NEURAL NETWORKS

LEARNING AND EVALUATION

BATCH NORMALISATION

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- Data Preprocessing

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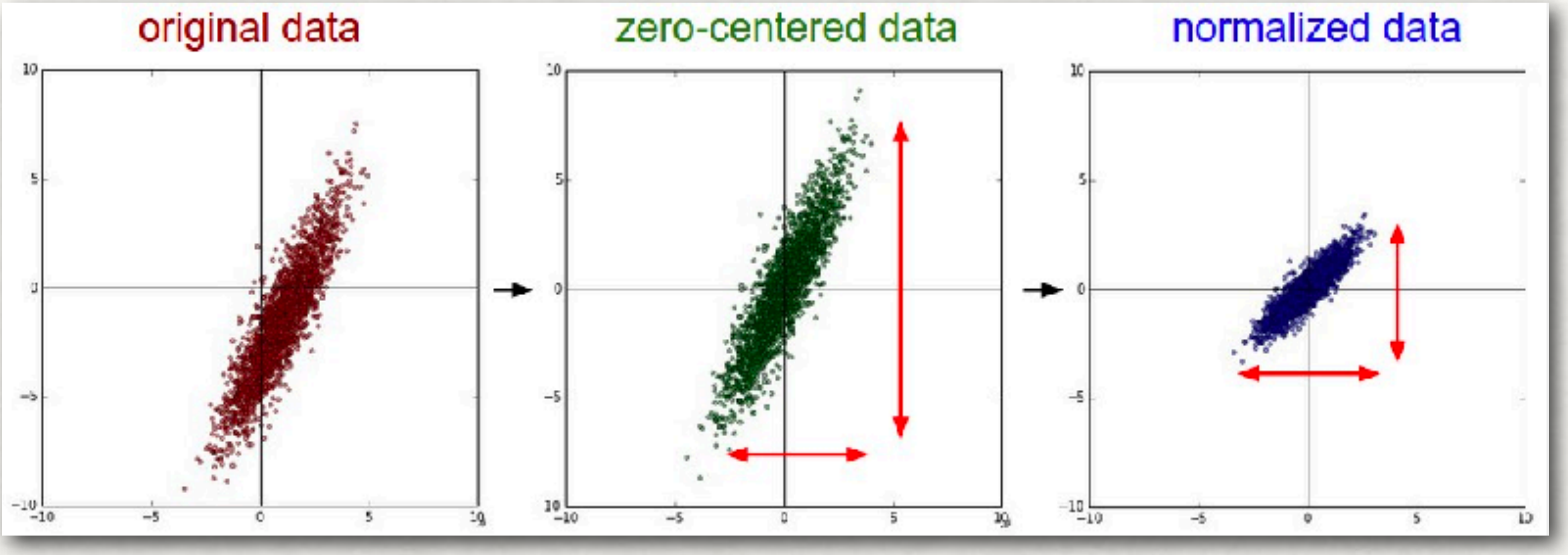

UPDATING WEIGHTS - VANILLA SGD

DONEC QUIS NUNC

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- Manual Initial Estimation
- Sensitive learning process as the network converges

SGD + MOMENTUM UPDATE

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- We step in the direction of the velocity vector instead of position.
- No stops at minimas as we update on the basis of velocity. Similar for saddle points. Even though gradient might be zero

ADAGRAD

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```
# Assume the gradient dx and parameter vector x
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + eps)
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- Problem: What happens as we keep progressing the training using this algorithm?

RMSPROP

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- Add Momentum = Adam

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- RMSProp with Momentum

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- RMSProp with Momentum
- SGD Momentum with Squared Gradients