Machine learning algorithms for PID

#### Parameters

- Simulations provide space and time coordinates of photons
- can be extended to bigger parameter space with e.g. angles



- 5000



# Data representations



1D-Vector with time information



- 1.0

Image



Image with time information

# Evaluation of networks

true positive rate

- Modify parameters to maximize performance
- Result in sep. power not directly comparable
- Results shown as ROC-Curve
- Extract Efficiency/MissId



## CNN with time information

- Network tested for stability over different angles
- Each angle trained separately
- Missld for 95 % efficiency best at low angles
- Probably connected to photon numbers



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### Comparison of networks

- All networks perform at the same level
- CNN with time information should perform significantly better
  - time information not interpreted
- Best suited candidate not found yet



ROC curve 1.0 0.8 true positive rate 0.6 0.4 CNN w time, AUC = 0.980 0.2 CNN, AUC = 0.983 NN, AUC = 0.943 0.0 0.0 0.2 0.4 0.6 0.8 1.0 false positive rate

# Outlook

- Increase performance of networks
- Train networks over multiple angles
- Compare networks to classical algorithms





# Backup

# CNNs





# CNNs

- Conv2D(featurenumber, kernel\_size, padding)
  - extract complex characteristics
  - reduces dimensionality
- MaxPooling2D(pool\_size)
  - takes maximum of given pool size
  - reduces dimensionality
- Flatten()
  - transforms convolution/pooling layer to 1D-Vector
- normal neural net

#### cnnmodel= Sequential()

cnnmodel.add(Conv2D(32,kernel\_size=(5,5),activation='relu',input\_shape=(16,32,1),padding="same")) =
cnnmodel.add(MaxPooling2D(pool\_size=(2,2)))

cnnmodel.add(Conv2D(32,kernel\_size=(5,5),activation='relu',padding="same"))
cnnmodel.add(MaxPooling2D(pool\_size=(2,2)))

```
cnnmodel.add(Conv2D(64,kernel_size=(3,3),activation='relu',))
cnnmodel.add(MaxPooling2D(pool_size=(2,2)))
```

# cnnmodel.add(Conv2D(32,kernel\_size=(5,5),activation='relu',input\_shape=(16,32,1)))
# cnnmodel.add(MaxPooling2D(pool\_size=(2,2)))

```
cnnmodel.add(Flatten())
```

cnnmodel.add(Dense(128,activation='relu')) #128

#cnnmodel.add(Dense(20,activation='relu'))

cnnmodel.add(Dense(2,activation='softmax',name='last\_layer'))

#### cnnmodel.summary()

#learningrate and compiling
learningrate= 0.0005 #0,001
optimizer = keras.optimizers.Adam(learningrate)
cnnmodel.compile(loss='mean\_squared\_error',optimizer=optimizer,metrics=['accuracy'])
#model.compile(loss='binary\_crossentropy',optimizer='Adam',metrics=['accuracy'])
#model.compile(loss='mean\_squared\_error',optimizer='Adam',metrics=['accuracy'])

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#### Model: "sequential\_27"

Layer (type)	Output Shape	Param #
conv2d_81 (Conv2D)	(None, 16, 32, 32)	832
	(None, 8, 16, 32)	0
 conv2d_82 (Conv2D)	(None, 8, 16, 32)	25632
max_pooling2d_82 (MaxPooling	(None, 4, 8, 32)	0
conv2d_83 (Conv2D)	(None, 2, 6, 64)	18496
max_pooling2d_83 (MaxPooling	(None, 1, 3, 64)	0
flatten_27 (Flatten)	(None, 192)	0
dense_27 (Dense)	(None, 128)	24704
last_layer (Dense)	(None, 2)	258
Total params: 69,922 Trainable params: 69,922 Non-trainable params: 0		

### Layer types

- Conv2D(featurenumber,kernel\_size, padding)
- MaxPooling2D(pool\_size)
  - takes maximum of given pool size
- ► Flatten()
  - transforms convolution/pooling layer to 1D-Vector
- Dense(NodeNumber, activation)
- dropout(droupoutpercentage)
  - part of neurons will not be considered for each cycle