

# Using low-rank tensor formats to enable computations of cancer progression models in large state spaces

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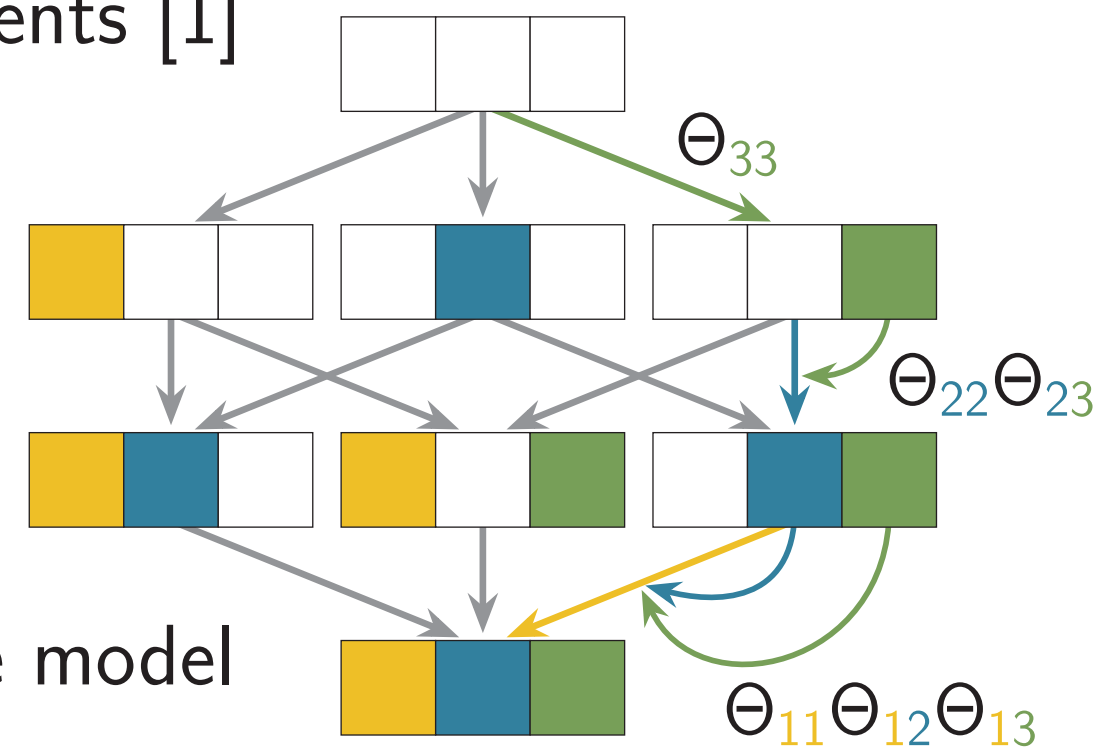
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## Summary

- Comprehensive cancer progression models should include a large number  $d$  of genomic events
- Mutual Hazard Networks model the progression process using only  $d^2$  parameters [1]
  - Computational complexity of a straightforward implementation still scales exponentially in  $d$
  - Calculations using  $\gtrsim 25$  events are computationally infeasible [2]
- Tensor Trains allow for cost-effective storage and calculations for high-dimensional tensors
  - This method reduces the computational complexity from exponential to polynomial in  $d$

