



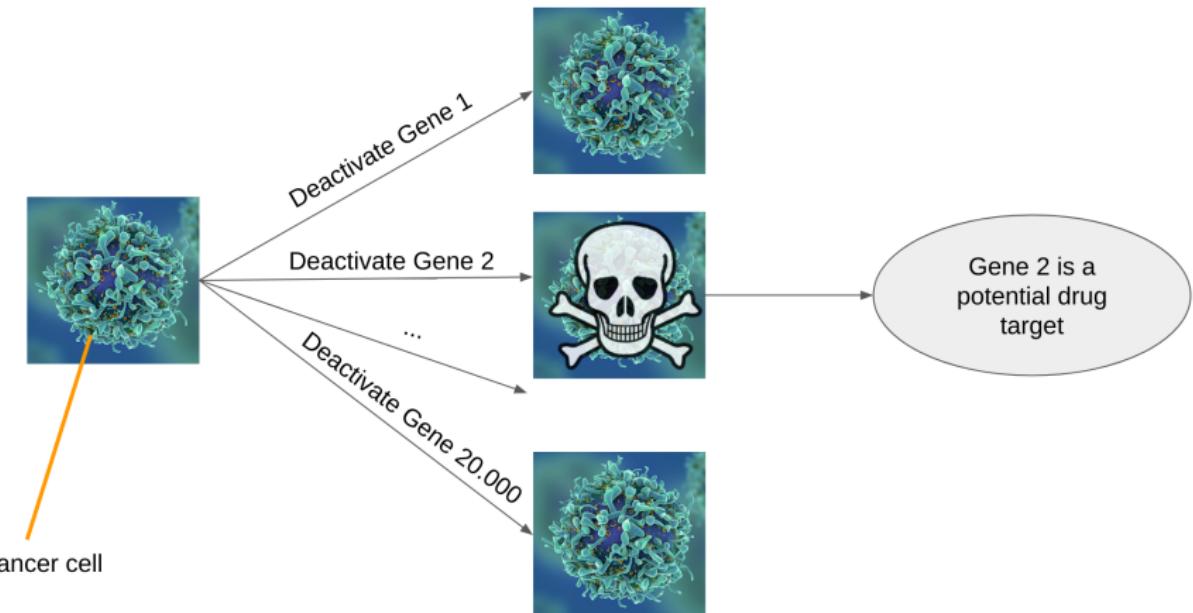
## PAVOOC - An AI integrated web-app for CRISPR target recommendation

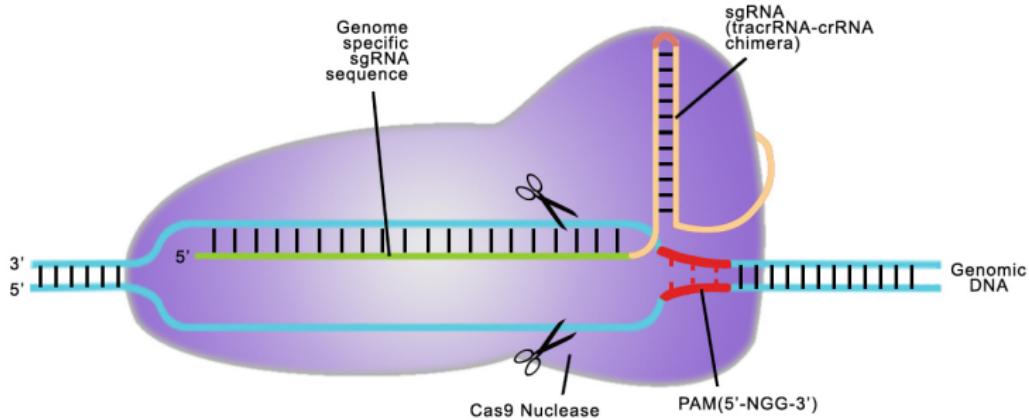
Moritz Schäfer | Technische Universität Berlin & Bayer Pharma | Prediction and visualization of on- and off-targets for CRISPR

