ASIAN INSTITUTE OF MANAGEMENT

COSCI223: MACHINE LEARNING 3

AUTOENCODERS

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Analytics, Computing, and Complex Systems Laboratory (ACCeSs@AIM)

28 April 2023

Description

- a neural network that is trained to attempt to copy its input to its output
- designed to be unable to learn to copy perfectly

Reference: Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. Retrieved from http://www.deeplearningbook.org

General Architecture

References: Hinton, GE, & Salakhutdinov (2006). Reducing the dimensionality of data with neural networks. *Science, 313 (5786)*, 504-507.
Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. Retrieved from http://www.deeplearningbook.org

Background

A Learning Algorithm for Boltzmann Machines*

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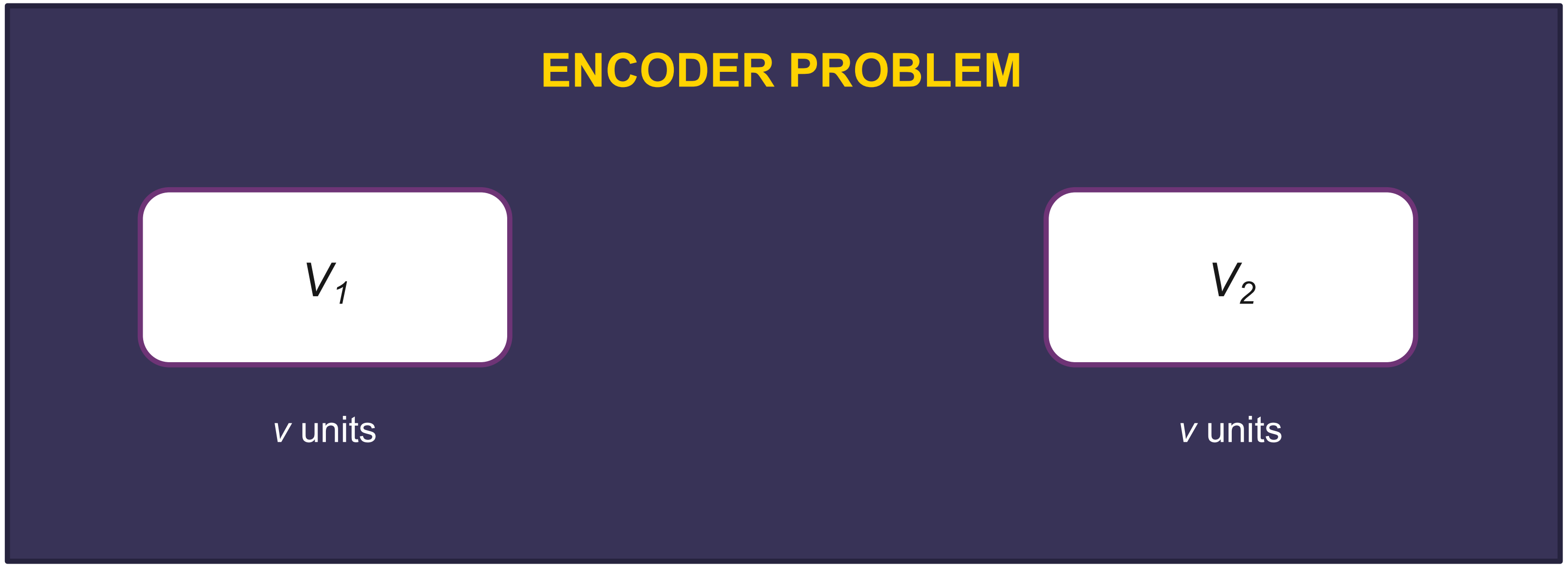
Computer Science Department
Carnegie-Mellon University
TERRENCE J. SEJNOWSKI
Biophysics Department
The Johns Hopkins University



Reference: Ackley, DH, Hinton, GE, & Sejnowski, TJ. (1985). A learning algorithm for Boltzmann Machines. *Cognitive Science, 9, 147-169.* Retrieved from http://www.cs.utoronto.ca/~hinton/absps/cogscibm.pdf

