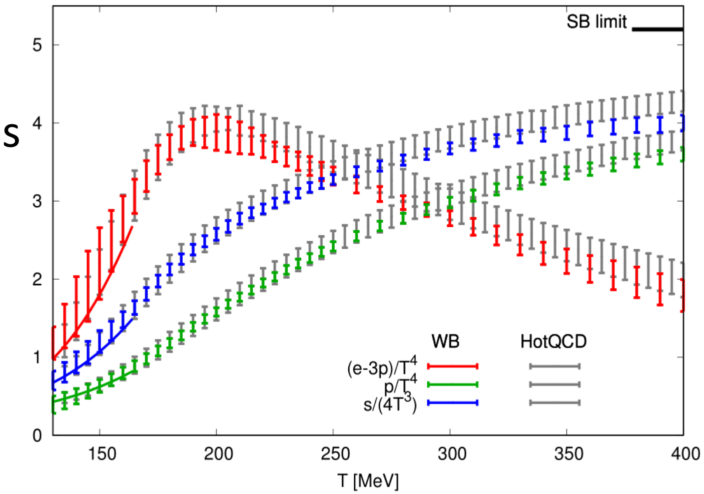
On practice: effective models for QGP

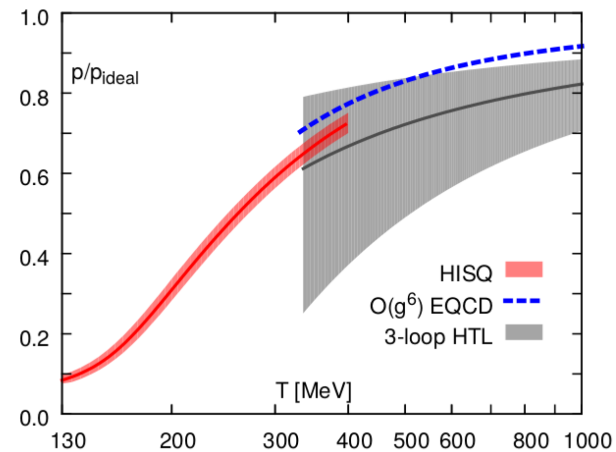


EoS(ε,n)
$\sigma(\sqrt{s}, m_q, m_q, T, \mu_B)$
$\mathbf{m}(T, \mu_B)$

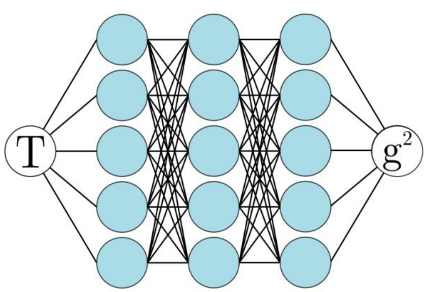
! QPM enables to estimate simultaneously of the EoS and transport coefficients also including jet and charm coefficients (talk by I Grishmanovskii)

Phenomenological models are based on lattice QCD thermodynamics



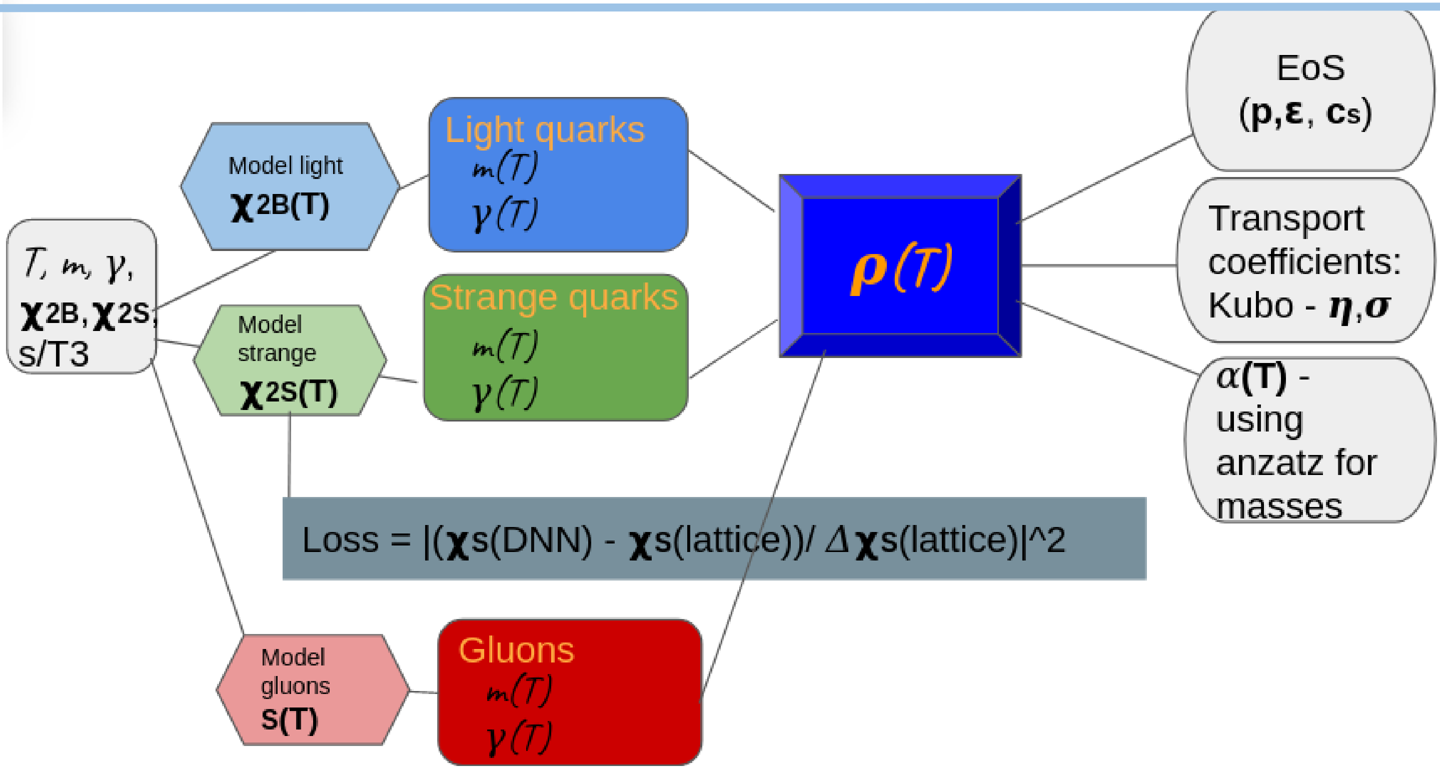


ML facilitated QGP description – by minimizing the loss function (can be chosen in various forms)
Output: spectral function, coupling constant – which later can be used for the extraction of transport coefficients



?

Regression task



For training we use: T, EoS(from lQCD as true value): $s/T^3(T),\ \ \chi_2^B(T), \chi_2^S(T)$

Goal: Extract microscopic quantities using thermodynamic quantities from 1st principle calculation (here lQCD)

Output: masses, widths, coupling constant – which later can be used for the tuning quasiparticle models used for QGP phase in transport simulations and extraction of transport coefficients of the QGP phase

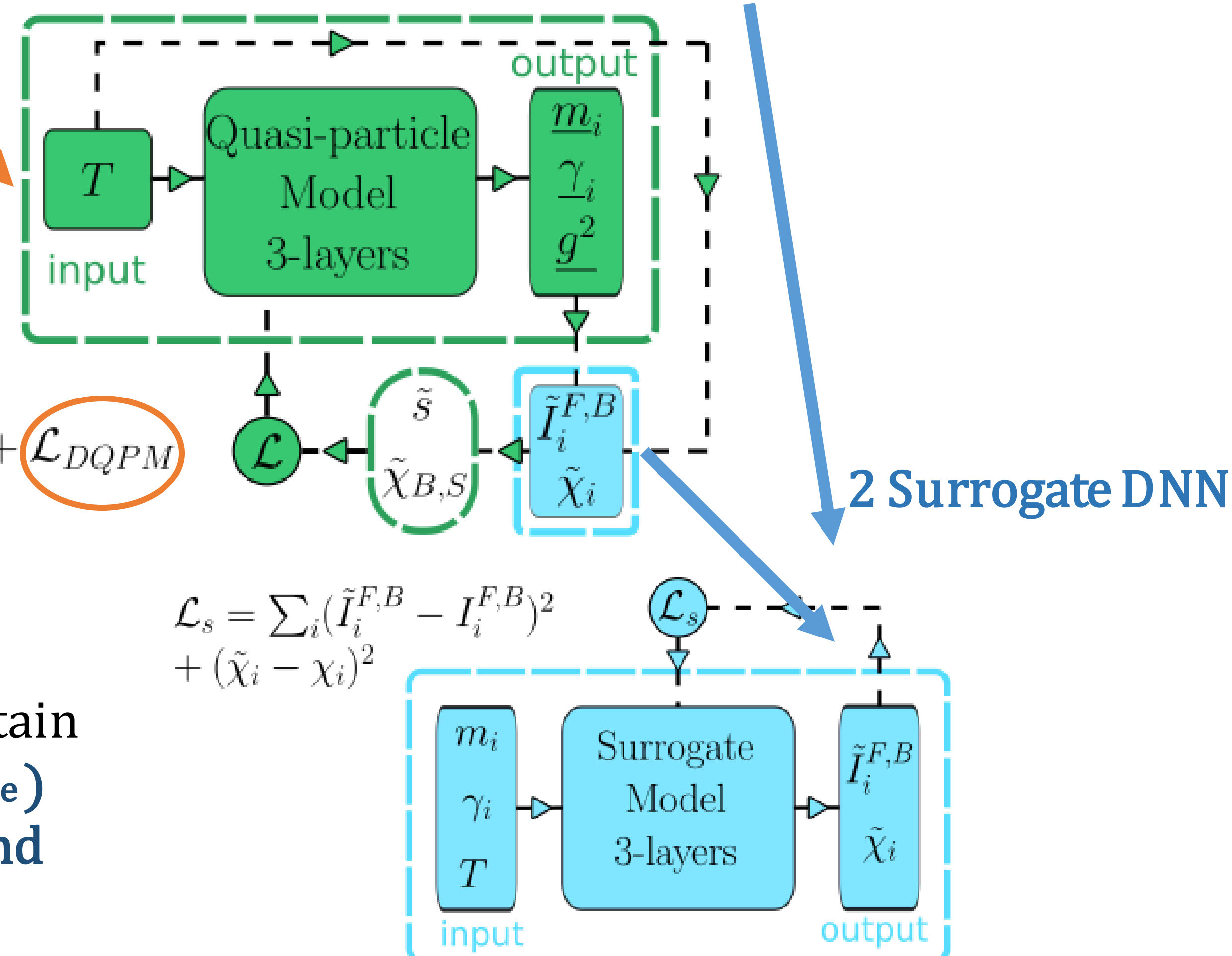
O.S., A. Palermo, E. Bratkovskaya in preparation

