Puzzle reassembly using deep reinforcement learning with adversarial model

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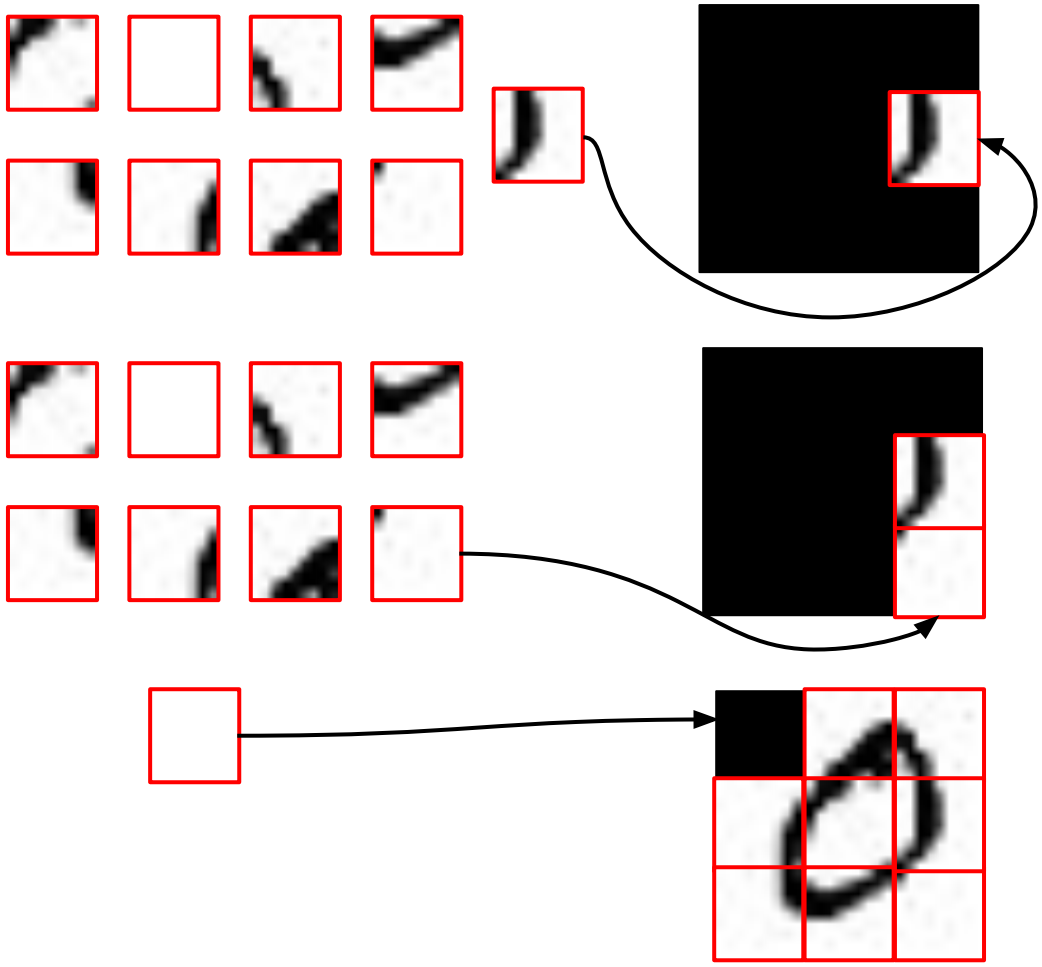
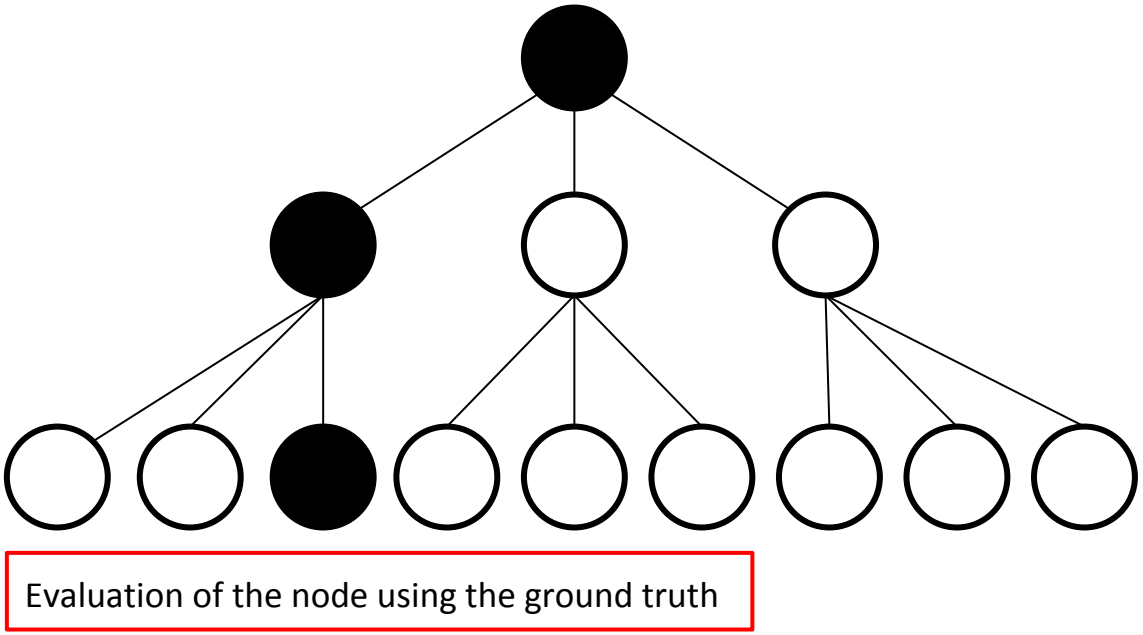
Introduction: Problem

