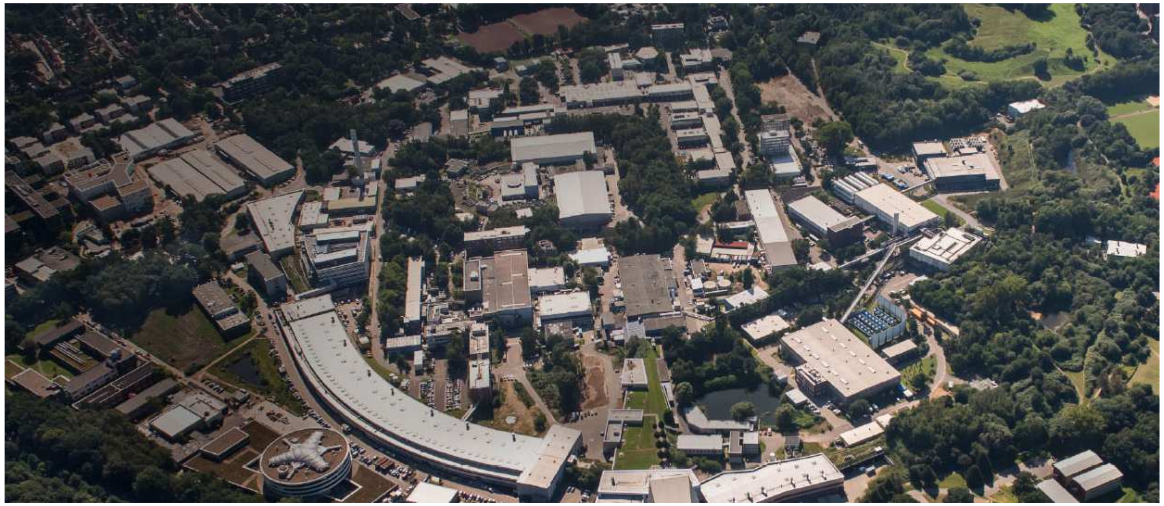
 

Quantum GANs at DESY.

Prof. Dr. Kerstin Borras and Dr. Dirk Krücker

Deutsches Elektronen-Synchrotron DESY and RWTH Aachen University

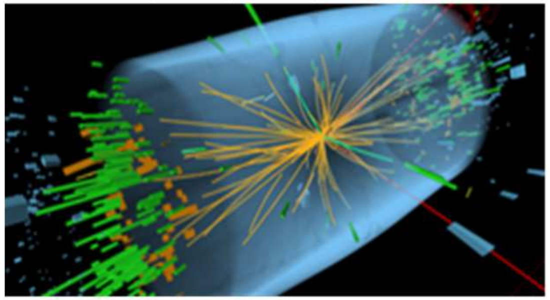
Quantum Machine Learning

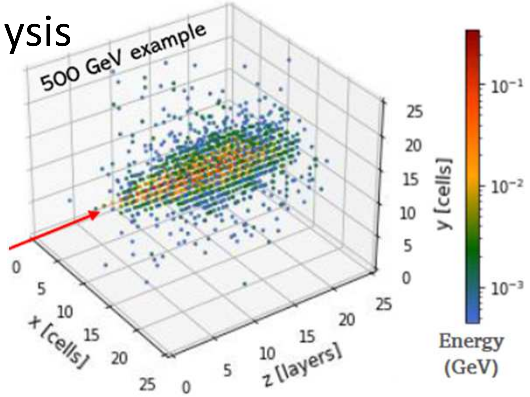
Early examples in Experimental Particle Physics

- **Quantum Maschine Learning lies at the intersection of Quantum Computing and Maschine Learning**

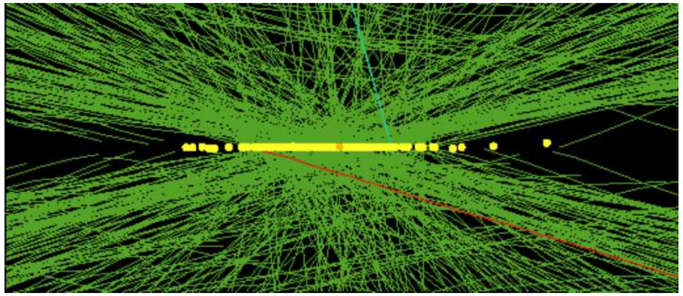
  - High Luminosity LHC (>2029) needs vast amount of simulations with 200 pile-up events, GRID Computing, Big Data Analysis