Flowchart of DNN model

To train the DNN we generate tables with masses, widths and EoS using
Off-shell quasi-particle description w/o any assumptions on masses and width

T	$\frac{M}{T} \in [\frac{\gamma}{T}, 9]$	$\frac{\gamma}{T} \in [0, 1]$	$I_B[GeV^3]$	$I_F[GeV^3]$	χ_q

Main DNN



- Loss function to minimize $\mathcal{L} = \mathcal{L}_0 + \mathcal{L}_{DQPM}$

To improve physical meaning of the output:

- Loss function can contain several terms: $(y - y_{true})$ with $[y_{true} = \text{EoS(lattice)}]$ and regularization terms $[y_{true} = \text{masses/widths (HTL) at high T}]$

O.S., A. Palermo, E. Bratkovskaya in preparation

Framework: off-shell Quasi-Particle Model

EoS from Φ - functional approach - entropy and quark density and susceptibilities expressed in dressed propagators in the quasiparticle limit (G. Baym 1998, Blaizot et al. 2001):

$$s^{dqp} =$$

$$-\int \frac{d\omega}{2\pi}\frac{d^3p}{(2\pi)^3}\left[d_g\frac{\partial n_B}{\partial T}\left(\mathrm{Im}(\ln -\Delta^{-1}) + \mathrm{Im}\,\Pi\,\mathrm{Re}\,\Delta\right)\right.$$
$$+\sum_{q=u,d,s} d_q\frac{\partial n_F(\omega-\mu_q)}{\partial T}\left(\mathrm{Im}(\ln -S_q^{-1}) + \mathrm{Im}\,\Sigma_q\,\mathrm{Re}\,S_q\right)$$
$$\left.+\sum_{\bar q=\bar u,\bar d,\bar s} d_{\bar q}\frac{\partial n_F(\omega+\mu_q)}{\partial T}\left(\mathrm{Im}(\ln -S_{\bar q}^{-1}) + \mathrm{Im}\,\Sigma_{\bar q}\,\mathrm{Re}\,S_{\bar q}\right)\right]$$

- We need to estimate during training to estimate Loss

$$s(T) = -d_g I_g^B - d_q \sum_{i=q,s} I_i^F,$$

$$\chi_2^B(T) = \frac{d_q}{9}(2\chi_l(T) + \chi_s),$$
$$\chi_2^S(T) = d_q\chi_s,$$

original DQPM model - QGP in the PHSD (Elena's talk) - coupling constant is fixed using entropy density

- Input: entropy density as a f(T , $\boldsymbol{\mu_B = 0}$)

$$g^2(s/s_{SB}) = d\left((s/s_{SB})^e - 1\right)^f$$

$$s^{DQPM}(\Pi,\Delta,S_q,\Sigma) = s^{lattice}$$ **fit S from QP to S from lQCD**

fix the model parameters

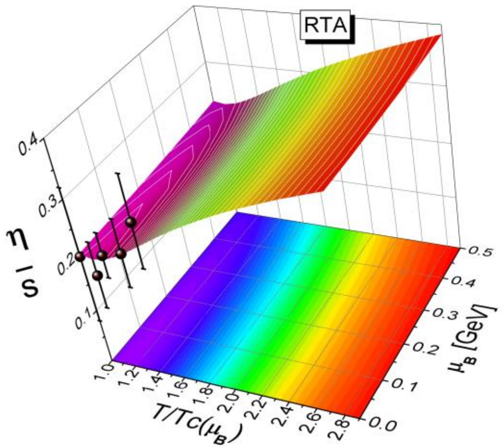
$$g^2(T/T_c,\mu_B) = g^2\left(\frac{T^*}{T_c(\mu_B)},\mu_B=0\right)$$ with $$T^* = \sqrt{T^2+\mu_q^2/\pi^2}$$

- Scaling hypothesis for the crossover region at finite $\boldsymbol{\mu_B}$

DQPM: EoS and transport coefficientst

- DQPM: off-shell Quasi-Particle Model - can provide simulaniously **Transport coefficients + EoS**

O. S., P. Moreau and E. Bratkovskaya, PRC 101 (2020), 045203

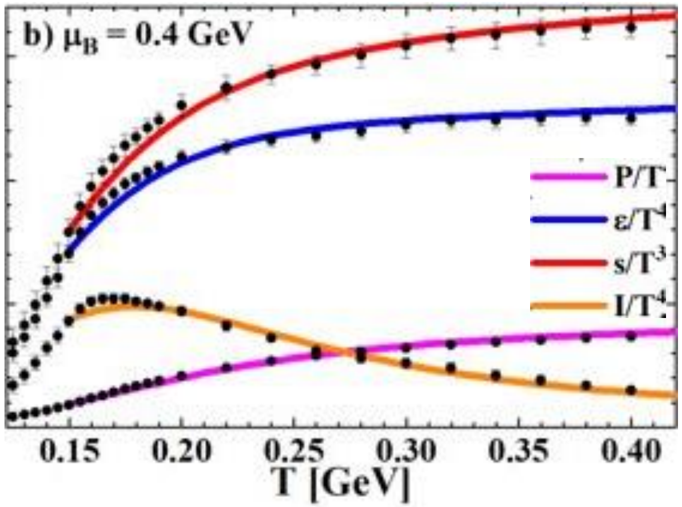


$$\eta \nabla^{<\mu} u^{\nu>}$$

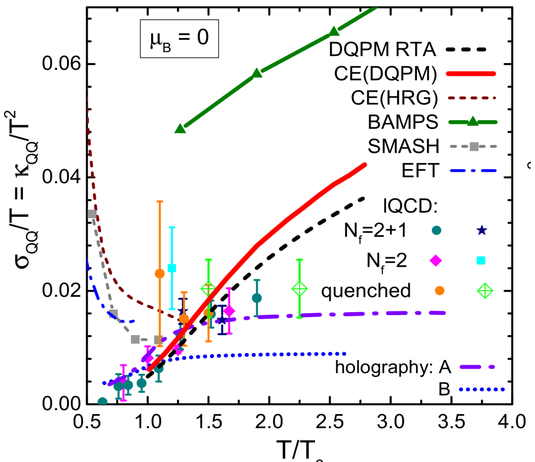
$$-\zeta \nabla u$$

(B, Q, S) diffusion coefficients

$$\kappa_q \nabla \frac{\mu_q}{T}$$



+ Full diffusion coefficient matrix



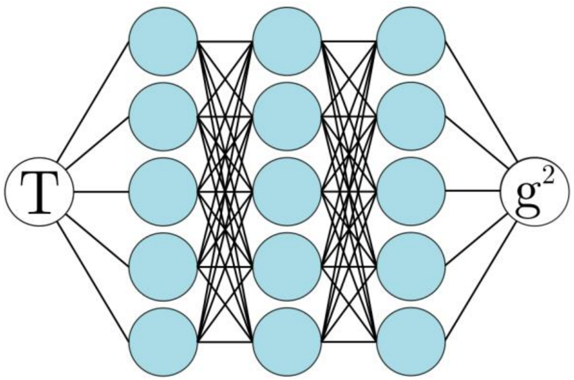
J. A. Fotakis, O. S., C. Greiner, O. Kaczmarek and E. Bratkovskaya PRD 104 (2021) , 034014

- Main thermodynamic quantites are within the errorbars in agreement with lQCD EoS at moderate
- Baryon and strange susceptibilities are lower than LQCD data– improve!
- Improve strange quark description

Cassing, NPA 791 (2007) 365; H. Berrehrah, E. Bratkovskaya, T. Steinert, W. Cassing, Int. J. Mod. Phys. E 25 (2016), 164200; P. Moreau, O. S, L. Oliva, T. Song, W. Cassing, E. Bratkovskaya, PRC 100 (2019) , 014911;

DNN with Dynamical Quasi-Particle Model

NN:
3layers, 24x12x12x1 and swish/sigmoid



Output: coupling constant
masses and widths falls from the DQPM Anzatz – in HTL form

Re $\mathbf{\Pi}_i$: thermal mass $(\boldsymbol{M_g}, \boldsymbol{M_q})$

$$m_g^2(T) = C_a \frac{g^2(T)}{6} T^2 \left(1 + \frac{N_f}{2N_c}\right) = \frac{3}{4} g^2(T) T^2$$

$$m_{l(\bar{l})}^2(T) = C_f \frac{g^2(T)}{4} T^2 = \frac{1}{3} g^2(T) T^2$$

Strange quark:

$$m_{s(\bar{s})}(T) = m_{q(\bar{q})}(T) + \Delta m$$

Im $\mathbf{\Pi}_i$: interaction width $(\boldsymbol{\gamma_g}, \boldsymbol{\gamma_q})$

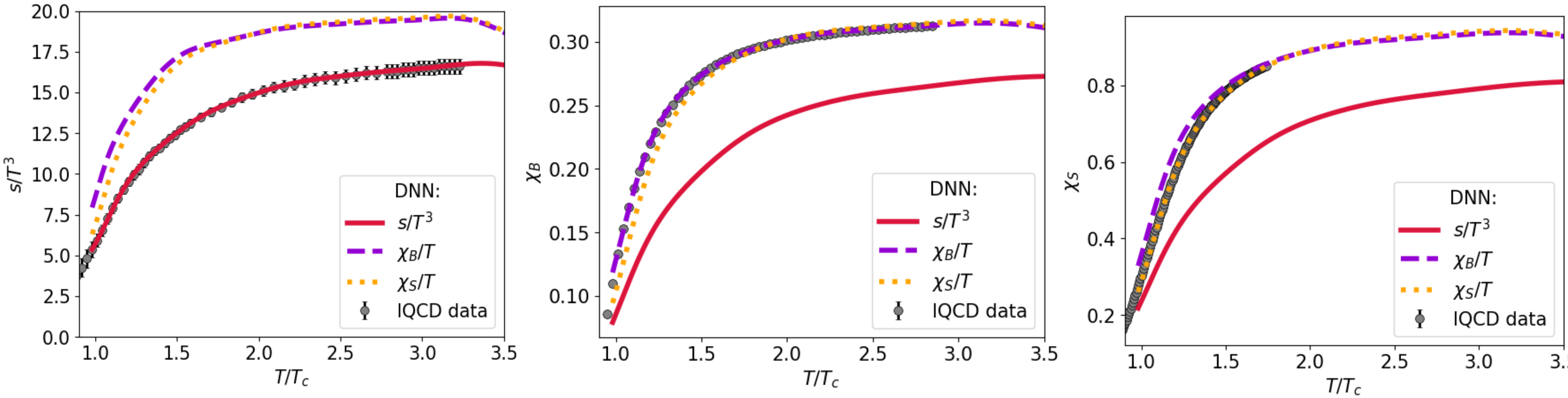
$$\gamma_j(T, \mu_B) = \frac{1}{3} C_j \frac{g^2(T, \mu_B) T}{8\pi} \ln\left(\frac{2c_m}{g^2(T, \mu_B)} + 1\right)$$