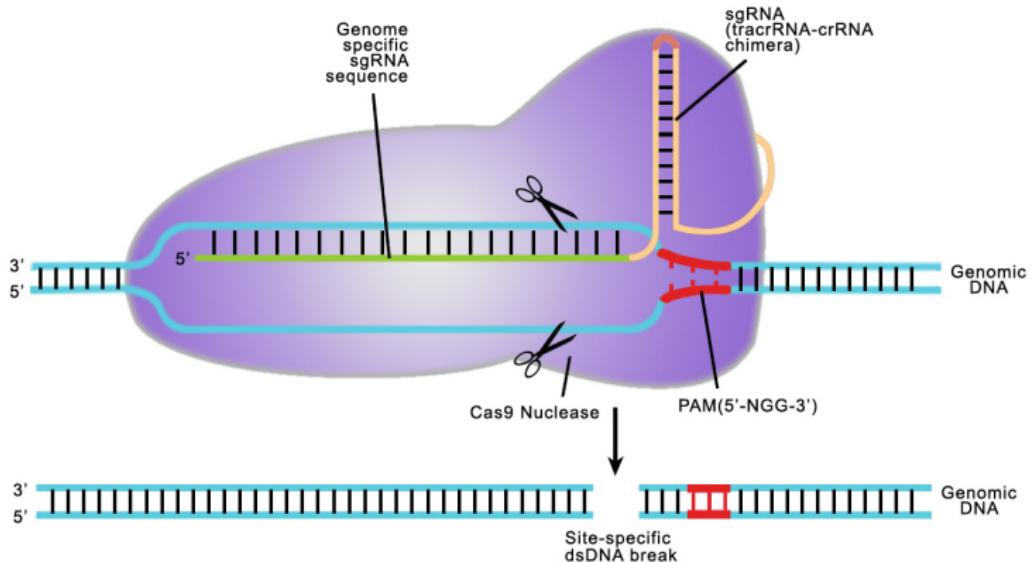


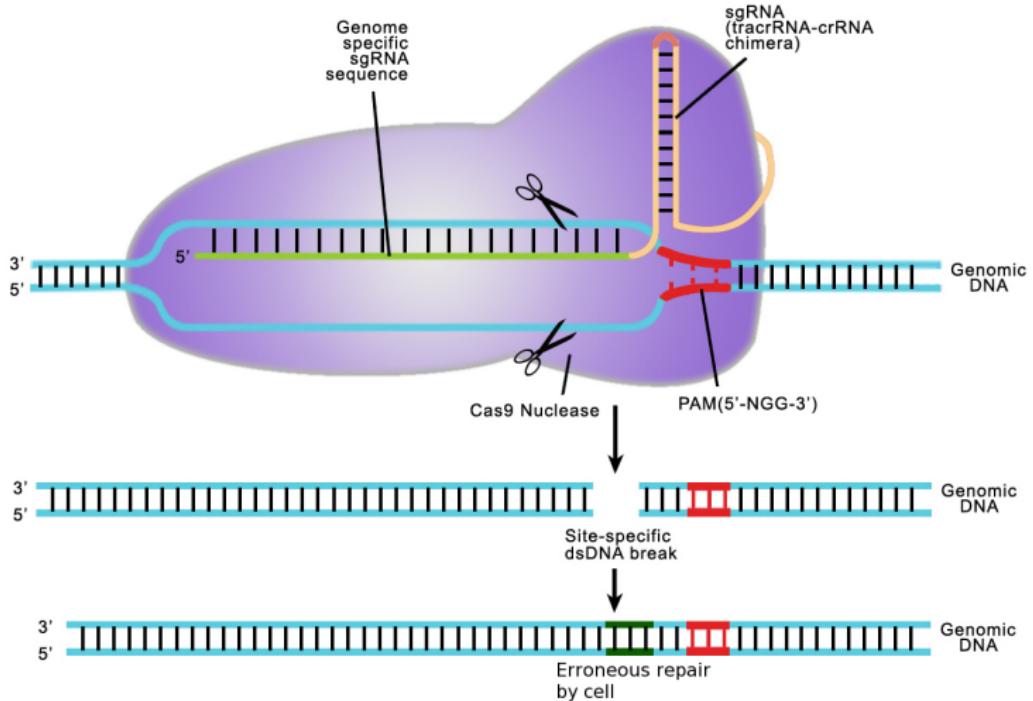


## Target discovery



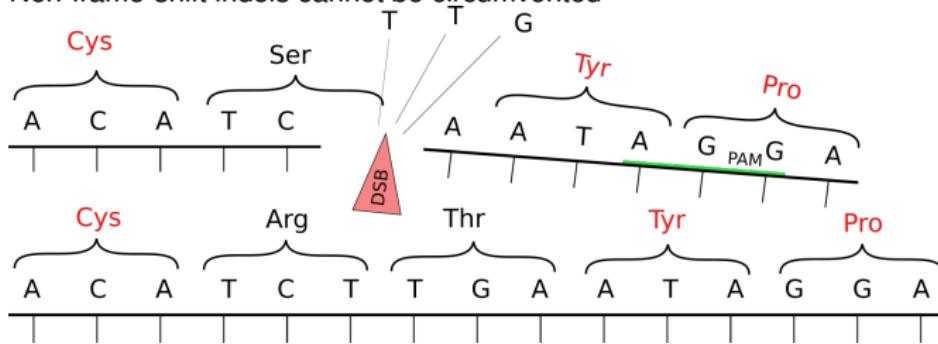






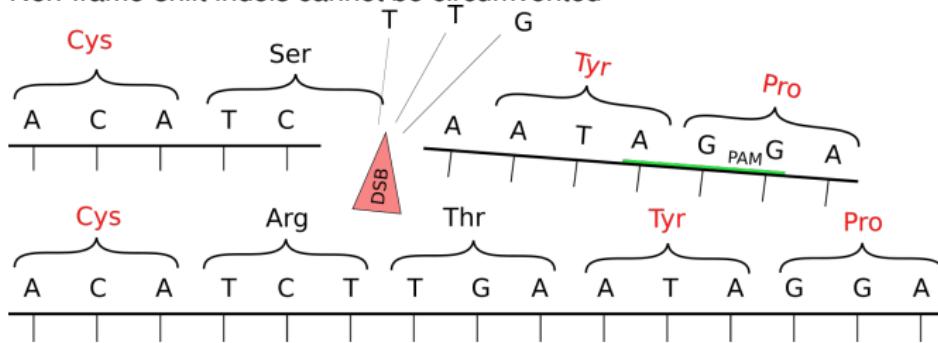
## Problems

- Non-frame-shift-indels cannot be circumvented



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- Guide performance varies significantly



## Solution

- Cutting-edge guide efficacy scoring



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- Web based guide design tool