LHC (~20 pile-up events)





LHC (~140 pile-up events)

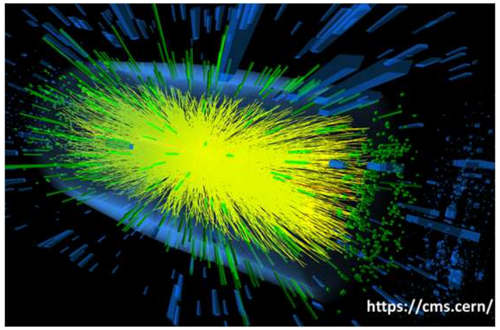


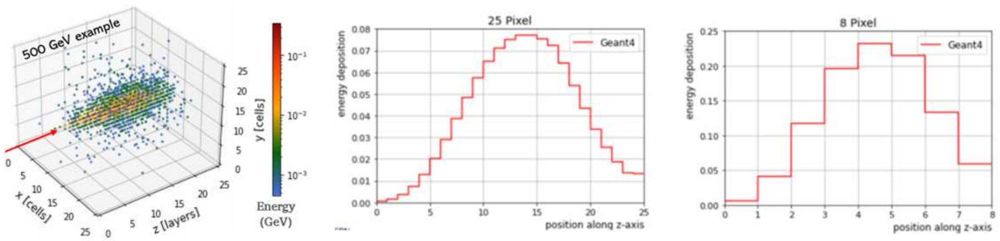
- **Develop machine learning and tensor network methods for QC**
  - Quantum GAN (Quantum Generative Adversarial Network) simulations for detectors (CERN Openlab with joint Gentner PhD Student)
  - Tracking with Quantum Computers for LUXE and ATLAS

Quantum GANs in One Dimension

Quantum Generative Adversarial Network

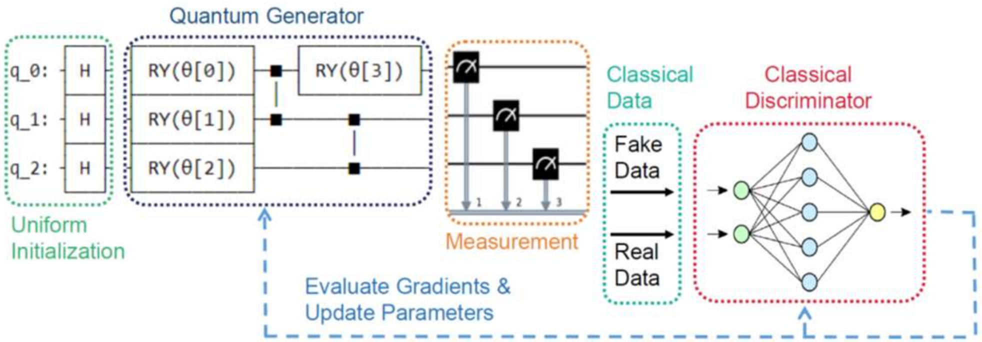
- **Down sample 3D shower image → 8 pixels → 3 qubits**



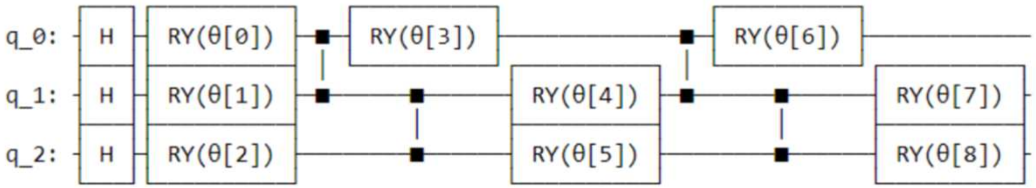


8 quantum states:
|000⟩, |001⟩, |010⟩, |011⟩,
|100⟩, |101⟩, |110⟩, |111⟩

- **Use hybrid approach: quantum + classical**



- **Employ a Quiskit qGAN model developed by IBM***



Initial work by CERN Openlab et al:

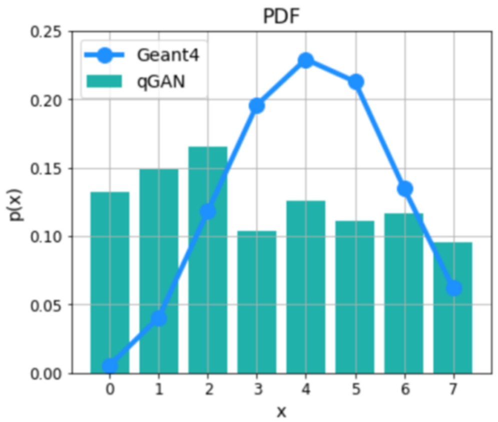
Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors:
arXiv:2101.11132 [quant-ph]

Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics
EPJ Web of Conferences 251, 03050 (2021)

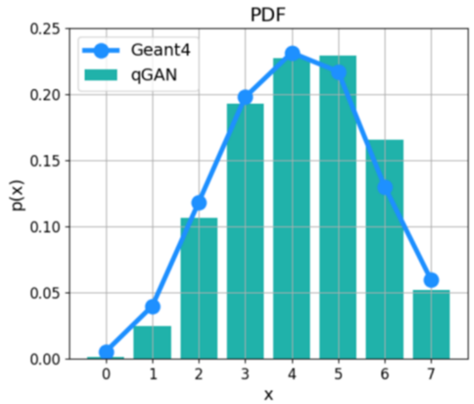
* https://qiskit.org/documentation/machine-learning/tutorials/04_qgans_for_loading_random_distributions.html

Quantum GAN in One Dimension without Noise

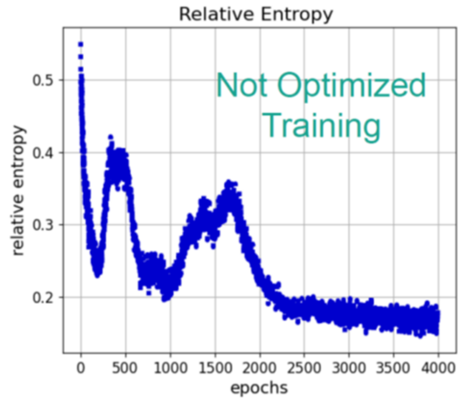
F. Rehm, S. Vallecorsa, K. Borras, D. Krücker http://symsim.jinr.ru/grid2021/363-368-paper-67.pdf

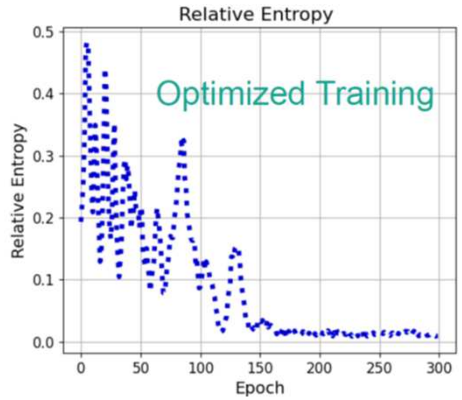


Uniform Initialization



Trained Model





- ➢ training time ~ 1 day for 3000 epochs → speed up training
- ➢ hyperparameter optimizations:
  - higher learning rate
  - implement exponential learning rate decay
  - different generator and discriminator learning rate
  - train discriminator more often than generator
- ➢ **Result:**
  10x speed up in training time → need only ~300 epochs instead of > 3000

CERN openlab DESY.

QUANTUM MACHINE LEARNING FOR HEP DETECTOR SIMULATIONS
Proceedings of the 9th International Conference "Distributed Computing and Grid Technologies in Science and Education" (GRID'2021), Dubna, Russia, July 5-9, 2021 http://symsim.jinr.ru/grid2021/363-368-paper-67.pdf