Peshier, Cassing, PRL 94 (2005) 172301; Cassing, NPA 791 (2007) 365; H. Berrehrah, E. Bratkovskaya, T. Steinert, W. Cassing, Int. J. Mod. Phys. E 25 (2016), 164200; P. Moreau, O. Soloveva , L. Oliva, T. Song, W. Cassing, E. Bratkovskaya, PRC 100 (2019) , 014911;

EoS from DNN with DQPM Ansatz

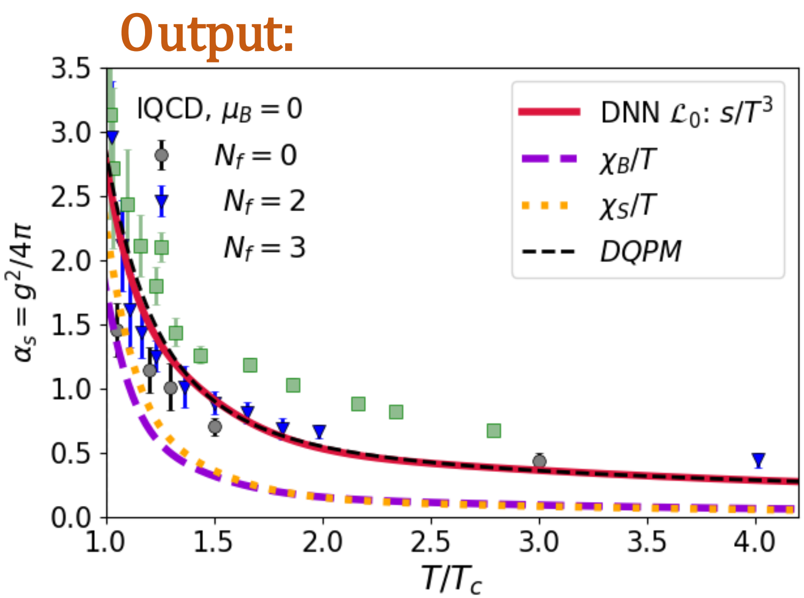
- Loss function to minimize

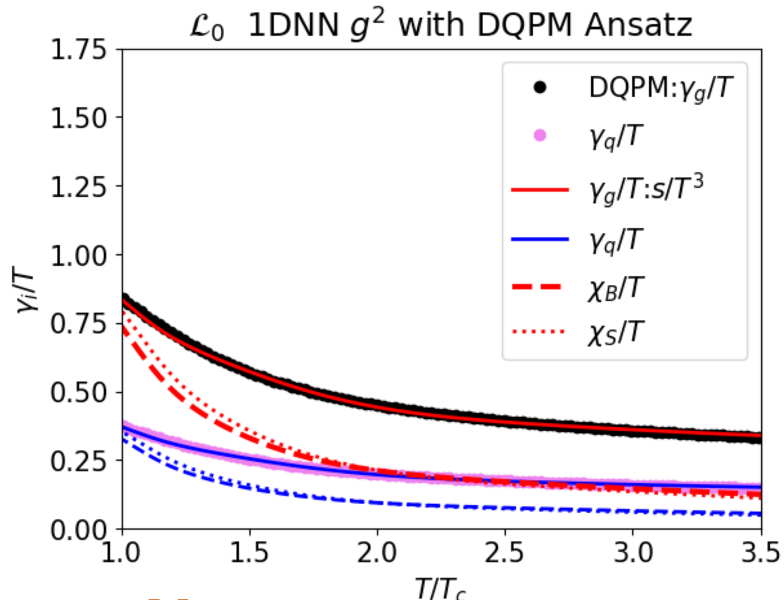
$$\mathcal{L}_0 = \beta_G \left[\frac{\tilde{s}(T) - s_{\rm lQCD}}{\Delta s_{lQCD}}\right]^2 + \beta_L \left[\frac{\tilde{\chi}^B(T) - \chi^B_{\rm lQCD}}{\Delta \chi^B_{lQCD}}\right]^2 + \beta_S \left[\frac{\tilde{\chi}^S(T) - \chi^S_{\rm lQCD}}{\Delta \chi^S_{lQCD}}\right]^2$$

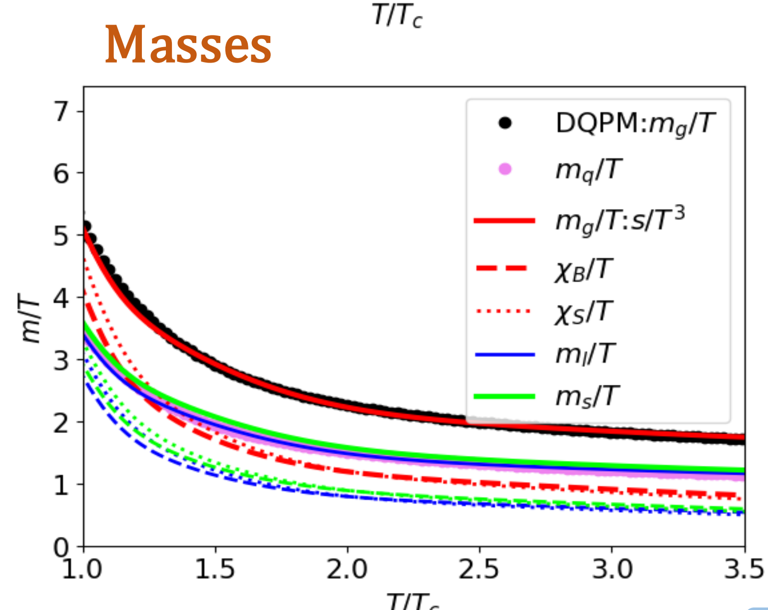


- Impossible to fit all 3 and get not huge masses
- Simple consideration of different contribution – results in different estimations of effective coupling constant
- DNN: in which direction we can improve the model?

Proof of principle: DQPM Ansatz







Possible improvements -

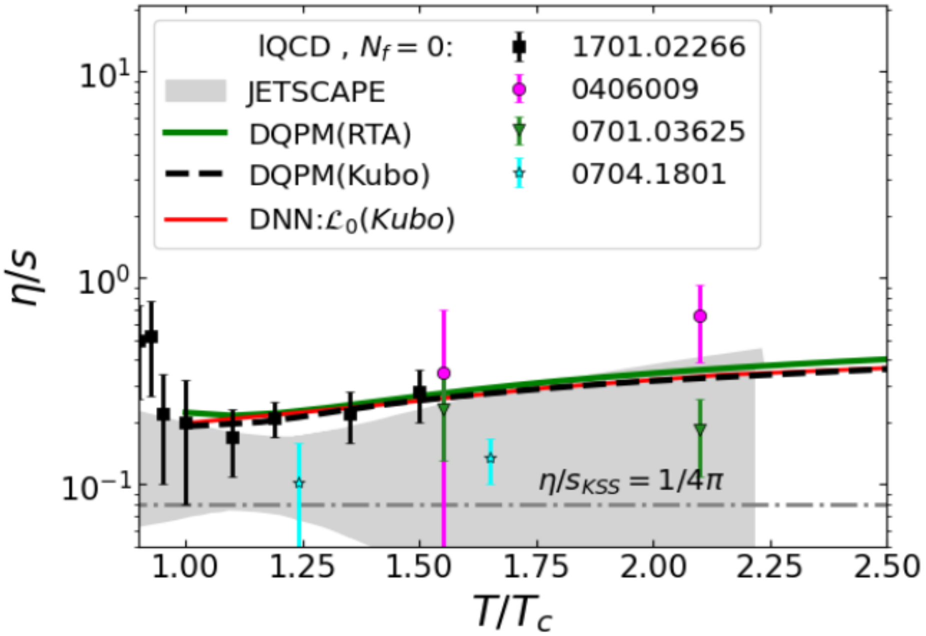
- change the form of Ansatz in that way to keep **masses/widths in a physical range.**
- change **width/mass** for strange quark

Transport coefficients : Kubo formalism

$$\eta^{\mathrm{Kubo}}(T) = \frac{1}{15T}\int \frac{d^4p}{(2\pi)^4} \sum_{i=q,\bar{q},g} d_i \left((1 \pm f_i(\omega)) f_i(\omega)\right) \rho_i(\omega,\mathbf{p})^2 \Pi_i$$

Contain all degrees of freedom

$$\Pi_g = 7\omega^4 - 10(\omega\mathbf{p})^2 + 7\mathbf{p}^4 \qquad \Pi_q = p_x^2 p_y^2$$



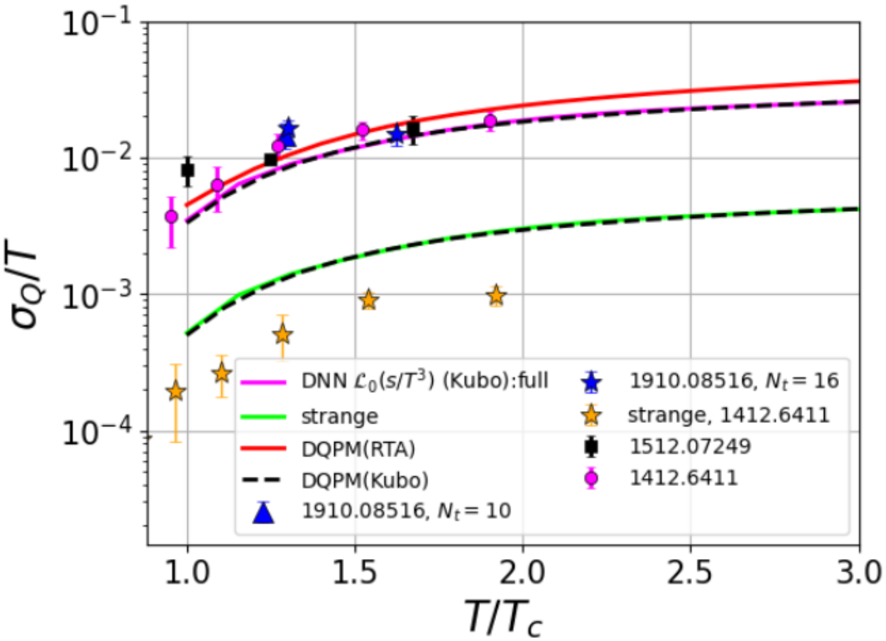
- Kubo formalism allows the evaluation of transport coefficients without involving estimations of cross-sections