- Visual jigsaw puzzles
- 9 fragments
- Iterative reconstruction



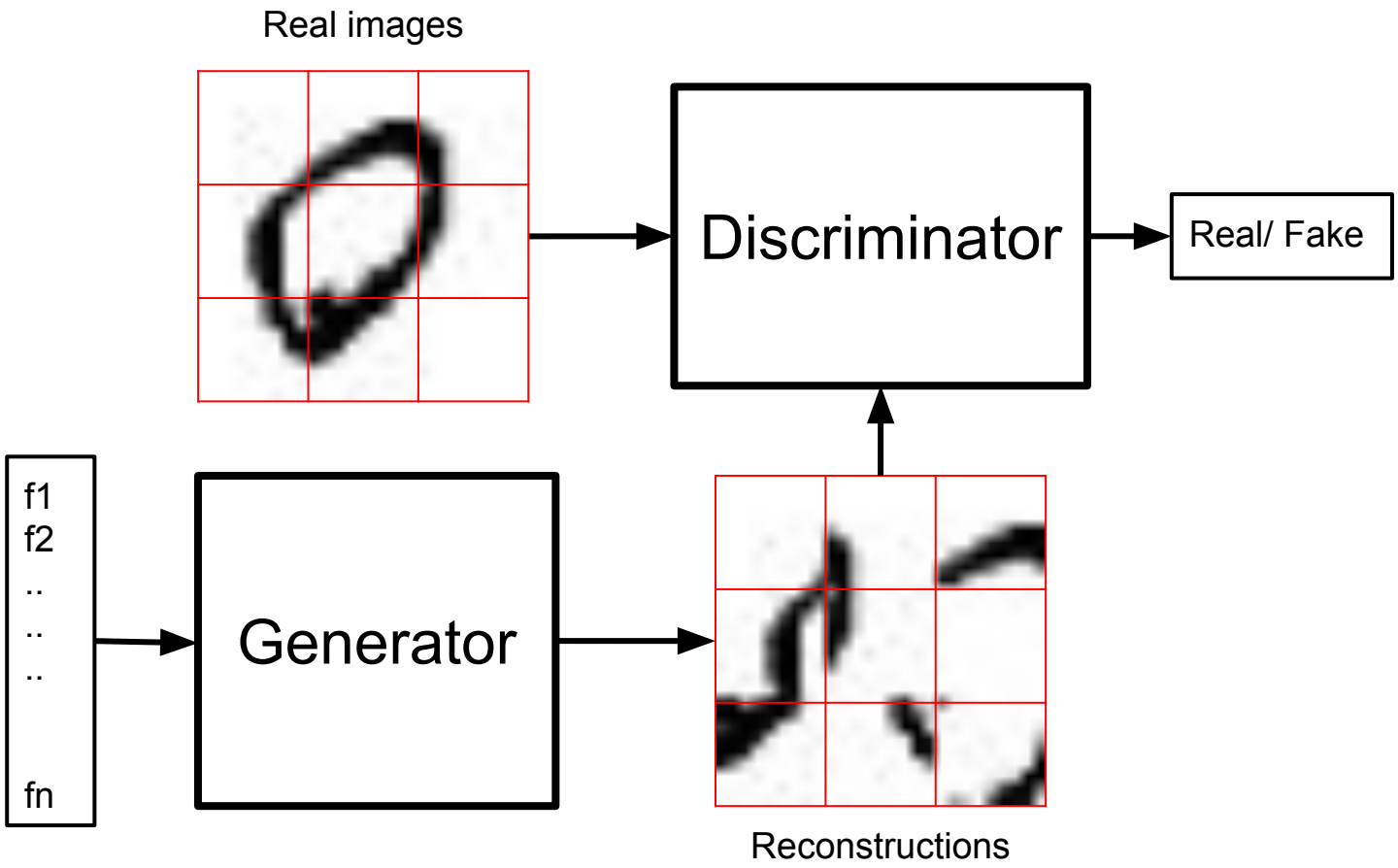
Introduction: Methods

Reinforcement learning problem:
Popular solution: AlphaZero → Monte Carlo Tree Search:



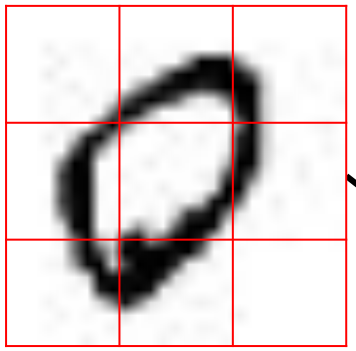
Discriminator Value Estimator: Unsupervised learning

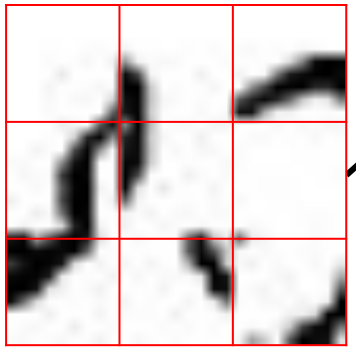
Puzzle reassembly using discriminative value estimation