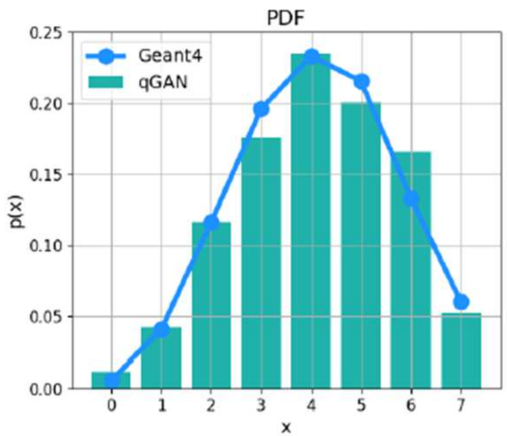
Quantum GAN in One Dimension with Noise

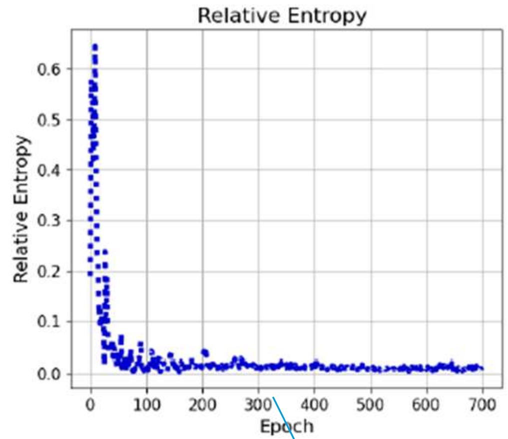
F. Rehm, S. Vallecorsa, K. Borras, D. Krücker http://symsim.jinr.ru/grid2021/363-368-paper-67.pdf

➢ Apply Readout Noise (model IBMq belem)

Qubit Number:	0	1	2
Readout Error:	3.6%	4.7%	9.6%

no decrease in accuracy
fast convergence

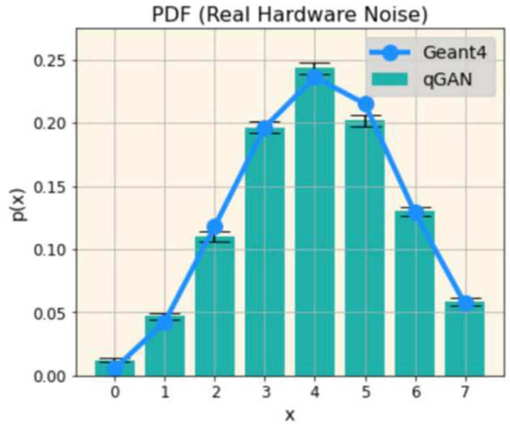


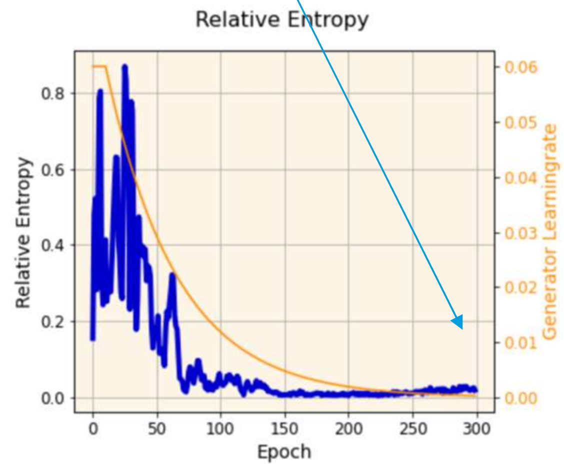


➢ Apply Full Noise (model IBMq manila)

Qubit Number	0	1	2	Average
Readout Error	2.34%	2.66%	2.05%	**2.35%**
CX-gate Error	1.11%		1.75%	**1.43%**

no decrease in accuracy
fast convergence





Impact of quantum noise on the training of Quantum GANs

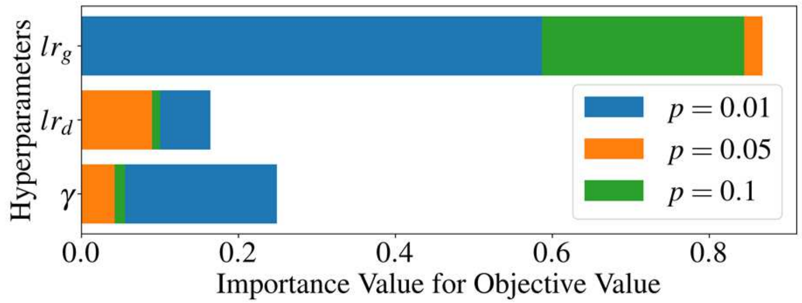
K.Borras,S.Y.Chang,L.Funcke,M.Grossi,T.Hartung,K.Jansen, D.Kruecker,S.Kühn,F.Rehm, C.Tüysüz,S.Vallecorsa