R. Lang and W. Weise, EPJ. A 50, 63 (2014) (NJL model)
A. Harutyunyan et al,PRD 95, 114021, (2017)

Conductivity: improve strange quark

Only quark sector
– separate strange sector

$$\sigma^{\text{Kubo}}(T) = \frac{1}{3T}\int \frac{d^4p}{(2\pi)^4}\,\mathbf{p}^2 \sum_{i=q,\bar{q}} d_i\left((1 \pm f_i(\omega))f_i(\omega)\right)\rho_i(\omega,\mathbf{p})^2$$



- Conductivity shows how good we describe quark sector – we can compare to the strange quark conductivity
- Check how strangeness is described within the quasi-particle models and its influence on conductivity

Generalization of QP Ansatz - Ag DNN Model

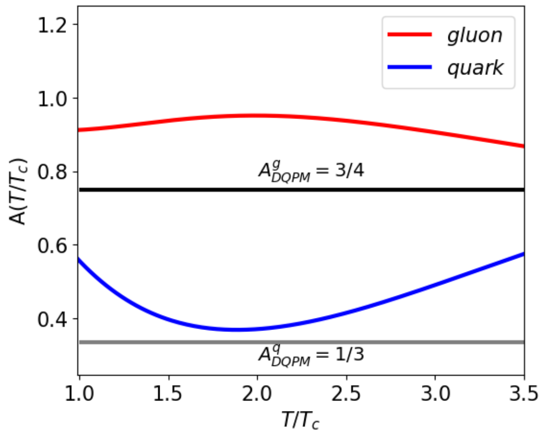
Main ingredients

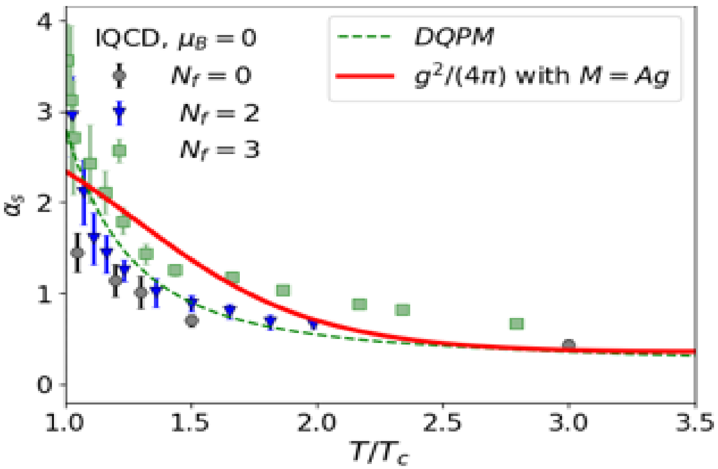
- 6 outputs (before just g)
- Modified loss function

$$\mathcal{L}_1 = \mathcal{L}_0 + \beta_{as}\mathcal{L}_{as} + \beta_{reg}\mathcal{L}_{DQPM}$$

$$\mathcal{L}_{as} = \left[\underline{\gamma}_l(T)/\underline{\gamma}_s(T) - 1\right]^2 |_{T>2.5T_c}$$

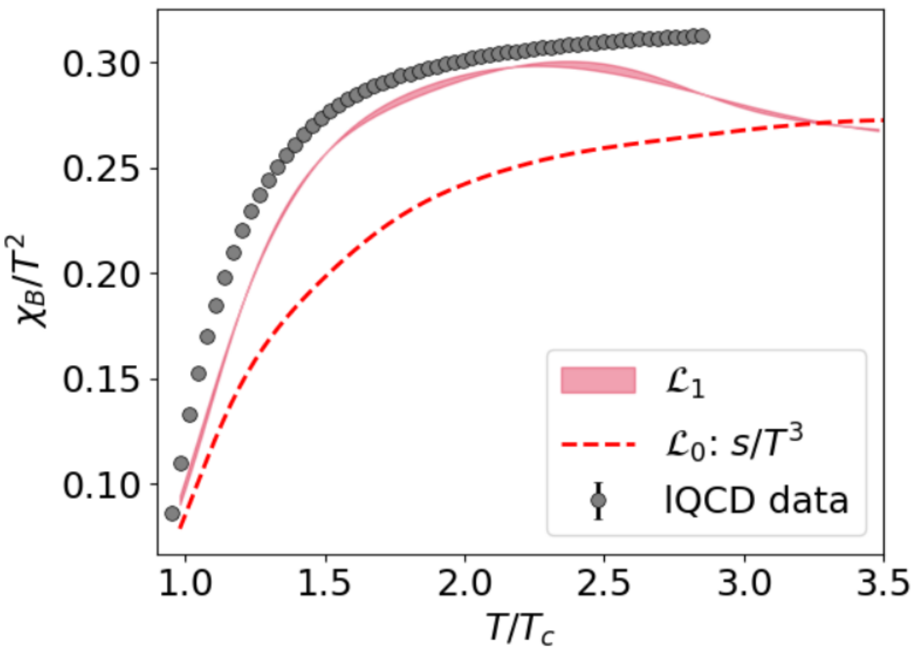
- No strict parametrization for widths
- Coupling constant extracted from the masses employing non perturbative corrections : $\frac{\underline{m}_{q/g}(T)}{T} = \underline{A}_{q/g}(T/T_c)\underline{g}(T/T_c)$

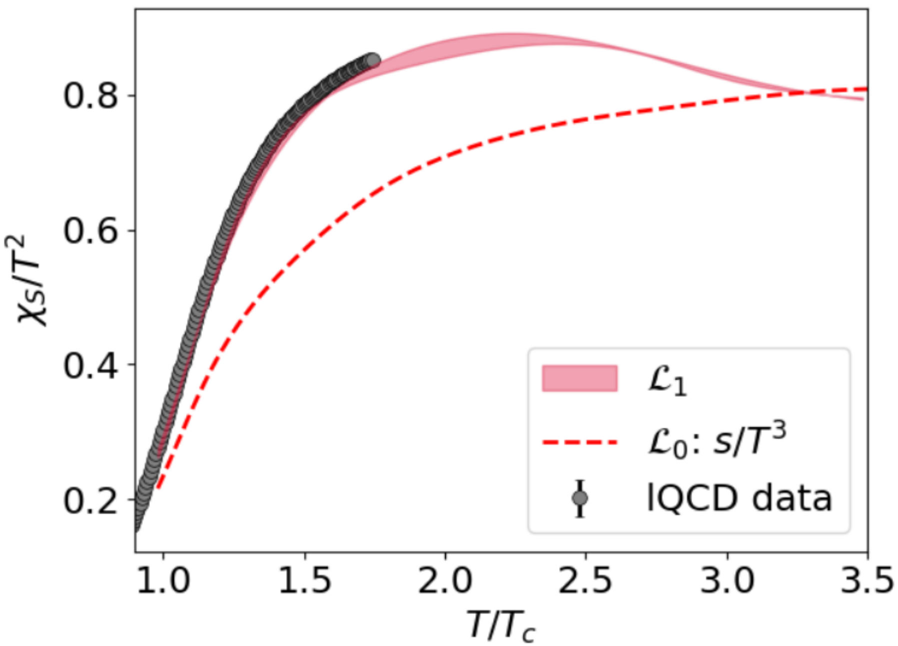




- Modification of strangeness

Improved EoS from AgDNN

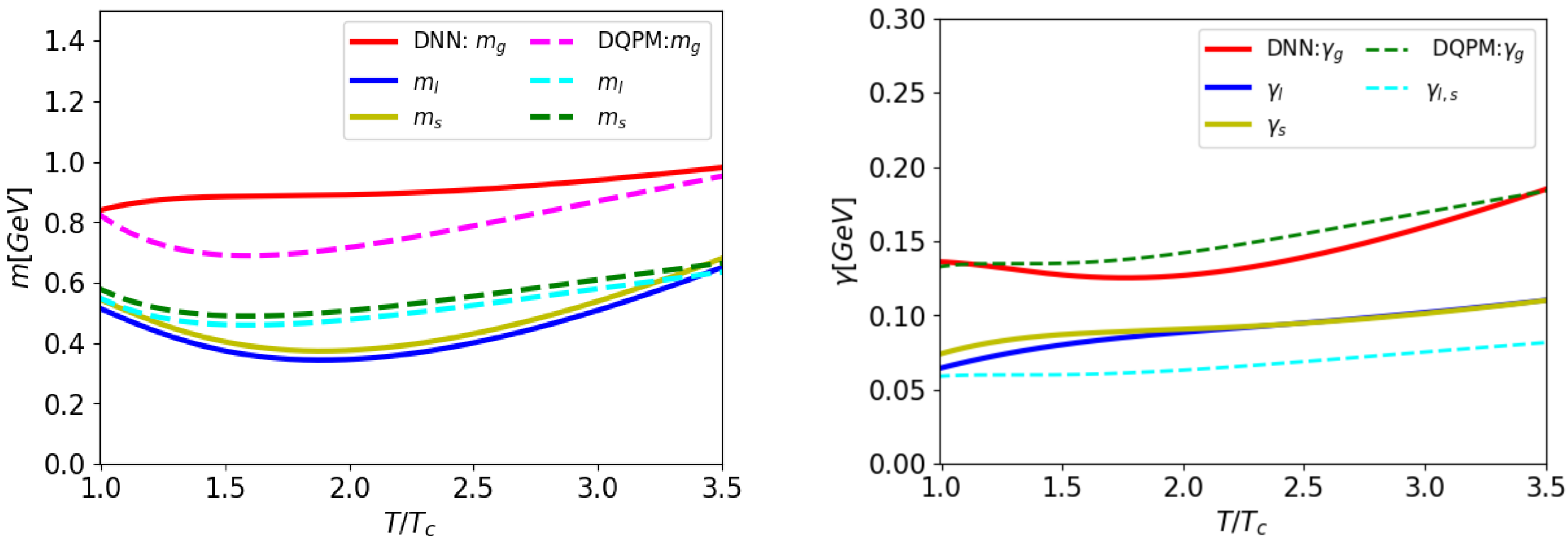




- Improved susceptibililties $\chi_2^B(T), \chi_2^S(T)$
- Microscopic quantities have changed – but close to the original QDPM at 3Tc