## Guide efficacy prediction – Dataset

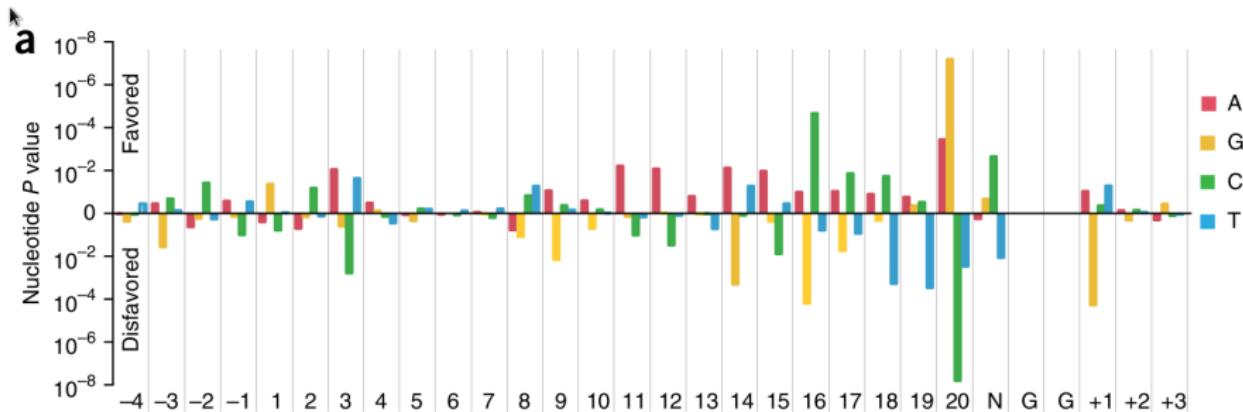
Guide	Measured efficacy
GTTAGGGGTCCGTACTCAGCAAGG	0.86
ACACTGCCGAGCGATGAGGATGG	0.42
AAGGTGAAGGAGGATGCGGCGGG	0.53
GAAAAGATAAGGTCACTGACCCGG	0.12
GCAAGTCACTGAGTGCAGAACGG	0.73
GCATTGGTAAGCGCACAGGAAGG	0.70
AAGACTGGCGCATGGTCCACTGG	0.57
...	...

- 1,837 data rows from 2014
- 3,473 data rows from 2016
- Efficacy relates to cell proliferation after CRISPR application

"Optimized sgRNA design to maximize activity and minimize off-target effects of CRISPR-Cas9", 2016, John G. Doench et al.



## Guide efficacy prediction – 2014



"Rational design of highly active sgRNAs for CRISPR-Cas9–mediated gene inactivation", 2014, John G. Doench et al.



## Guide efficacy prediction – 2016 (Azimuth)

Pairwise nucleotide features



## Guide efficacy prediction – 2016 (Azimuth)

Pairwise nucleotide features

ACTATCTATCGTACGA**TT**GA



## Guide efficacy prediction – 2016 (Azimuth)

Pairwise nucleotide features

ACTATCTATCGTACGA**TT**GA

ACTATCTATCGTACGAC**AAG**

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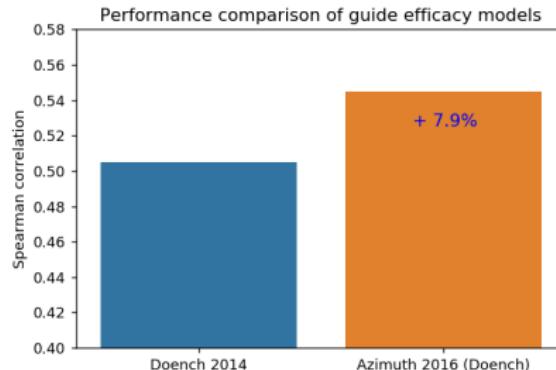
## Guide efficacy prediction – 2016 (Azimuth)

Pairwise nucleotide features

ACTATCTATCGTACGA**TT**GA

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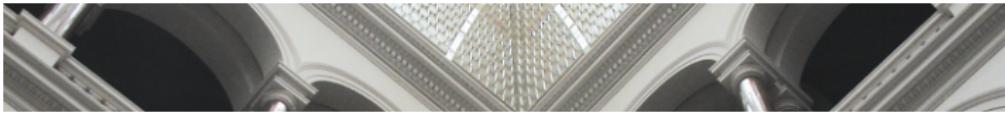




## Convolutional neural networks

Well performing guides:

GTAGGGGTCCGTACTCAGCA  
CAGGGTCCGTACTCAGAGGA  
CTAGCGTAGAGCGCACTGCA  
ACTGAGCTAGCGTAGAAGCA  
TGAGCTAGCGTAGAGCACCA  
ACTGAGCTAGCGTAGTAGCT  
AGCGTAGAGCGCGCTGCC  
GAGCGCACTGAGCTAGAGAA  
ATAGAGCGCCTGAGCTCGCA  
CGTAGAGCGCACTGAGAGCT



## Convolutional neural networks

Well performing guides:

AGCA

AGGA

TGCA

AGCA

ACCA

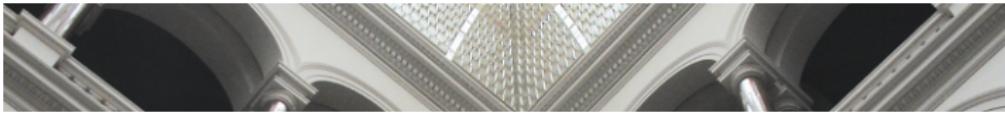
AGCT

CGCC

AGAA

CGCA

AGCT



## Convolutional neural networks

Well performing guides:

AGCA

AGGA

TGCA

AGCA

ACCA

AGCT

CGCC

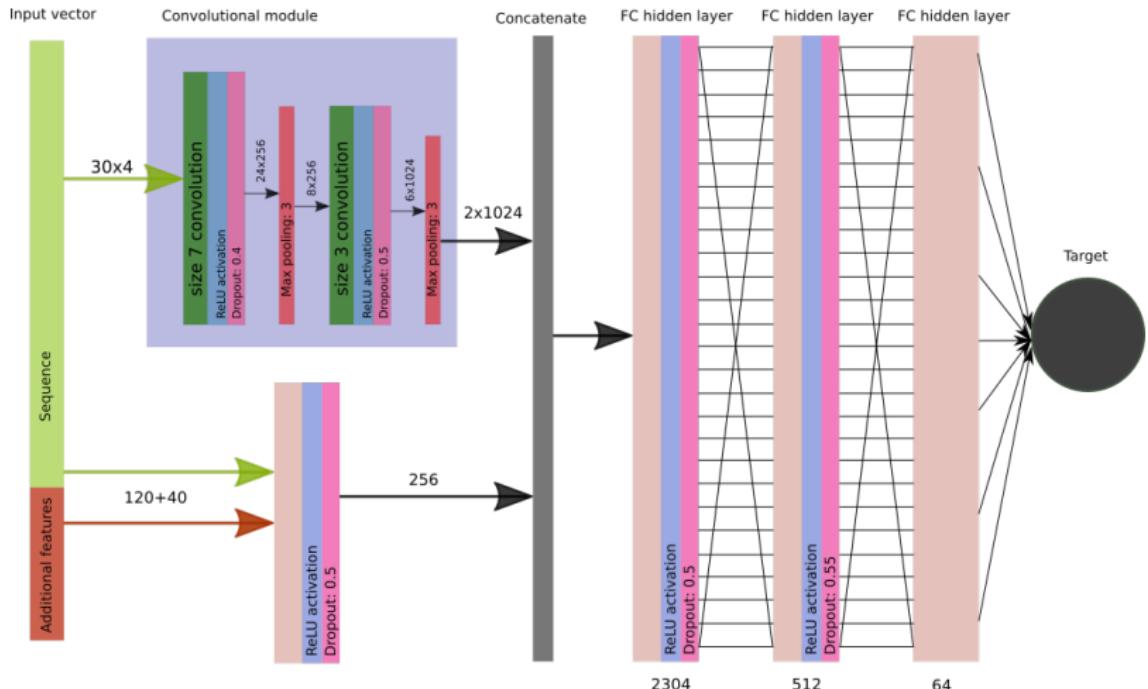
AGAA

CGCA

AGCT

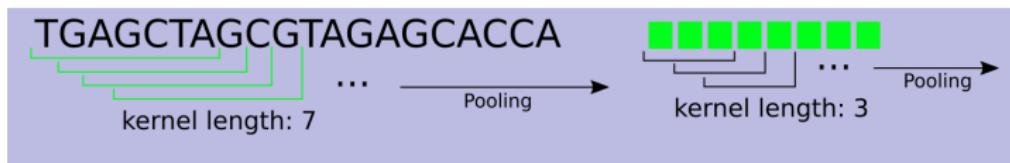
Learned filter: [A G C A]