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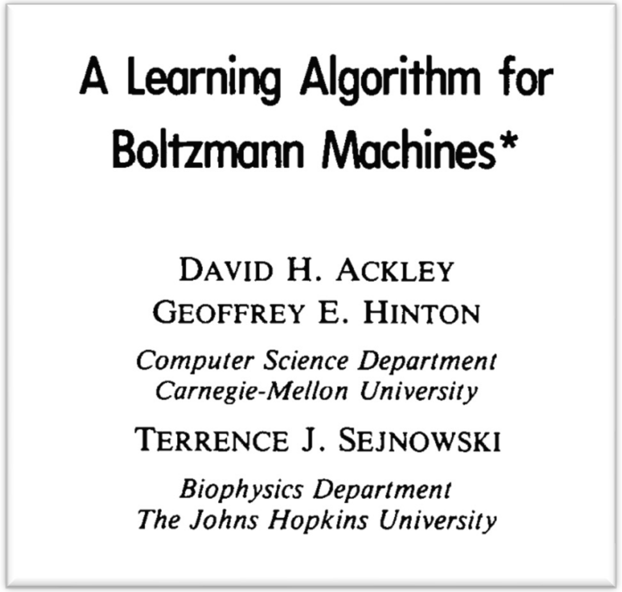
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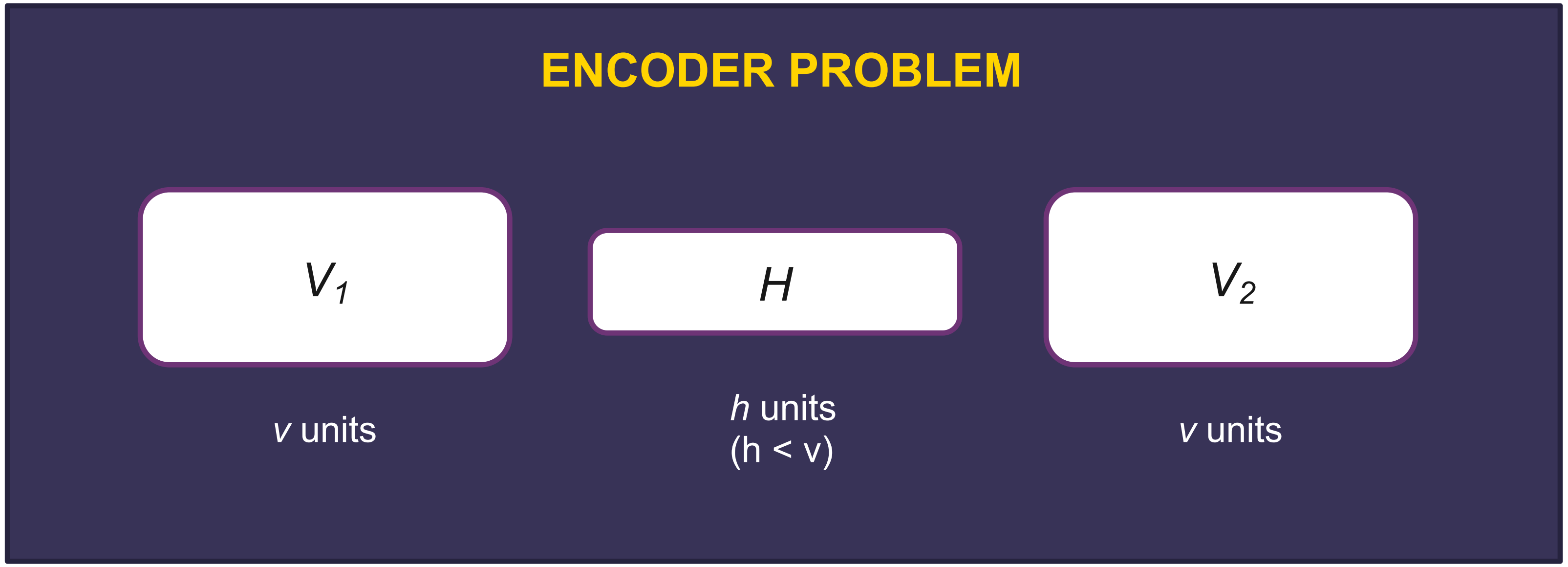