Microscopic properties from AgDNN

- Strangeness – simple shift $m_{s(\bar{s})}(T) = m_{q(\bar{q})}(T) + \Delta m$

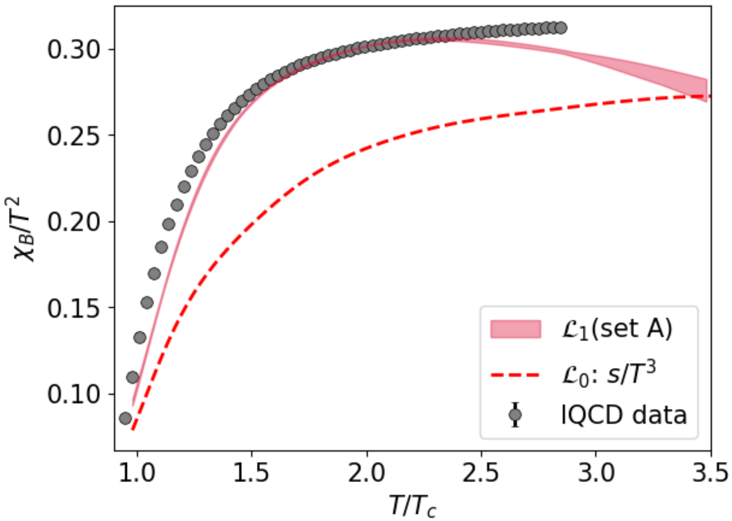


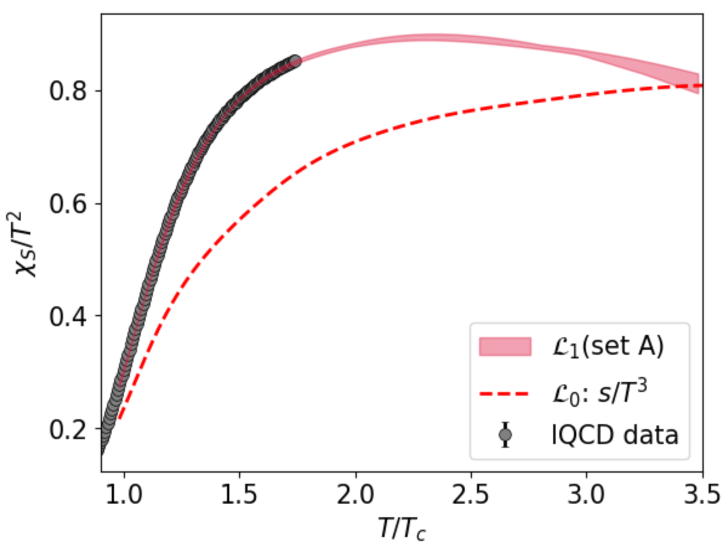
- Massive gluon shows – almost no T –dependence at small T<3Tc
- Smaller masses – but close to the original QDPM at 3Tc
- No constraints on widths at small T – only asymptotics

$$\mathcal{L}_{as} = \left[\gamma_l(T)/\gamma_s(T) - 1\right]^2 |_{T>2.5T_c}$$

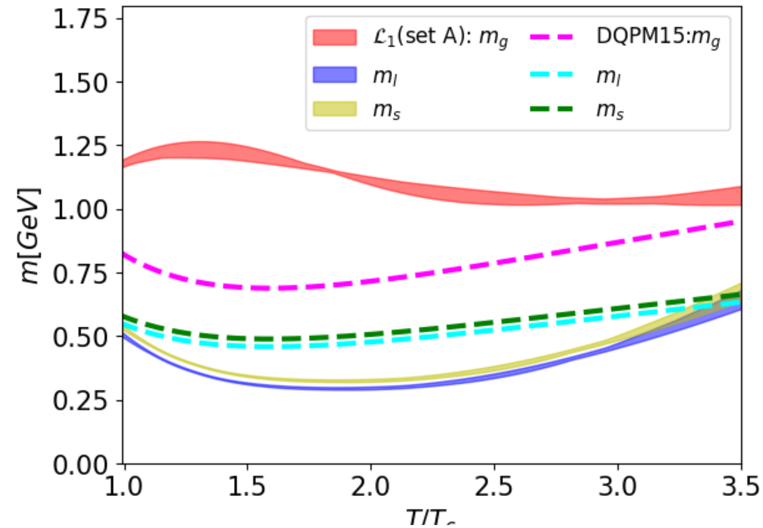
Microscopic properties from AgDNN

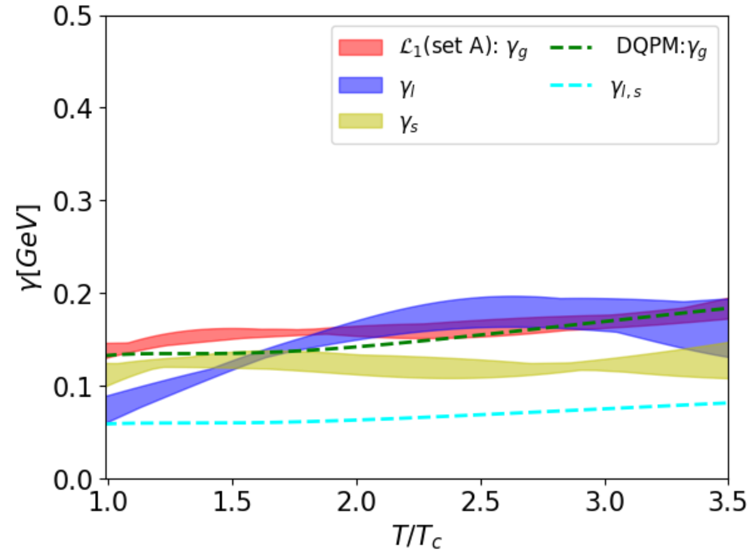
- Set A – higher susceptibilities



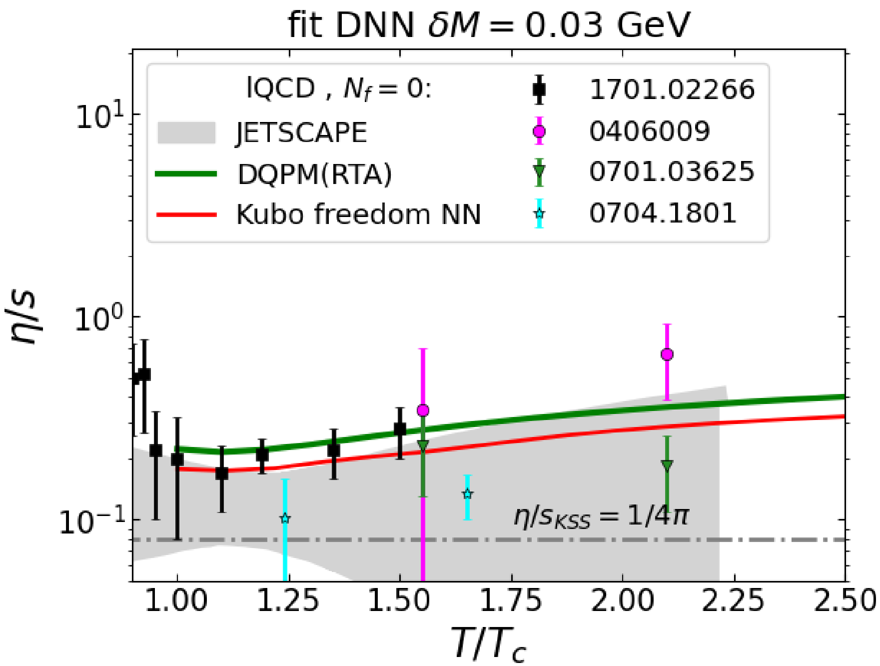


heavy gluons:

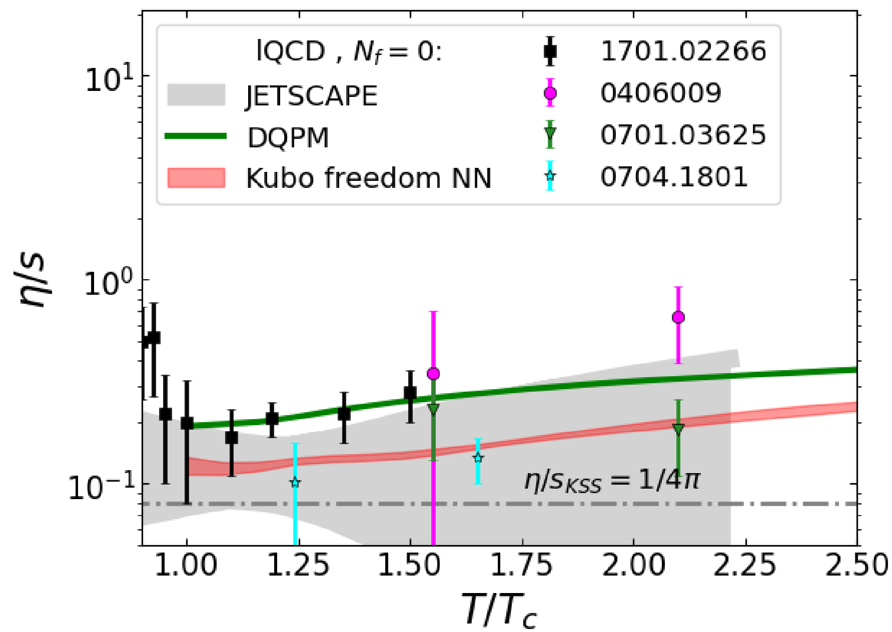




Transport coefficients from AgDNN



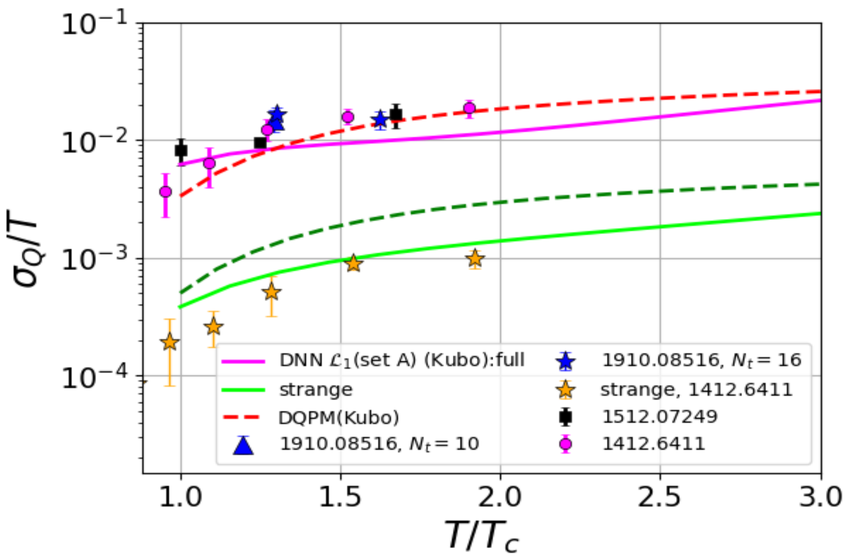
heavy gluons:

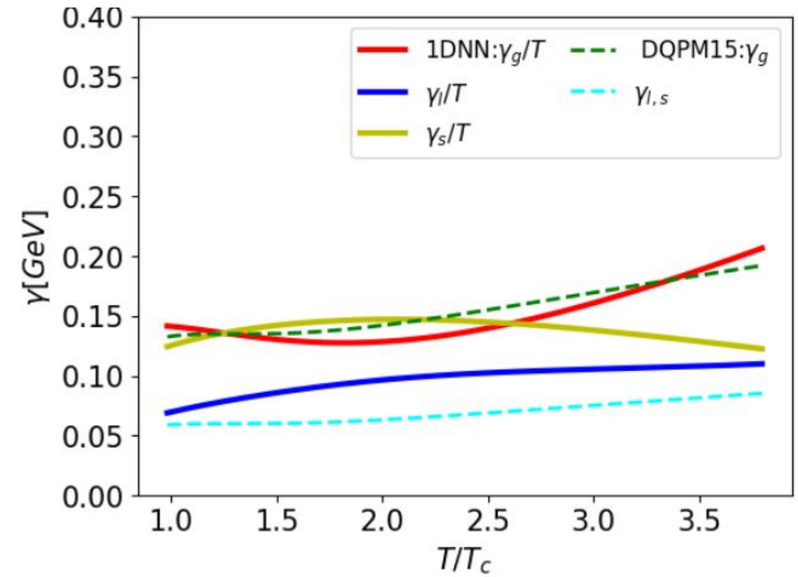


- Cross-check how good we describe the QGP: shear viscosity in a physical range
- Increase in gluon/light quark masses and widths affect the shear viscosity

Tweak the strangeness – improve conductivity

- Strangeness – higher widths



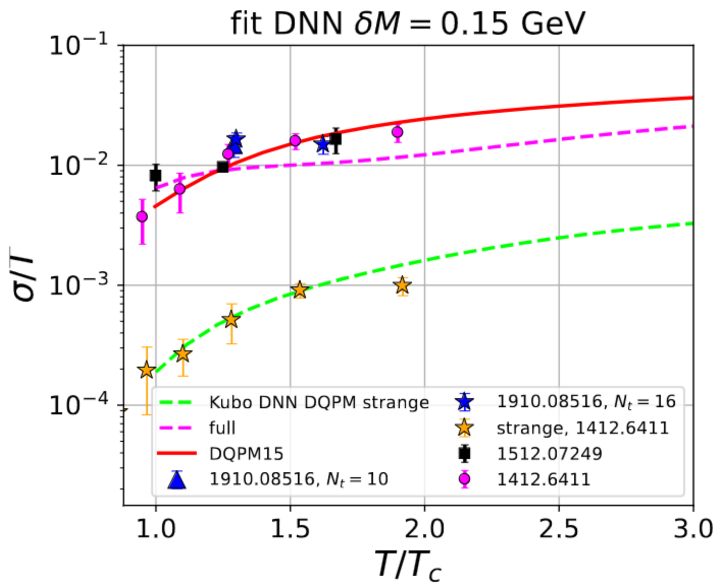


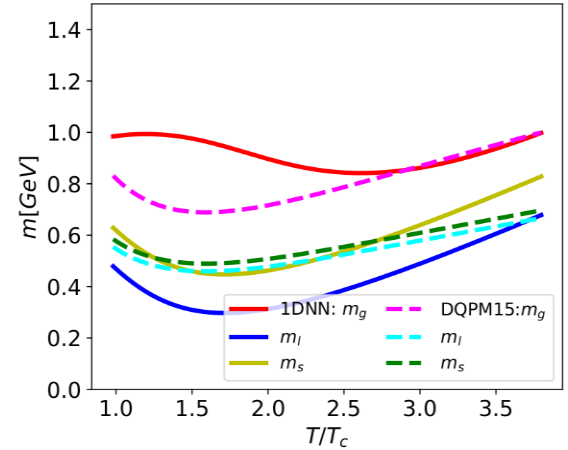
- Masses and widths of strange quark should differ from light sector
- DNN suggests higher widths and smaller masses compare to original parametrization

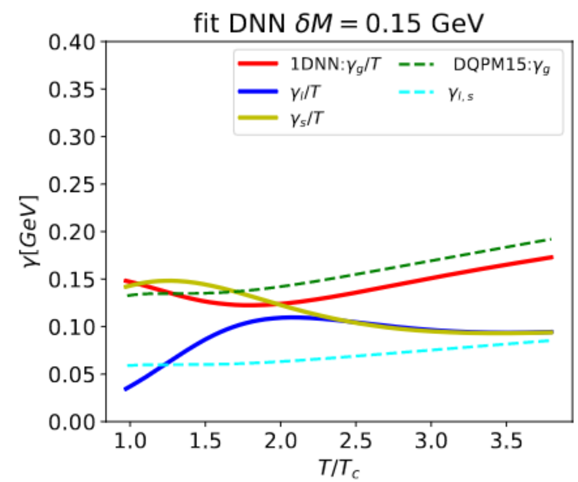
Tweak the strangeness – improve conductivity

- Strangeness – simple shift

$$m_{s(\bar{s})}(T) = m_{q(\bar{q})}(T) + \Delta m$$







- DNN suggests higher widths and smaller masses compare to original parametrization, simple shift also works!
- 2 scenarios looks similar – we need more input from theory

Summary

- We have created framework with small size NN to adjust model parameter (here quasi-particle description) microscopic properties of QGP phase using 3 thermodynamic quantities and transport coefficients (Kubo formalism)
- We found that effective masses/widths of strange quark should differ from the light quark to describe strange conductivity and susceptibility
- DNN can be useful for phenomenology only when regularization terms are provided
- Future application for other models – unsupervised learning can provide hints for the improvements of a model description

Thank you for your attention!

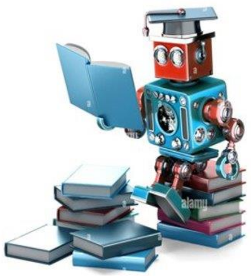
Bonus: ML for HEP

Theory:

- Classify phases of matter - phase transitions in QCD
- Exploring QCD matter in extreme conditions with Machine Learning (recent review: https://arxiv.org/abs/2303.15136)

Jet flavour identification:

› https://arxiv.org/abs/1407.5675 - CNN, Josh Cogan et al;
› https://arxiv.org/abs/1603.09349 - DNN for jets, Pierre Baldi et al;
› https://arxiv.org/abs/1701.05927 - GAN for jets, Luke de Oliveira et al;
› https://arxiv.org/abs/1702.00748 - RNN for jets, Gilles Louppe et al;



And much more in

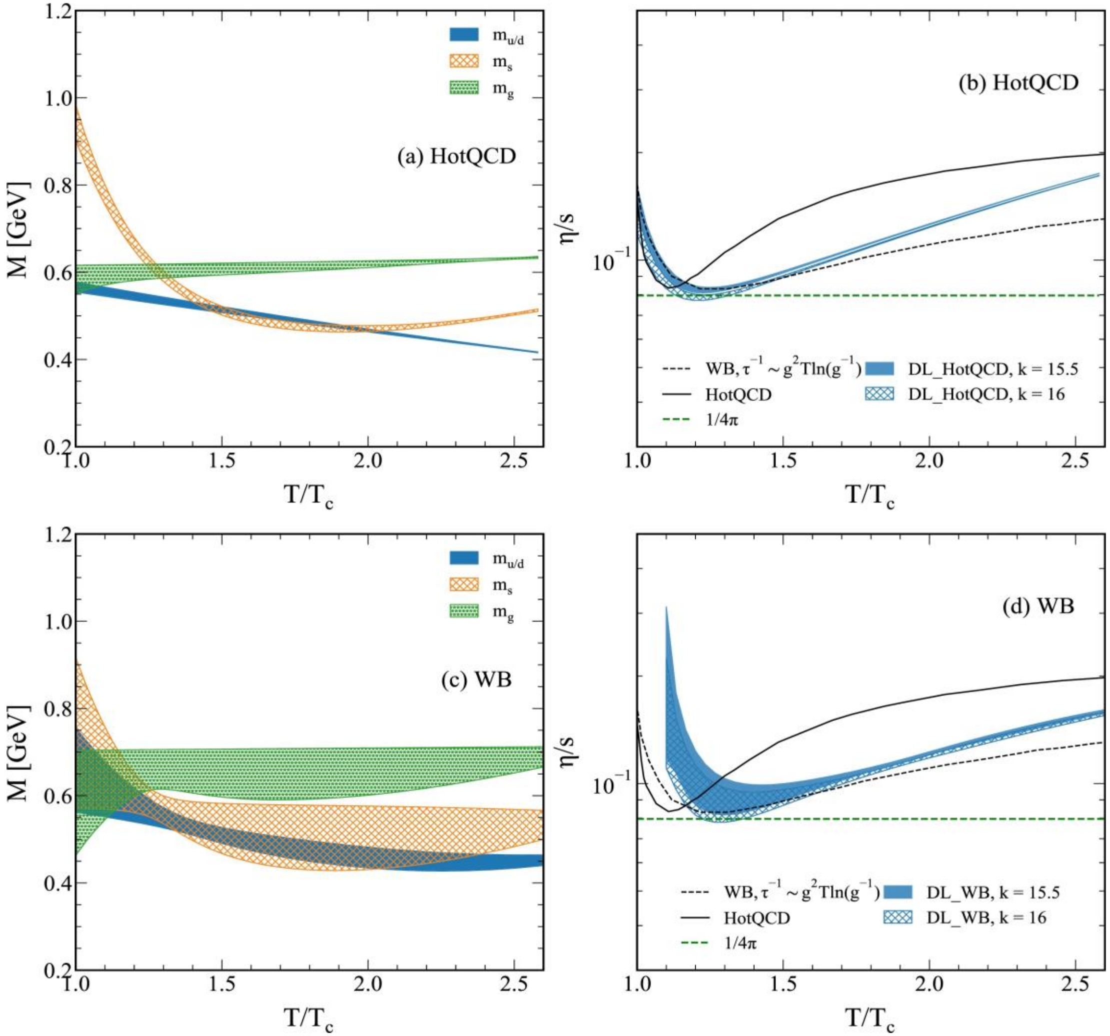
Living Review of ML for Particle Physics ->

https://github.com/iml-wg/HEPML-LivingReview

Thank you for your attention!