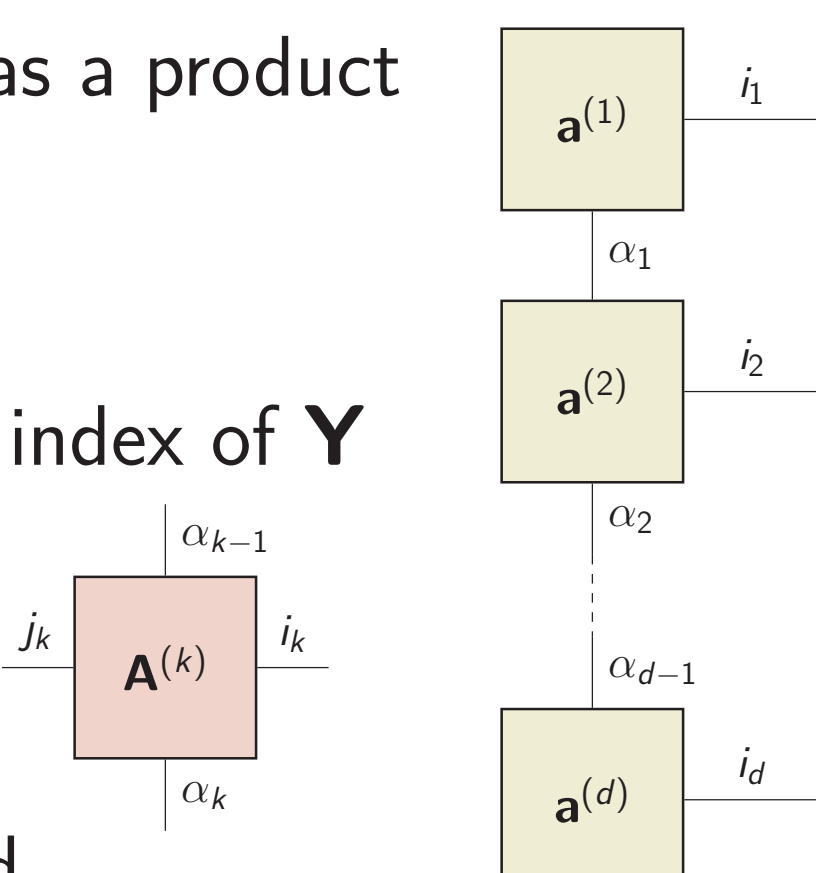
## Mutual Hazard Network (MHN) model

- MHN models tumor progression as a continuous-time Markov chain on the  $2^d$ -dimensional state space of possibly active events [1]
- Events can only occur one at a time
- Transition rates are given by
 
$$(Q_\Theta)_{\mathbf{x} \rightarrow \mathbf{x}+i} = \underbrace{\Theta_{ii}}_{\text{base rate}} \prod_{j=1}^d \underbrace{\Theta_{ij}}_{\text{influences}}$$
- $Q_\Theta \in \mathbb{R}^{2^d \times 2^d}$  is sparse,  $\Theta \in \mathbb{R}^{d \times d}$  describes the model in compact form using only  $d^2$  parameters
- Time marginal probability distribution from  $\Theta$ :
 
$$\mathbf{p}_\Theta = (\mathbf{Id} - Q_\Theta)^{-1} \mathbf{p}_\emptyset \quad \mathbf{p}_\emptyset = (100\%, 0\%, 0\%, \dots, 0\%)^T$$
- Optimal  $\Theta$  matrices are found by optimizing the time-marginalized Kullback-Leibler divergence from the given data distribution  $\mathbf{p}_D$ :
 
$$S_{KL}(\mathbf{p}_\Theta) = \sum_{\mathbf{x}} (\mathbf{p}_D)_{\mathbf{x}} \log((\mathbf{p}_\Theta)_{\mathbf{x}})$$
- Gradients can be calculated analytically:
 
$$\frac{\partial S_{KL}}{\partial \Theta_{ij}} = \sum_{\mathbf{y}, \mathbf{z}} \underbrace{\sum_{\mathbf{x}} \frac{\partial S_{KL}}{\partial (\mathbf{p}_\Theta)_{\mathbf{x}}} (\mathbf{Id} - Q_\Theta)^{-1}_{\mathbf{xy}} \left( \frac{\partial Q_\Theta}{\partial \Theta_{ij}} \right)_{\mathbf{yz}} (\mathbf{p}_\Theta)_{\mathbf{z}}}_{=:\mathbf{q}_{\mathbf{y}}}$$
- KL divergence and gradient calculation time is dominated by solution time of two linear equations:
 
$$(\mathbf{Id} - Q_\Theta) \mathbf{p}_\Theta = \mathbf{p}_\emptyset \quad (\mathbf{Id} - Q_\Theta)^T \mathbf{q} = \frac{\partial S_{KL}}{\partial \mathbf{p}_\Theta}$$