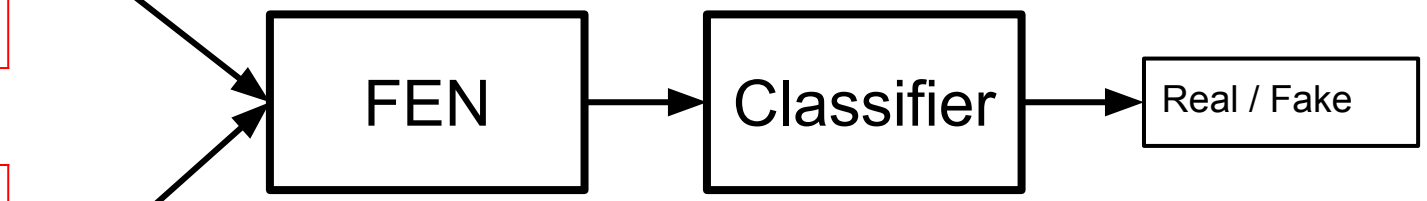
DVE: Discriminator

Real images



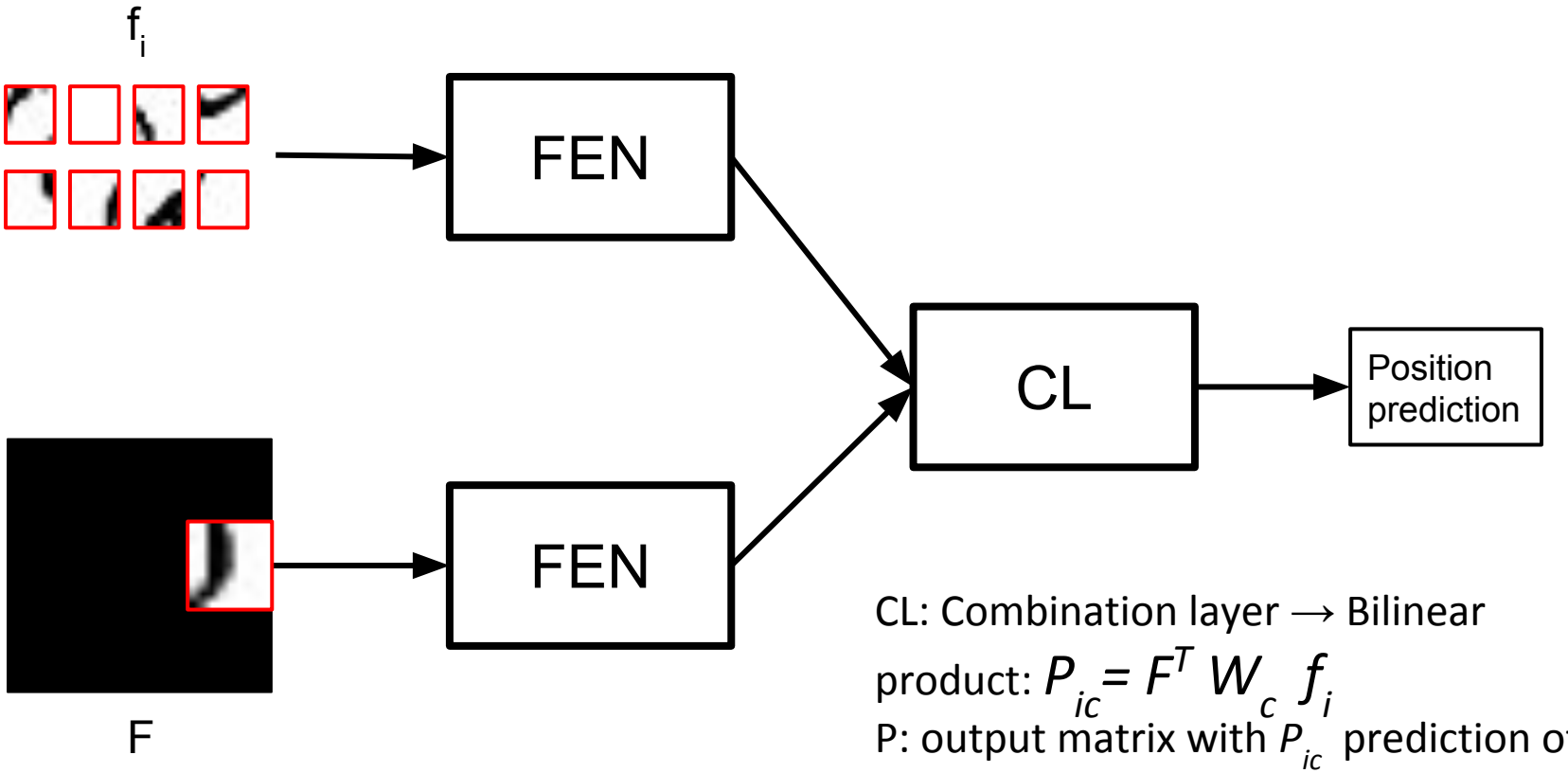


Reconstructions



FEN: Feature Extractor Network
Classifier: Multi-layer perceptron
Output: 0 ⟶ 1 with 0 for a reconstruction and 1 for a real

DVE: Generator



CL: Combination layer → Bilinear product: $P_{ic} = F^T W_c f_i$

P: output matrix with P_{ic} prediction of the evaluation by the discriminator for the fragment *i* in position *c*.