Comparison: on-shell results

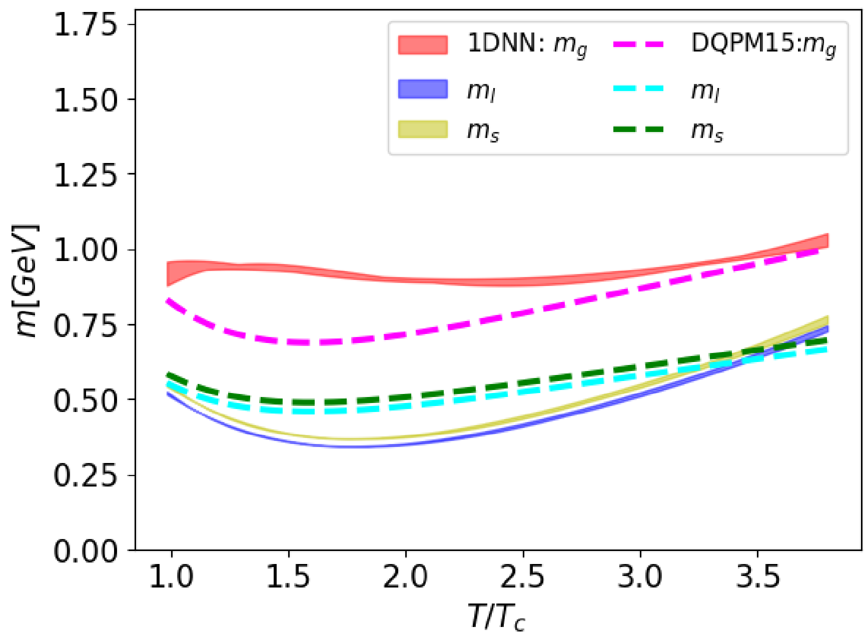
- 3 outputs – only masses – strong dependence on EoS

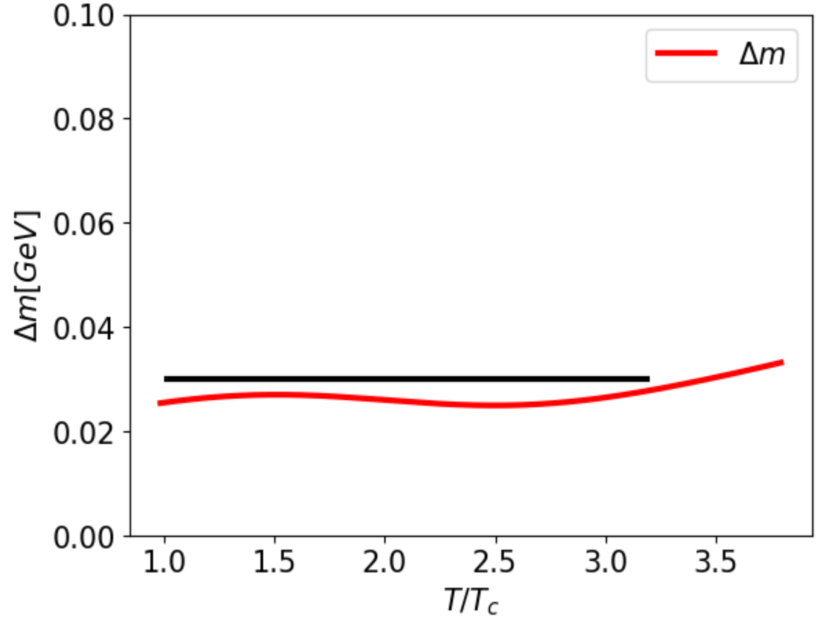


F.P.Li, H.L.Lu, L.G. Pang and G.Y.Qin, arXiv:2211.07994 Phys Let B (2023)

Microscopic properties from AgDNN

- Strangeness – free parameter





- No constraints on strange quark mass/widths
- Original mass difference is preferable

Framework: off-shell Quasi-Particle Model

$$\mathcal{L}_0 = \beta_G \left[\frac{\tilde{s}(T) - s_{\text{lQCD}}}{\Delta s_{lQCD}}\right]^2 + \beta_L \left[\frac{\tilde{\chi}^B(T) - \chi^B_{\text{lQCD}}}{\Delta \chi^B_{lQCD}}\right]^2 + \beta_S \left[\frac{\tilde{\chi}^S(T) - \chi^S_{\text{lQCD}}}{\Delta \chi^S_{lQCD}}\right]^2$$

$$s(T) = -d_g I_g^B - d_q \sum_{i=q,s} I_i^F,$$

$$\chi_2^B(T) = \frac{d_q}{9}(2\chi_l(T) + \chi_s),$$

$$\chi_2^S(T) = d_q \chi_s,$$

$$I_i^B(T,m,\gamma) = \frac{1}{2\pi^2 T}\int \mathrm{d}\,p^2 \frac{4p^2 + 3m_i^2}{3\sqrt{\omega^2 + p^2}} f_B(\omega,T) + 2\int_0^\infty \frac{\mathrm{d}\omega}{2\pi}\int \frac{\mathrm{d}^3p}{(2\pi)^3}\frac{\partial f_B(\omega,T)}{\partial T} h(\omega,p,m_i,\gamma_i),$$

$$I_i^F(T,m,\gamma) = \frac{1}{2\pi^2 T}\int \mathrm{d}\,p^2 \frac{4p^2 + 3m_i^2}{3\sqrt{\omega^2 + p^2}} f_F(\omega,T) + 2\int_0^\infty \frac{\mathrm{d}\omega}{2\pi}\int \frac{\mathrm{d}^3p}{(2\pi)^3}\frac{\partial f_F(\omega,T)}{\partial T} h(\omega,p,m_i,\gamma_i),$$

$$\chi_i(T,m,\gamma) = \frac{1}{2\pi^2 T}\int_0^\infty \mathrm{d}p\, \frac{p^2}{1 + \cosh\left(\sqrt{m_i^2 + p^2}/T\right)} + 2\int_0^\infty \frac{\mathrm{d}\omega}{2\pi}\int \frac{\mathrm{d}^3p}{(2\pi)^3}\frac{\sinh(\omega/T)}{T^2(1 + \cosh(\omega/T))^2} h(\omega,p,m_i,\gamma_i)$$

How to evaluate transport coefficient?

- **Kubo formalism: transport coefficients are expressed through correlation functions of stress-energy tensor**

used in lattice QCD, transport approaches(hadrons), effective models

$$\eta = \frac{1}{20} \lim_{\omega\to 0} \frac{1}{\omega} \int d^4x\, e^{i\omega t} \left\langle \left[\mathcal{S}^{ij}(t,\mathbf{x}),\, \mathcal{S}^{ij}(0,\mathbf{0}) \right] \right\rangle \theta(t)$$

$$\zeta = \frac{1}{2} \lim_{\omega\to 0} \frac{1}{\omega} \int d^4x\, e^{i\omega t} \langle [\mathcal{P}(t,\mathbf{x}),\, \mathcal{P}(0,\mathbf{0})] \rangle \theta(t)$$

$$\mathcal{S}^{ij} = T^{ij} - \delta^{ij}\mathcal{P}$$

$$\mathcal{P} = -\tfrac{1}{3} T^{i}{}_{i}$$

R. Lang and W. Weise, EPJ. A 50, 63 (2014) (NJL model)
A. Harutyunyan et al,PRD 95, 114021, (2017)

Kinetic theory:

- **Relaxation time approximation(RTA): consider relaxation time** $\frac{d f_a^{\text{eq}}}{dt} = \mathcal{C}_a = -\frac{f_a^{\text{eq}} \phi_a}{\tau_a}$

  P. Chakraborty and J. I. Kapusta, PRC 83,014906 (2011)
  G.S. Rocha, M. N. Ferreira, G. S. Denicol and J. Noronha, PRD 106 (2022) no.3, 036022

- **Chapman-Enskog: expand the distribution in terms of the Knudsen number**

  J. A. Fotakis et al, PRD 101 (2020) 7, 076007 (HRG)

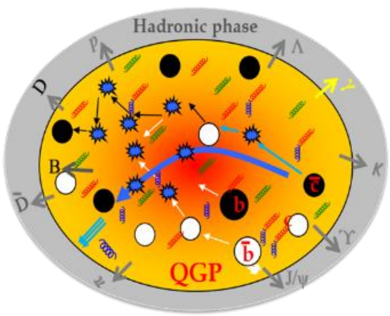
And more!

Holographic models: AdS/CFT correspondence

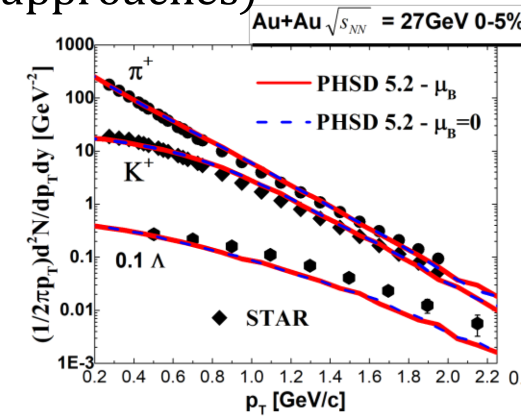
D. T. Son and A. O. Starinets, JHEP 0603, 052 (2006)
M. Attems et al , JHEP 10 (2016), 155.
J. Grefa, M. Hippert, J. Noronha, J. Noronha-Hostler, I. Portillo, C. Ratti and R. Rougemont, PRD 106 (2022) no.3, 034024 <- near CEP and across the first-order line

Properties of QGP: transport coefficients

! One has to specify transport and microscopic properties as well as EoS for theoretical simulations of HICs (hydro / transport approaches)



Evolution of QCD medium



Hybrid simulations:

vHLLE/Music+UrQMD/SMASH

Iu.A. Karpenko, P. Huovinen, H. Petersen and M. Bleicher PRC 91 (2015), 064901.

CORE-CORONA – EPOS (K. Werner), DCCI(Y. Kanakuba)

MUFFIN

Transport simulations with QGP phase:

Catania transport – QuasiParticle Model

F. Scardina, S. K. Das, V. Minissale, S. Plumari, and V. Greco, PRC 96, 044905 (2017).

AMPT – PNJL EoS (Mean field potentials)

K.J. Sun, C. M. Ko, and Z.-W. Lin, PRC 103(2021)

PHSD – off-shell transport approach derived from Kadanoff-Baym many-body theory (Quantumm Boltzmann) with hadronic and QGP phase – 2PI Dynamical QuasiParticle Model