## Tensor Train (TT) representation

- A  $d$ -dimensional tensors  $\mathbf{a} \in \mathbb{C}^{n_1 \times \dots \times n_d}$  can be written as a product of  $d$  Tensor Train cores  $\mathbf{a}^{(k)} \in \mathbb{C}^{r_{k-1} \times n_k \times r_k}$ :
 
$$\mathbf{a} = \mathbf{a}^{(1)} \circ \dots \circ \mathbf{a}^{(d)}$$
- $\mathbf{X} \circ \mathbf{Y}$  denotes contraction of last index of  $\mathbf{X}$  with first index of  $\mathbf{Y}$
- Similar for operators  $\mathbf{A} \in \mathbb{C}^{(m_1 \times \dots \times m_d) \times (n_1 \times \dots \times n_d)}$ :
 
$$\text{TT cores } \mathbf{A}^{(k)} \in \mathbb{C}^{r_{k-1} \times m_k \times n_k \times r_k}$$
- Storage cost is reduced from exponential to linear in  $d$ , but additional dependency on TT ranks  $r_k$  is introduced
- Many arithmetic operations can be performed directly in the TT format, reducing the computational complexity [3]:
  - Superposition  $\lambda \mathbf{a} + \nu \mathbf{b}$ :  $\mathcal{O}(dn(r_{\mathbf{a}} + r_{\mathbf{b}})^2)$
  - Inner product  $\langle \mathbf{a}, \mathbf{b} \rangle$ :  $\mathcal{O}(dn r_{\mathbf{a}} r_{\mathbf{b}} (r_{\mathbf{a}} + r_{\mathbf{b}}))$
  - Operator-by-Tensor product  $\mathbf{A} \mathbf{b}$ :  $\mathcal{O}(dmn(r_{\mathbf{A}} r_{\mathbf{b}})^2)$
- Linear equations  $\mathbf{A} \mathbf{x} = \mathbf{b}$  can also be solved efficiently directly in this format



## References

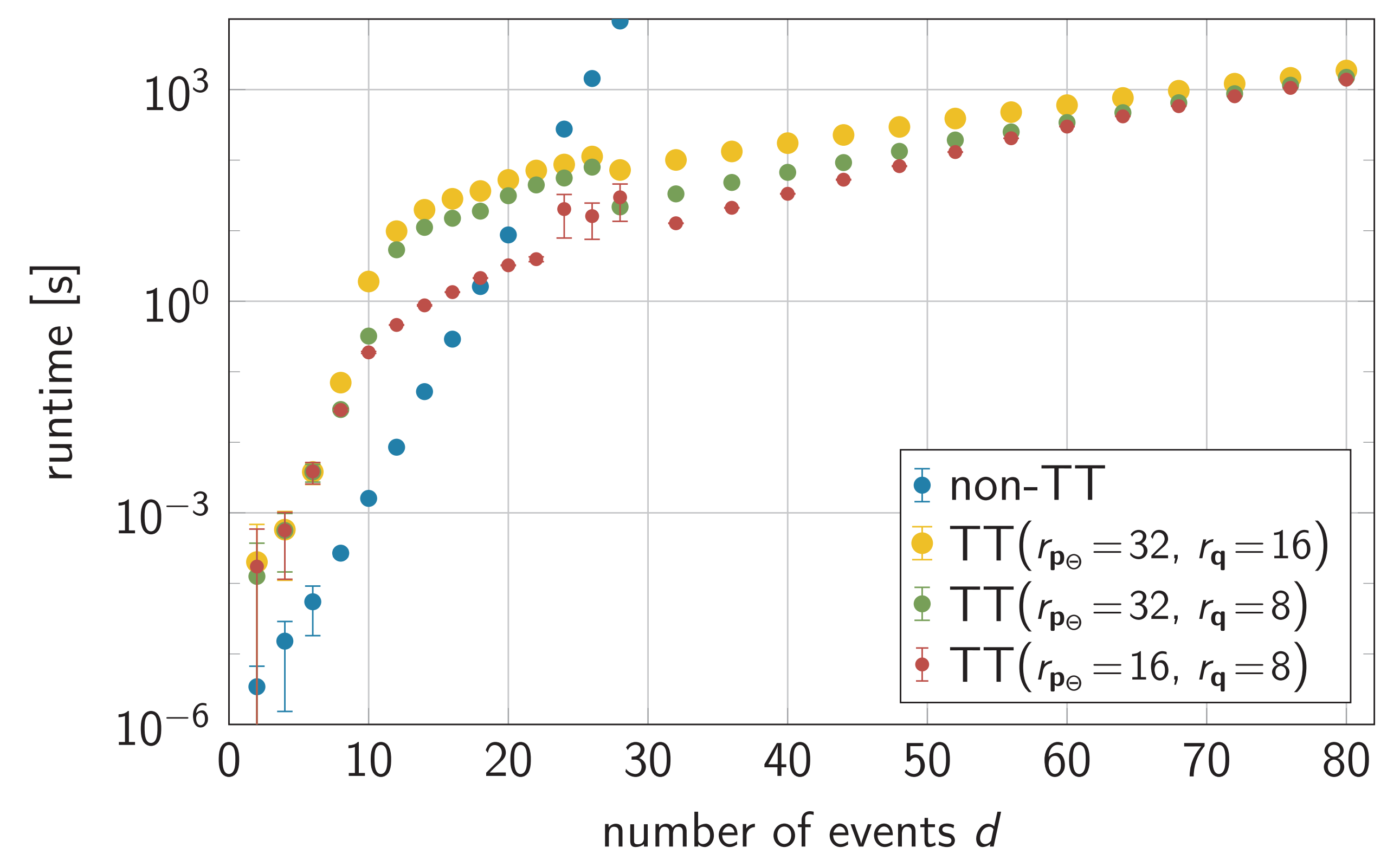
- [1] R. Schill, S. Solbrig, T. Wettig, and R. Spang, *Modelling cancer progression using Mutual Hazard Networks*, *Bioinformatics* **36** (January, 2020) 241.
- [2] P. Georg, L. Grasedyck, M. Klever, R. Schill, R. Spang, and T. Wettig, *Low-rank tensor methods for Markov chains with applications to tumor progression models*, *Journal of Mathematical Biology* **86** (December, 2022).
- [3] P. Georg, *Tensor Train Decomposition for solving high-dimensional Mutual Hazard Networks*, PhD thesis, Universität Regensburg, October, 2022.