## Model architecture

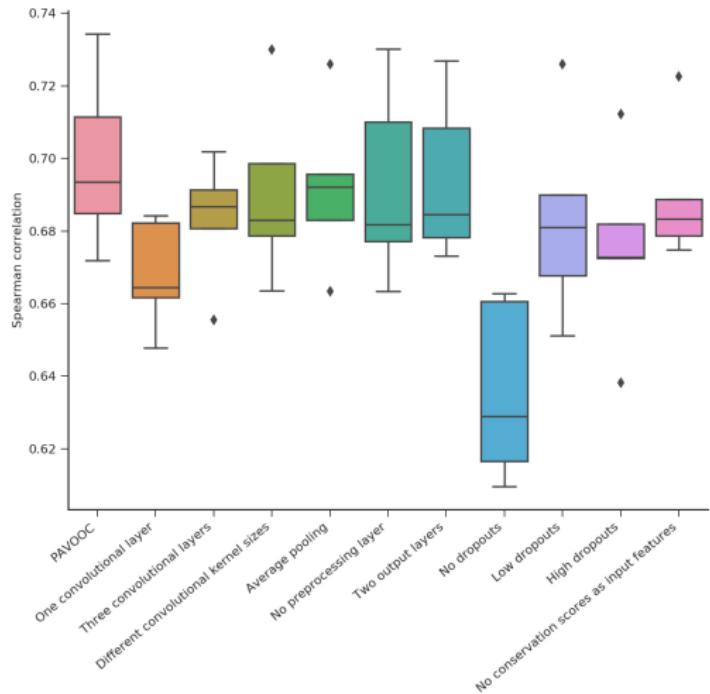




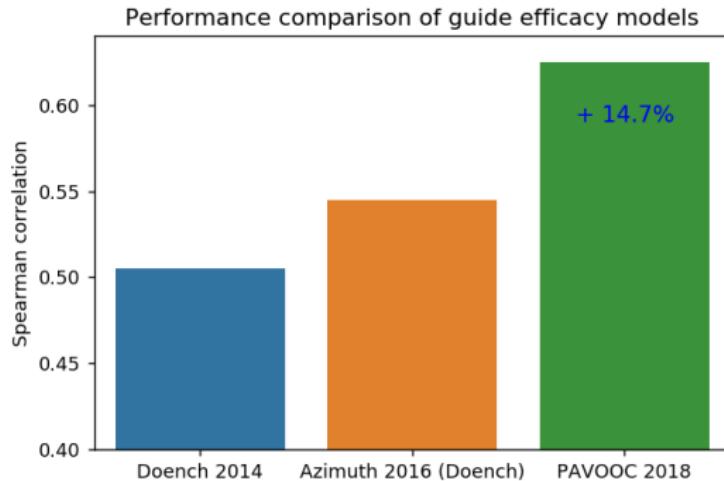
## Model architecture – Convolution module



## Model optimization



## Model architecture





## Conclusion and Takeaways

- Cas9 efficacy depends on complex biological coherences
- DL improves guide efficacy prediction
- DL feasible with ~5,000 rows



## Future Work & Discussion

- Additional input features (chromatin accessibility)
- Evaluate model on different datasets
- Support additional species