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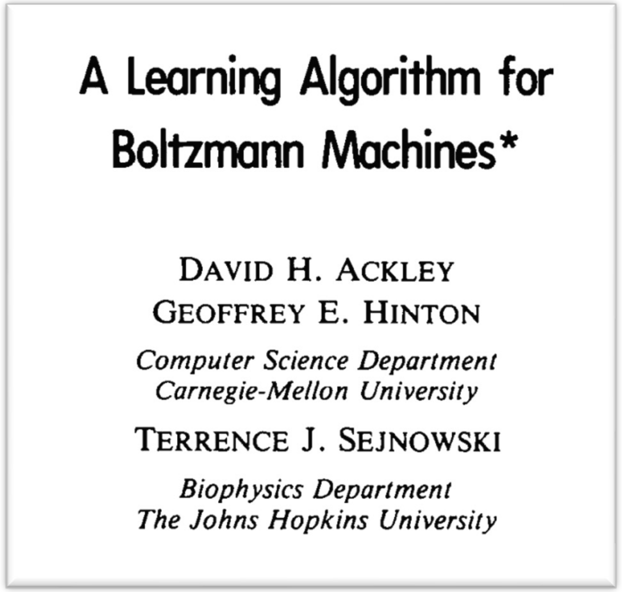
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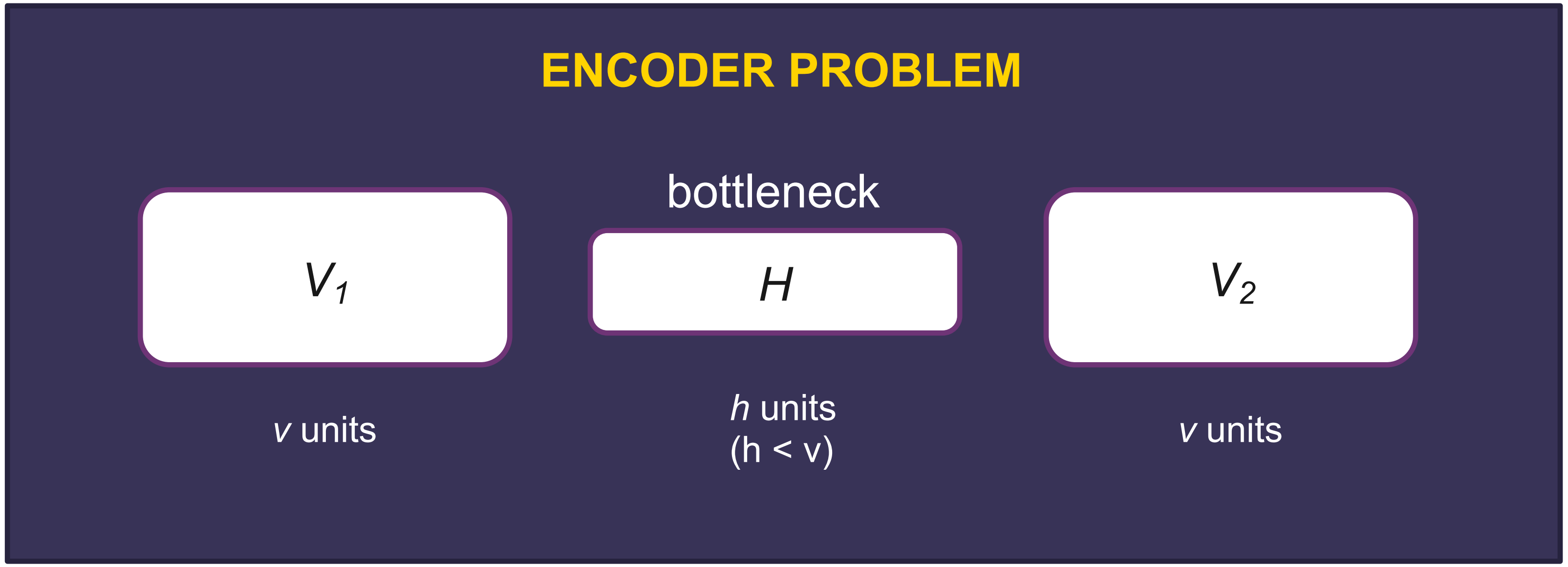