## Tensor Trains for MHN

- Events are binary  $\rightarrow n_k = 2$  for all mode sizes
- $Q_\Theta$  can naturally be written as a Tensor Train [1]:
 
$$Q_\Theta = \sum_{i=1}^d \left( \bigotimes_{j=1}^{i-1} \begin{pmatrix} 1 & 0 \\ 0 & \Theta_{ij} \end{pmatrix} \right) \otimes \begin{pmatrix} -\Theta_{ii} & 0 \\ \Theta_{ii} & 0 \end{pmatrix} \otimes \left( \bigotimes_{j=i+1}^d \begin{pmatrix} 1 & 0 \\ 0 & \Theta_{ij} \end{pmatrix} \right)$$
  - $Q_\Theta$  is a sum of  $d$  rank-1 Tensor Trains
  - All TT-ranks of  $Q_\Theta$  are equal to  $d$
- $\mathbf{p}_\emptyset$  is a canonical unit Tensor Train, with all TT-ranks equal to 1
- $\mathbf{p}_\Theta$  and  $\mathbf{q}$  can be calculated in the TT format (max. TT ranks  $r_{\mathbf{p}_\Theta}$  and  $r_{\mathbf{q}}$ )
- For gradients, each nonzero entry in  $\mathbf{p}_D$  has to be treated individually
  - One linear equation has to be solved for each nonzero entry (usually  $\sim 1000$ )
  - This can be parallelized trivially