W: weights

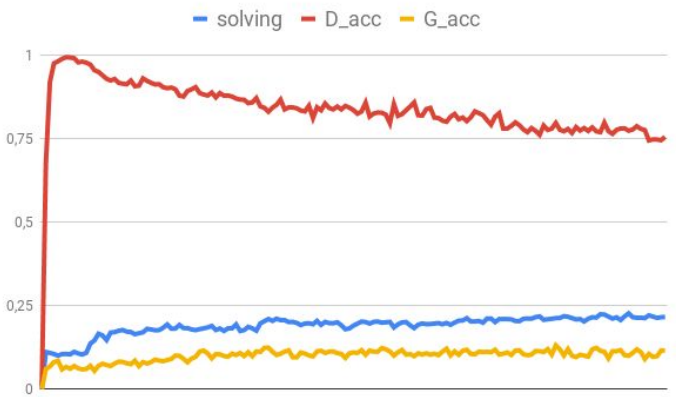
DVE: Training

Divided in 4 steps:

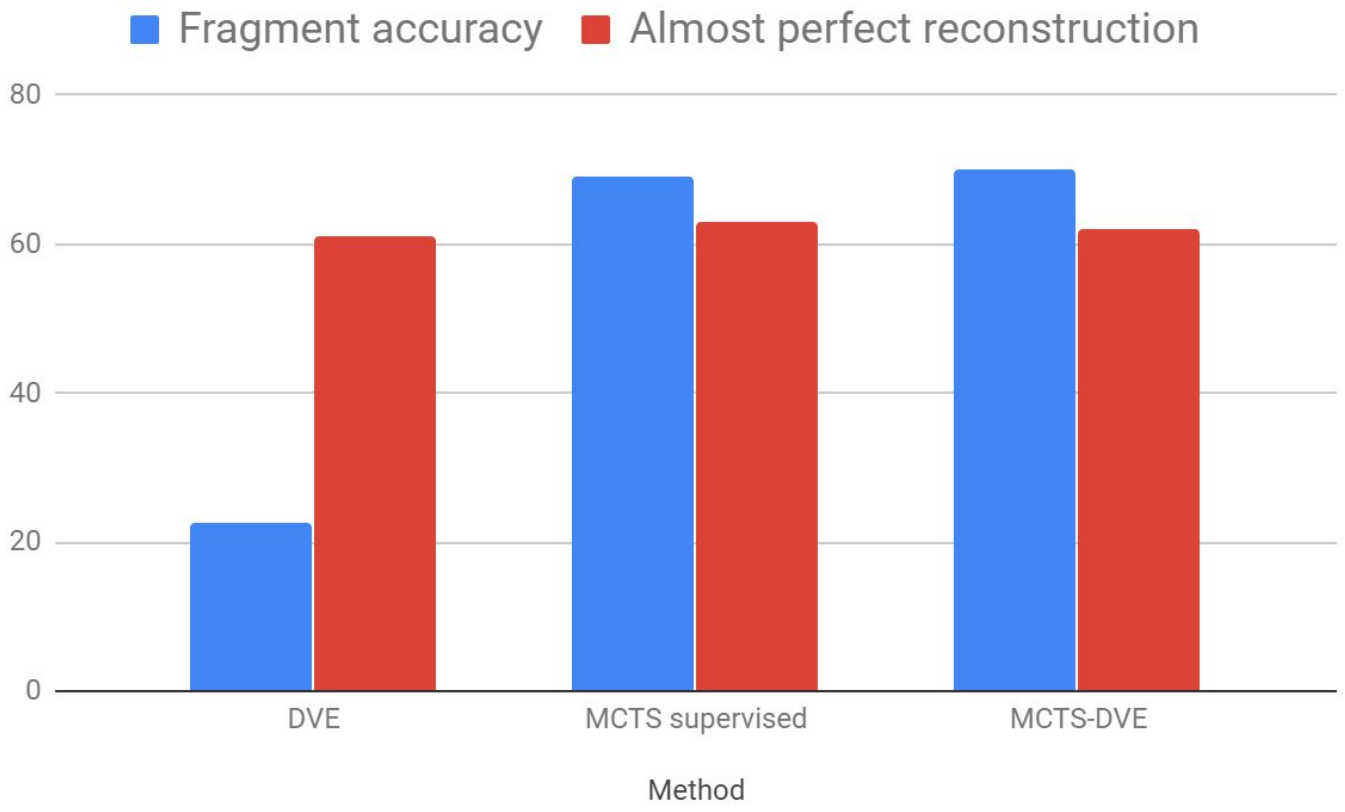
- Episodes generation: The generator is generating images and store it in memory
- Rating: The discriminator is rating some episodes in memory
- Training of the generator: Target: [0, 0, 0, ….. X, …., 0, 0] with X the score obtained with the discriminator
- Training of the discriminator: Real images with a target of 1 and generated with a target of 0