https://arxiv.org/abs/2203.01007

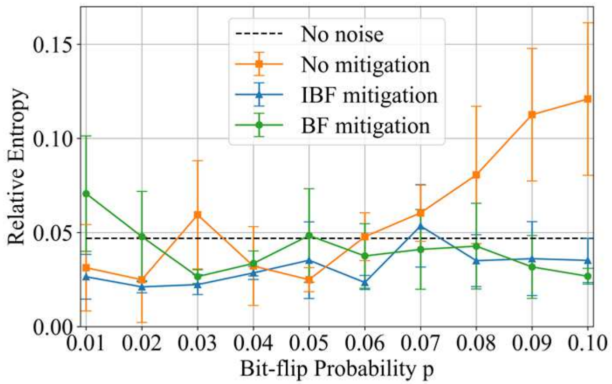
Detailed studies with noise and noise mitigation

- **Importance of hyperparameters for different values of the bit-flip probability, p = {0.01, 0.05, 0.1}**
  - generator learning rate lrg, discriminator learning rate lrd, exponential decay rate γ for the learning layers

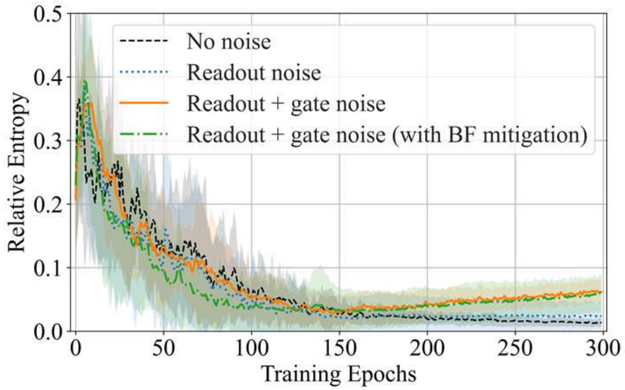
  → generator learning rate lrg has the highest impact → demonstrates the difficulty of training the quantum generator



- **Results without and with two different error mitigation methods**



Error mitigation plays a crucial role for qGAN training in the presence of the large readout errors on current NISQ devices

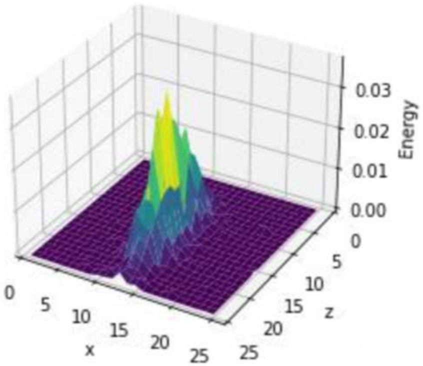


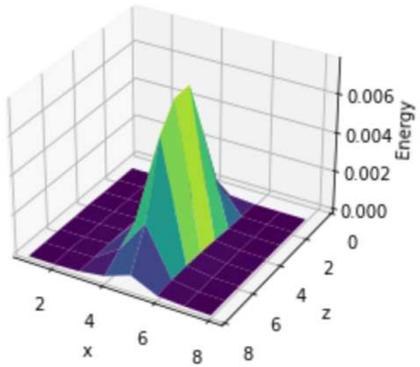
Average values quickly converge in the noise-free and readout-error only cases, but do not seem to converge when including two-qubit gate errors → reveal the critical effect of two-qubit gate errors on qGAN training with current NISQ devices.

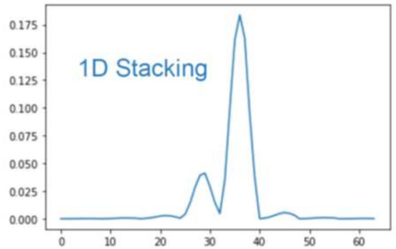
Quantum GAN in Two Dimensions

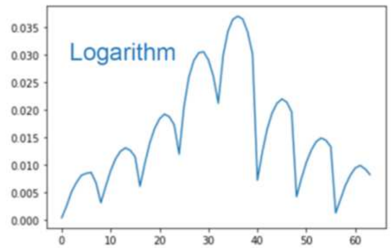
Early examples in Experimental Particle Physics