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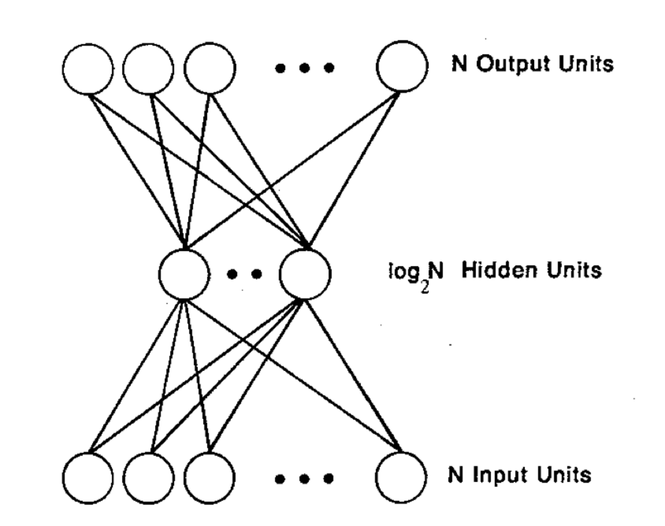
Background

Learning Internal Representations by Error Propagation

D. E. RUMELHART, G. E. HINTON, and R. J. WILLIAMS

NETWORK FOR SOLVING THE ENCODER PROBLEM



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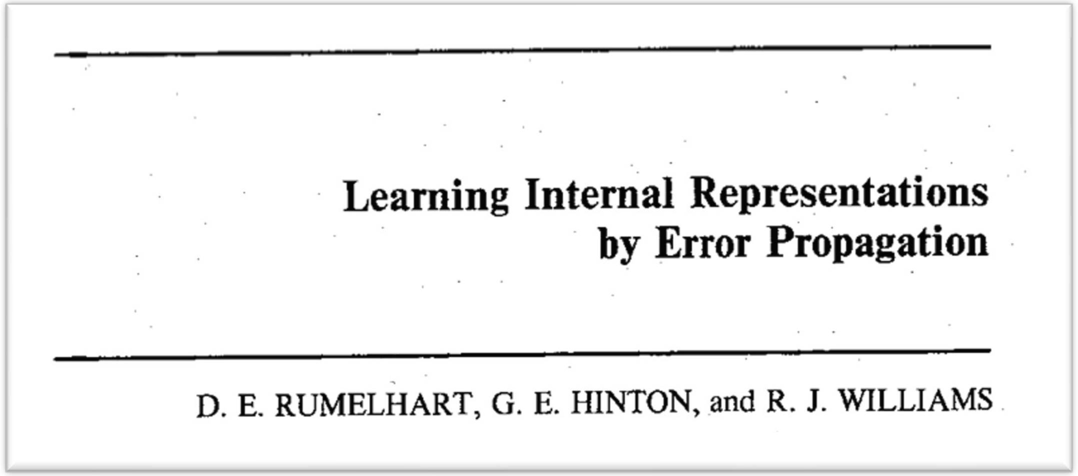

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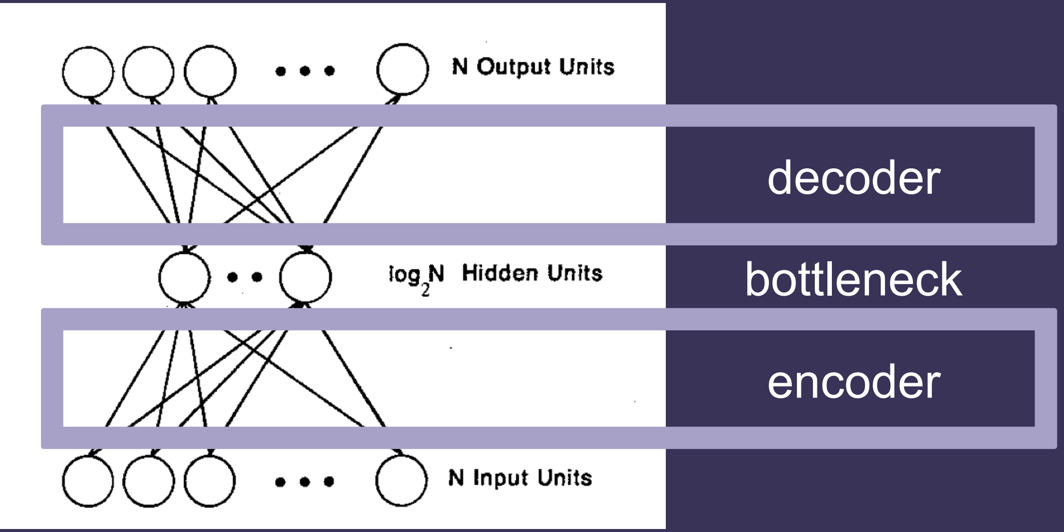