Adapt learning speed of the discriminator:

- Avoid perfect classification
  → G predict only 0
- Relevant features for the classification

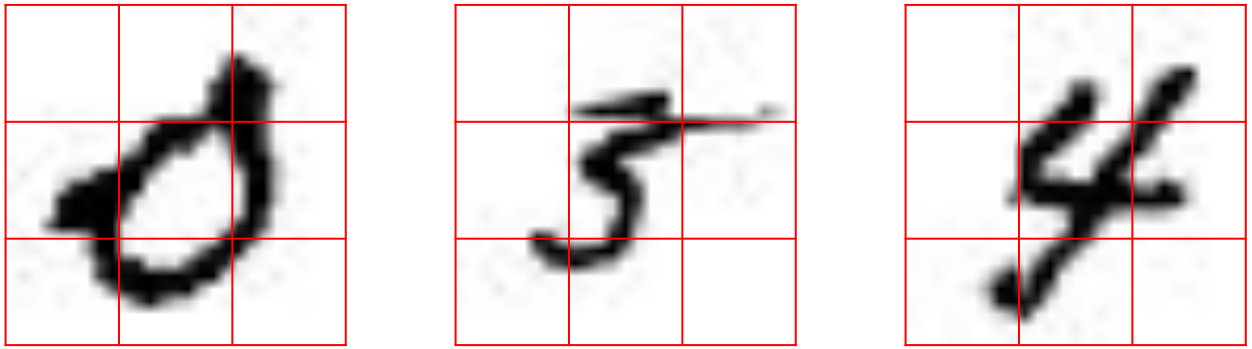


Results

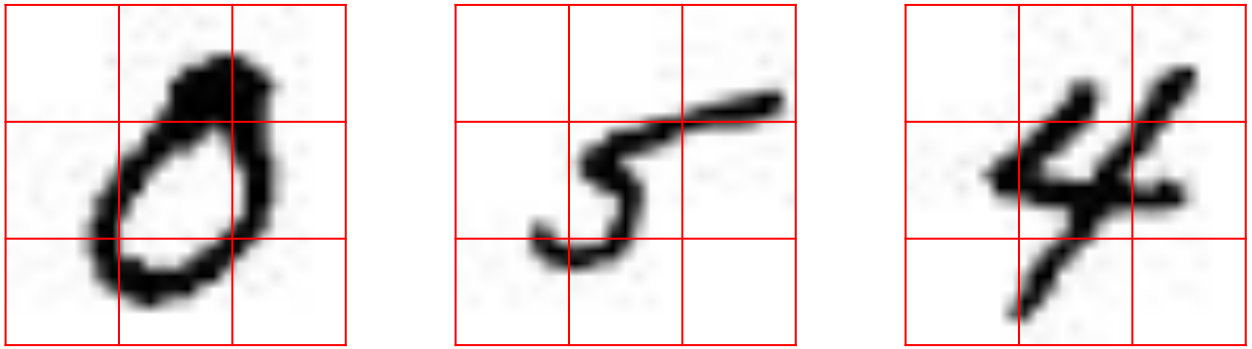

Fragment accuracy
Almost perfect reconstruction
80
60
40
20
0
DVE
MCTS supervised
MCTS-DVE
Method

Realistic reconstructions

Reconstructions



Real image



Results

Car dataset: promising results on a short time training
20% fragment accuracy
Some perfect reconstructions
FEN used: VGG16 pre-trained on ImageNet

Conclusion

MCTS - DVE: unsupervised training with as good results as the supervised MCTS

Next step, scaling to real images

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