W. Cassing, E. Bratkovskaya, PRC 78 (2008) 034919

P. Moreau, O. S , L. Oliva, T. Song, W. Cassing, E. Bratkovskaya, PRC 100 (2019) , 014911;

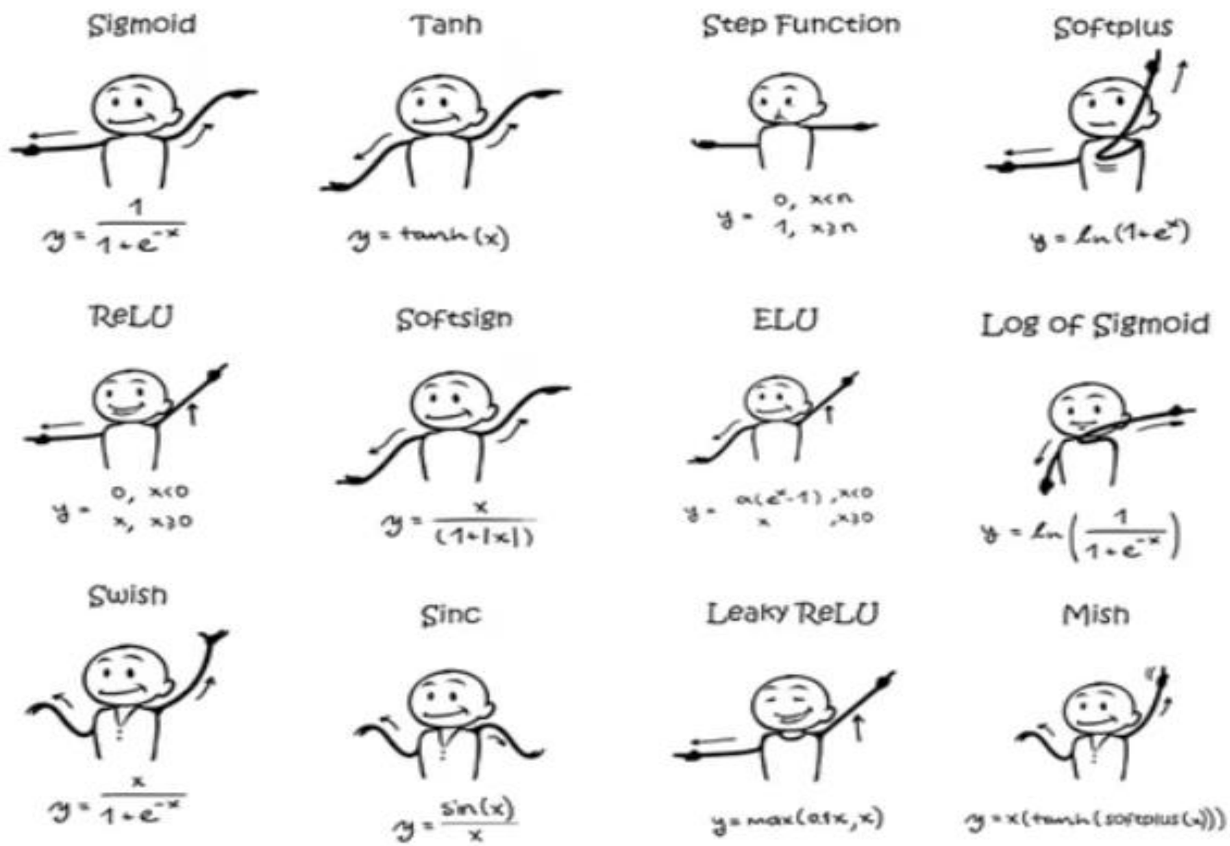
O. S, P. Moreau, L. Oliva, V. Voronyuk, V. Kireyeu, T. Song, E. Bratkovskaya, Particles 3 (2020)

Machine Learning: Basic concepts

$$h=\Theta\left(\sum w_i x_i + b\right)$$

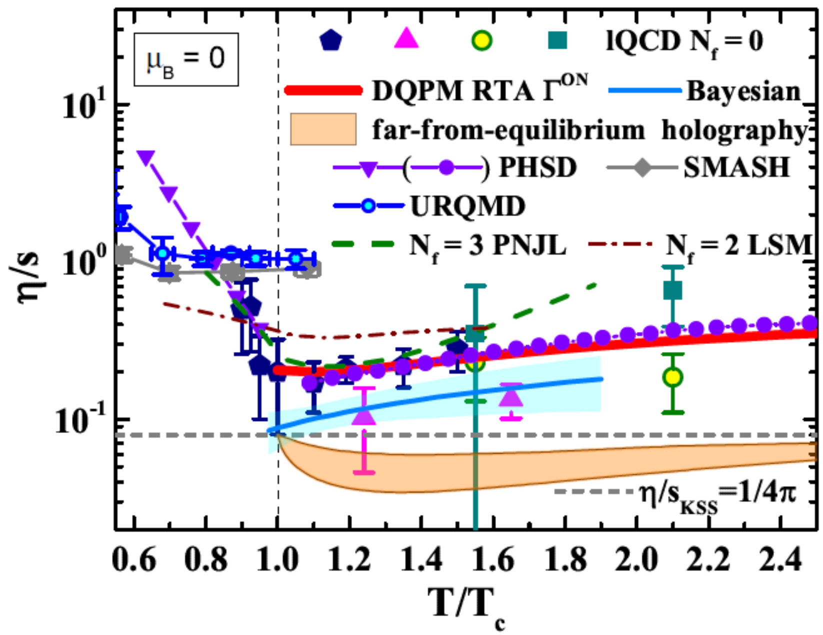
- $\Theta(x)$ — Heaviside function
  (0, if $x \le 0$, 1 otherwise)
- non-smooth ⇒ hard to optimize

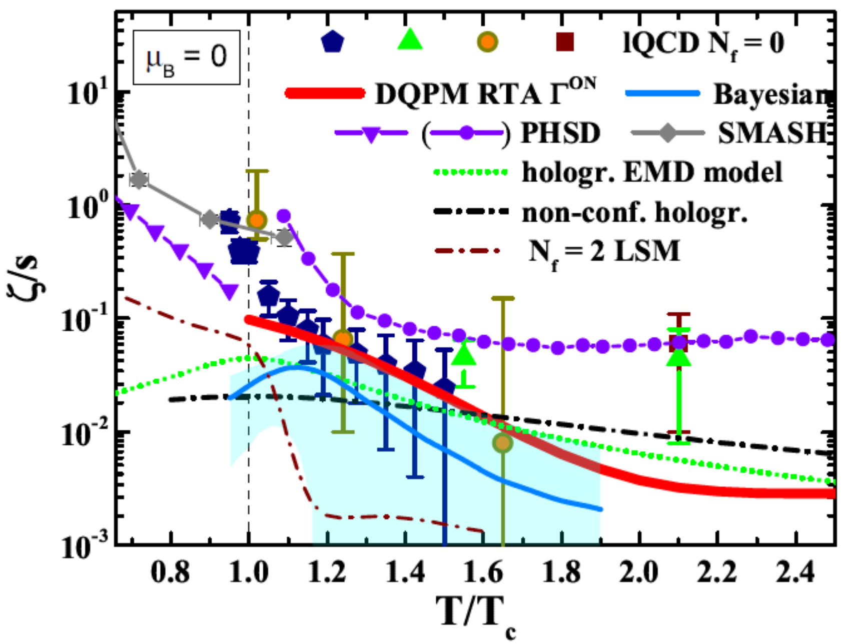
Alternatives: choose wisely!



Uncertainties in viscosities of QGP

Model predictions: from first principles to effective models – quest for consistency





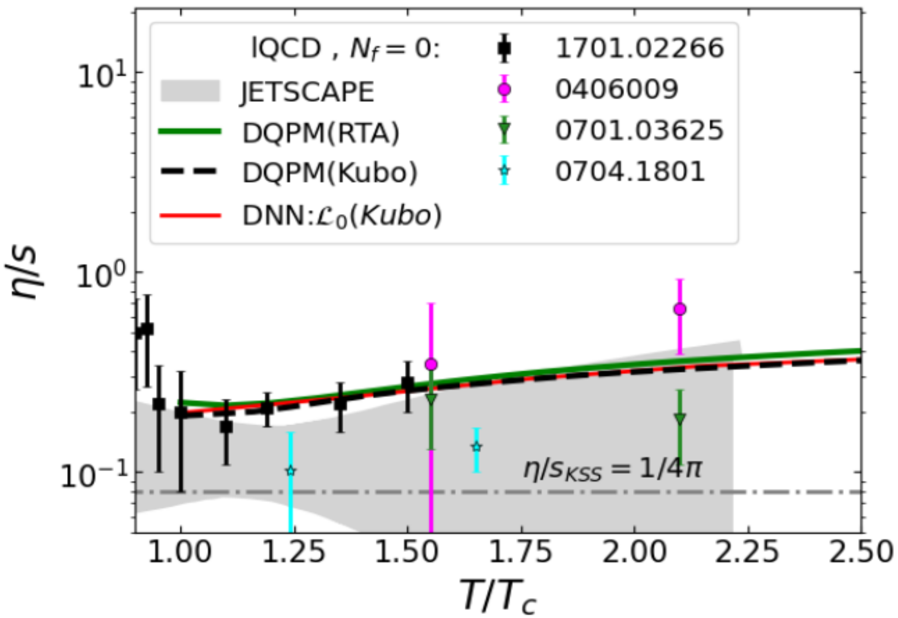
! Effective models of QGP using the same EoS predict completely different transport coefficients

Machine Learning: Unsupervised

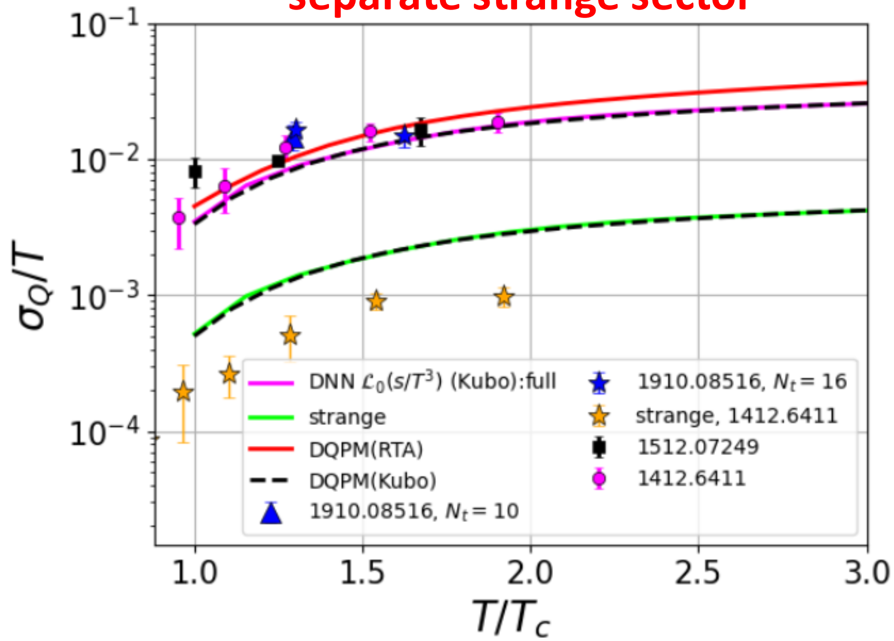
- Unsupervised Learning is most promsing/suitable for phenomenology and physics

Strange conductivity: reconsider strange quark

Contain all degrees of freedom



Only quark sector
– separate strange sector



- Kubo formalism allows to evaluate transport coefficients without involving cross-sections
- Conductivity shows how good we describe quark sector – in particular we can compare to the strange quark conductivity
- Check how strangeness is described within the quasi-particle models and its influence on conductivity