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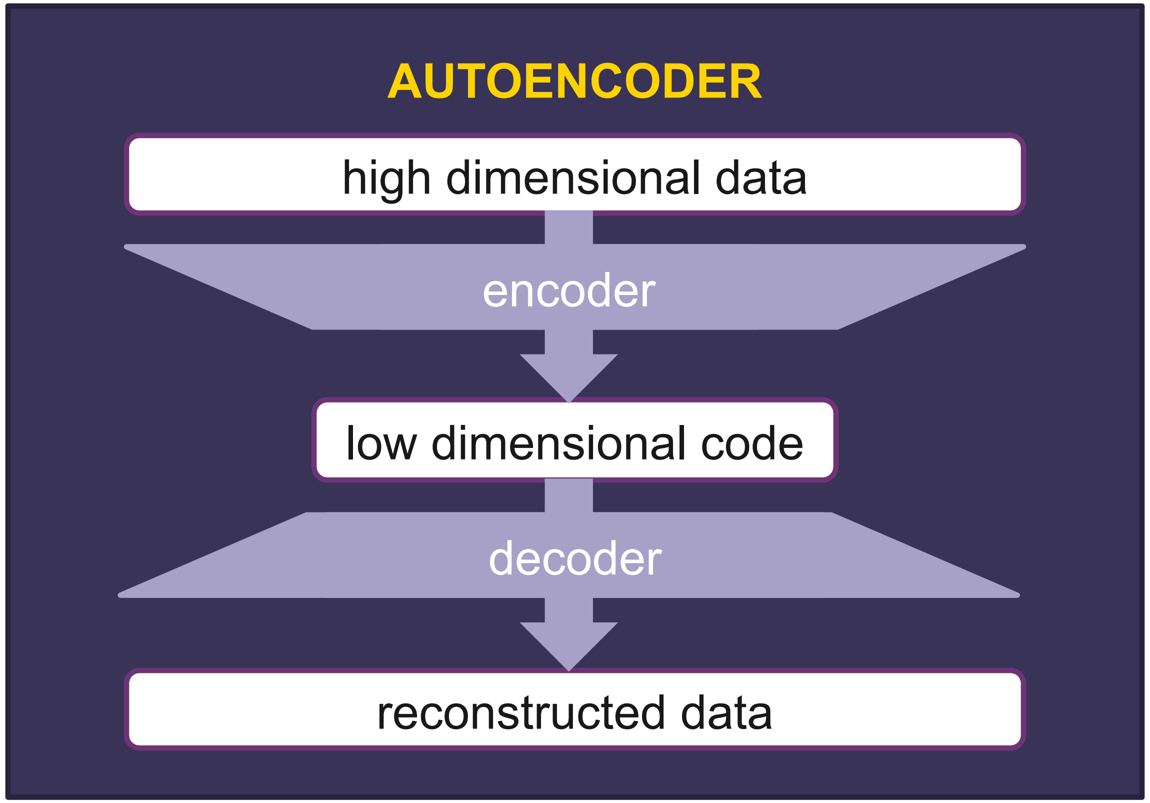
Background