- **Down sample → 8x8 pixels → 6 qubits**



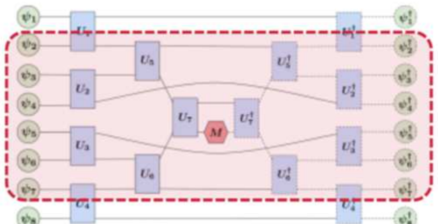




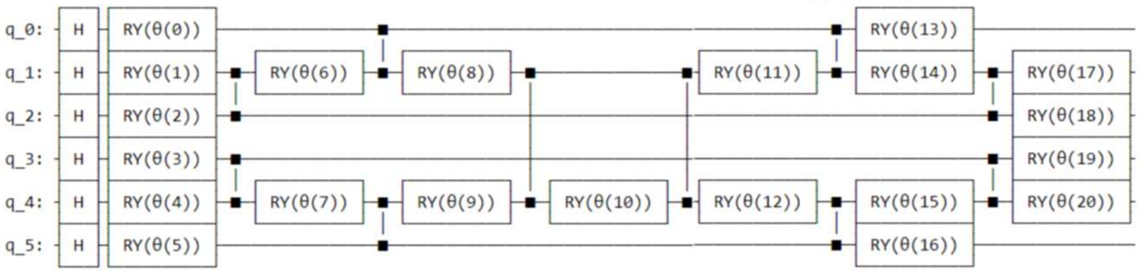


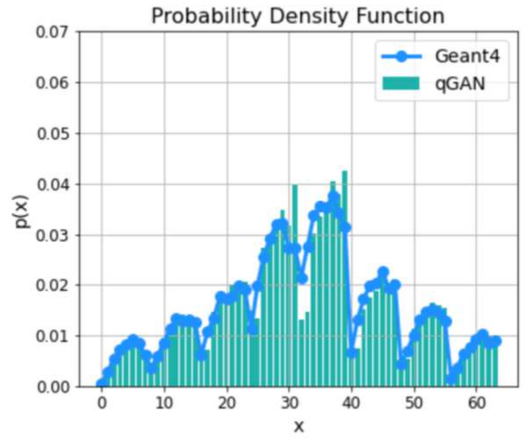
- **Adapt Tree Tensor Network**

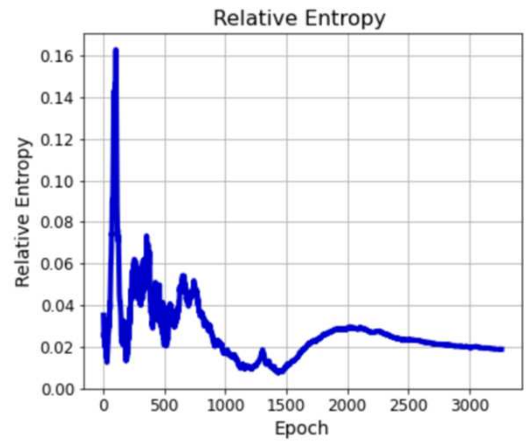
Grant, E., Benedetti, M., Cao, S.*et al.* Hierarchical quantum classifiers. *npjQuantum Inf***4**,65 (2018). https://doi.org/10.1038/s41534-018-0116-9



(a) TTN classifier







Work Package B - QGAN

Tasks and Milestones

Task	Partner	Beschreibung
BP1	DESY, USAAR	Übersicht von "state-of-the-art" klassischen GANs, wie sie am LHC eingesetzt werden, als Basis für die Entwicklung von QGANs. Identifizierung von Testfällen.
BP2	DESY, USAAR, Qruise, IBM	Implementierung von ausgewählten GANs mit Rauschen von der Quantenhardware. Bestimmung der Effizienz von QGANs als Funktion der Rauschcharakteristik.
BP3	DESY, USAAR	Entwicklung von rauschunterstützten GANs und QGANs.
BP4	Qruise, IBM	Coding von rauschunterstützten GANs und QGANs.
BP5	DESY, USAAR	Vergleich der neu entwickelten, rauschbehafteten GANs und QGANs mit den identifizierten Testfällen aus AP6.

Aufgabe / Zeitplan	Monate 1-6	Monate 7-12	Monate 13-18	Monate 19-24	Monate 25-30	Monate 31-36
BP1						
BP2						
BP3						
BP4						
BP5						