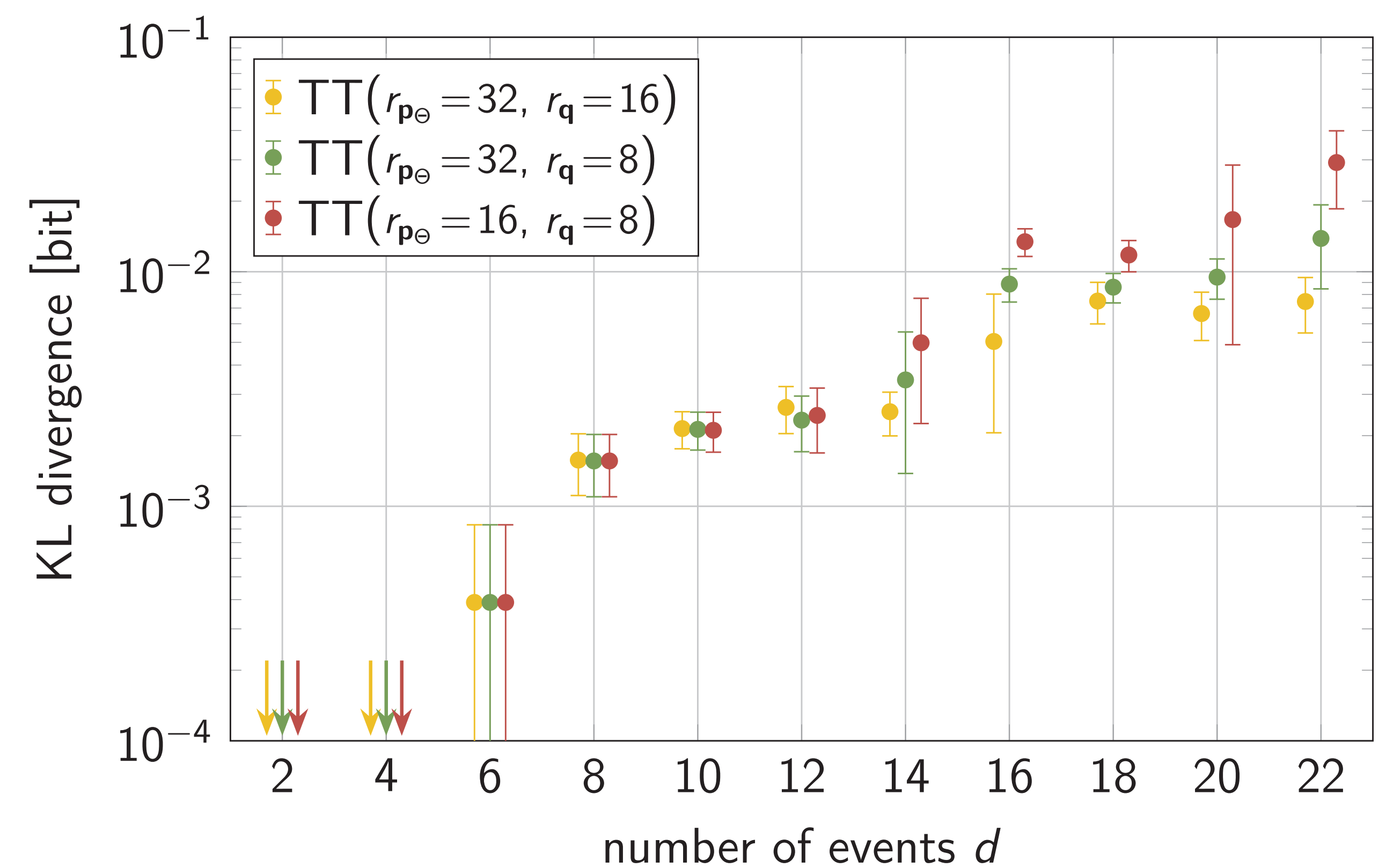
## Results: Runtime speedup

- Runtime for one score and gradient evaluation at  $\Theta$  = independence model
- $\mathbf{p}_D$  constructed from 1000 random samples
- Runtime grows with  $\sim d^{5.4}$  for large  $d \Rightarrow$  **polynomial growth!**



## Results: Accuracy of the TT solution

- KL divergence from exact result to TT solution after full optimization of  $\Theta$



## Code availability

- C++ library for TT-calculations pRC: [gitlab.com/pjgeorg/pRC](https://gitlab.com/pjgeorg/pRC)
- Application-specific C++ library cMHN that utilizes pRC for MHN-calculations: soon to be open-source

## Future improvements

- Reduce runtime by accelerating solution of linear equations in TT format
- Include formation of metastases in the model