What is the effect of different parameters on training the RBM, evaluate the performance visually by reconstructing unseen test images.



```
rbm1 = BernoulliRBM(n_components=10, learning_rate=0.01, random_state=0, n_iter=10, verbose=True) rbm1.fit(X_train) rbm8 = BernoulliRBM(n_components=20, learning_rate=0.06, random_state=0, n_iter=20, verbose=True) rbm8.fit(X_train)
```

I chose these values for these **parameters**: n_components —-> 10,20; learning_rate —-> 0.01,0.06; n iter —-> 10,20

we evaluate probabilities with the **pseudo-likelihood** (since conditional probabilities can be computed without knowledge of the partition function)

the performance of the training, evaluated with the pseudo-likelihood metric, is negatively correlated to the **time** of the training.

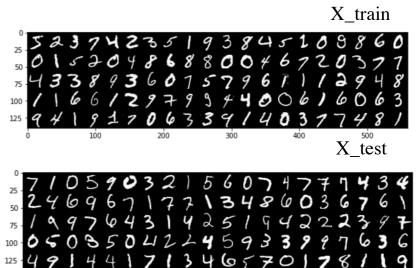
the **best training model** (which may overfits) is, in descending order:

rbm pseudolikelihood:

```
7, n_components: 20; learning_rate: 0.06; n_iter: 10; pseudo-likelihood = -128.93, time = 3.85s 8, n_components: 20; learning_rate: 0.06; n_iter: 20; pseudo-likelihood = -130.42, time = 3.74s 6, n_components: 20; learning_rate: 0.01; n_iter: 20; pseudo-likelihood = -137.32, time = 3.74s 5, n_components: 20; learning_rate: 0.01; n_iter: 10; pseudo-likelihood = -146.39, time = 3.75s 2, n_components: 10; learning_rate: 0.01; n_iter: 20; pseudo-likelihood = -178.26, time = 3.40s 4, n_components: 10; learning_rate: 0.06; n_iter: 20; pseudo-likelihood = -186.34, time = 3.27s 1, n_components: 10; learning_rate: 0.01; n_iter: 10; pseudo-likelihood = -186.68, time = 3.29s 3, n_components: 10; learning_rate: 0.06; n_iter: 10; pseudo-likelihood = -187.26, time = 3.26s
```

n_components: higher values leads to more defined results learning_rate —-> higher values leads to more defined results n_iter —-> higher values leads to more defined results



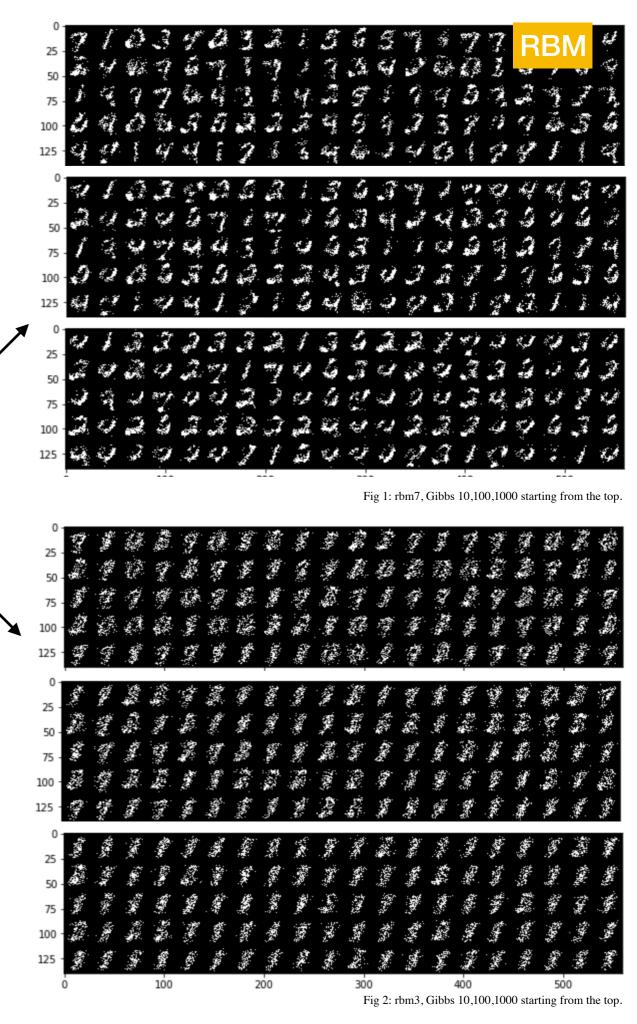


Change the number of Gibbs sampling steps, can you explain the result?

I tried values 10, 100, 1000 for the Gibbs steps, using my best and worst scoring model in the training step, ie respectively: rbm 7, n_components: 20; learning_rate: 0.06; n_iter: 10; rbm 3, n_components: 10; learning_rate: 0.06; n_iter: 10;



Notes: both for best and worst training models, a lower number of Gibbs sampling steps leads to better results.



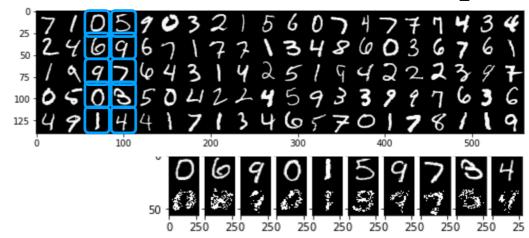
Reconstruct 10 images from the test set with different numbers of Gibbs steps



 X_{test}

Use the RBM to reconstruct missing parts of images¹.

- 1) What is the role of the number of hidden units, learning rate and number of iterations on the performance.?
- 2) How many rows can you remove such that reconstruction is still possible?
- 1) the learning rate didn't affect much my training, while a higher number of iterations and hidden units led to better performances without overfitting.
- 2) It's better to use a lower number of gibbs steps to reconstruct the image (here no more than 100), both for the best and worst trained RBM models; results are pretty much equal



reconstruction_gibbs_steps = 10 start_test_index = 10

nr = 10

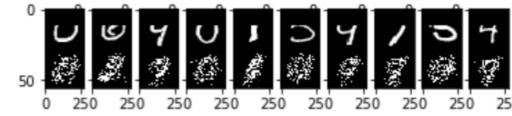
start_row_to_remove = 2

end_row_to_remove = 12

7, n_components: 20; learning_rate: 0.06; n_iter: 10;



3, n_components: 10; learning_rate: 0.06; n_iter: 10;



 $reconstruction_gibbs_steps = 100$

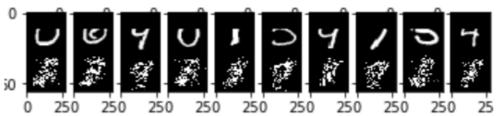
 $start_test_index = 10$

nr = 10

start_row_to_remove = 2

end_row_to_remove = 12





Reconstruct 10 images from the test set with best numbers of Gibbs steps and different numbers of missing pixels.

Notes:

rbm3 generalizes better when many test rows are missing, rbm7 overfits therefore only gets to reconstruct unseen images if the number of pixel rows removed is very little.

Using rbm3, I get to reconstruct removing 20 rows, with rbm7 only 1 becase then it starts making wrong guesses and predicts the wrong number.

rbm 7