## Live Demo

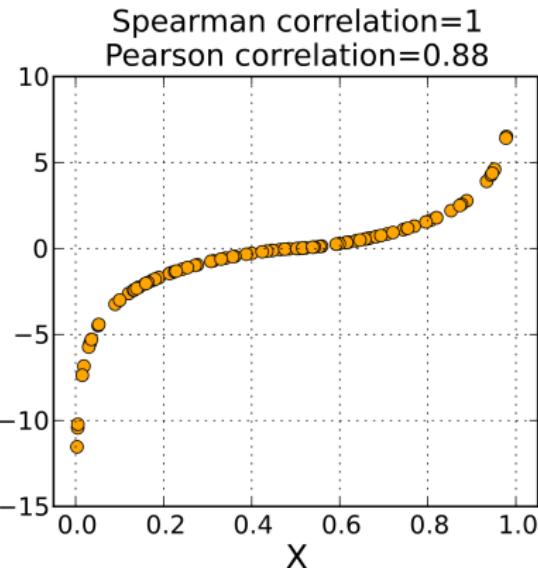
<http://pavooc.me>



End



## Spearman correlation





## Spearman correlation

- Test set labels: [0.2, 0.3, 0.5, 0.9]
- Test set predictions: [0.4, 0.6, 0.7, 0.8]
- Spearman correlation: 1.0

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### Advantages:

- Ranking mimicks the task of guide selection

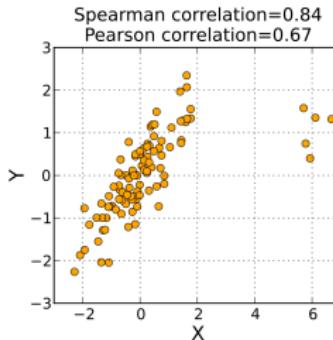


## Spearman correlation

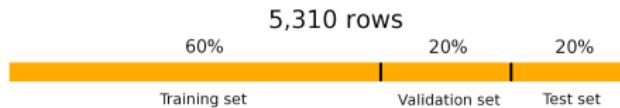
- Test set labels: [0.2, 0.3, 0.5, 0.9]
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### Advantages:

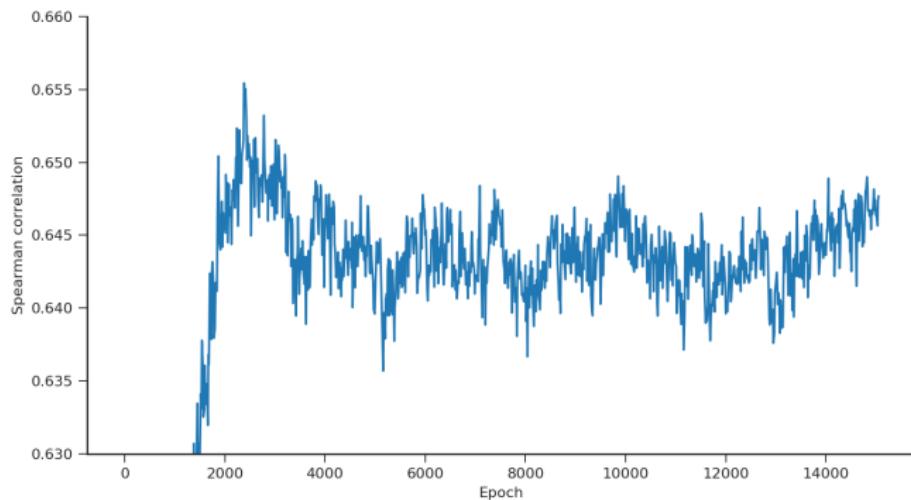
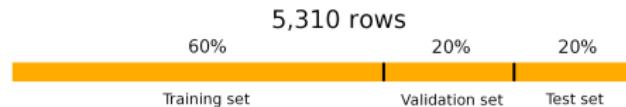
- Ranking mimicks the task of guide selection
- Robust against outliers



## Performance evaluation



## Performance evaluation





## Acknowledgements

- Prof. Manfred Opper (supervisor at TU Berlin)
- Dr. Andreas Steffen (supervisor at Bayer)
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- Bayer Pharma AG