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov



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Background

Reducing the Dimensionality of Data with Neural Networks

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high dimensional data

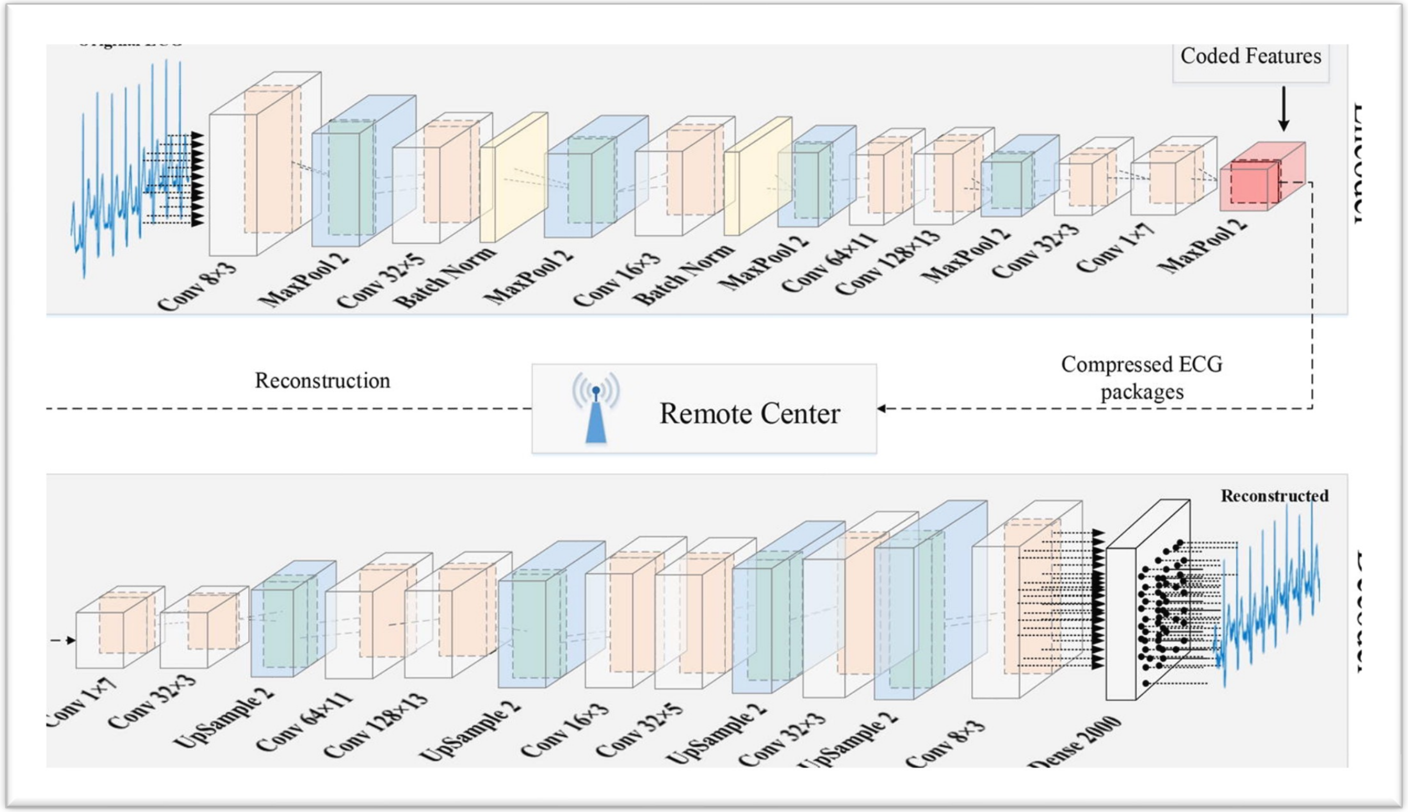
$\approx$

reconstructed data

Reference: Hinton, GE, & Salakhutdinov (2006). Reducing the dimensionality of data with neural networks. *Science, 313 (5786)*, 504-507.

Applications

- **IMAGE COMPRESSION**
  - ↘ ECG signal compression in wearables for lesser hardware resource requirements



Reference: Yildirim, O., Tan, RS, Acharya, UR. (2018). An efficient compression of ECG signals using deep convolutional autoencoders. *Cognitive Systems Research, 52, 198-211.* Retrieved from https://doi.org/10.1016/j.cogsys.2018.07.004

Applications

- **ANOMALY DETECTION**
  - ↘ Facilitate targeted visual inspection of civil infrastructure by detecting cracks/faults in unlabeled concrete images

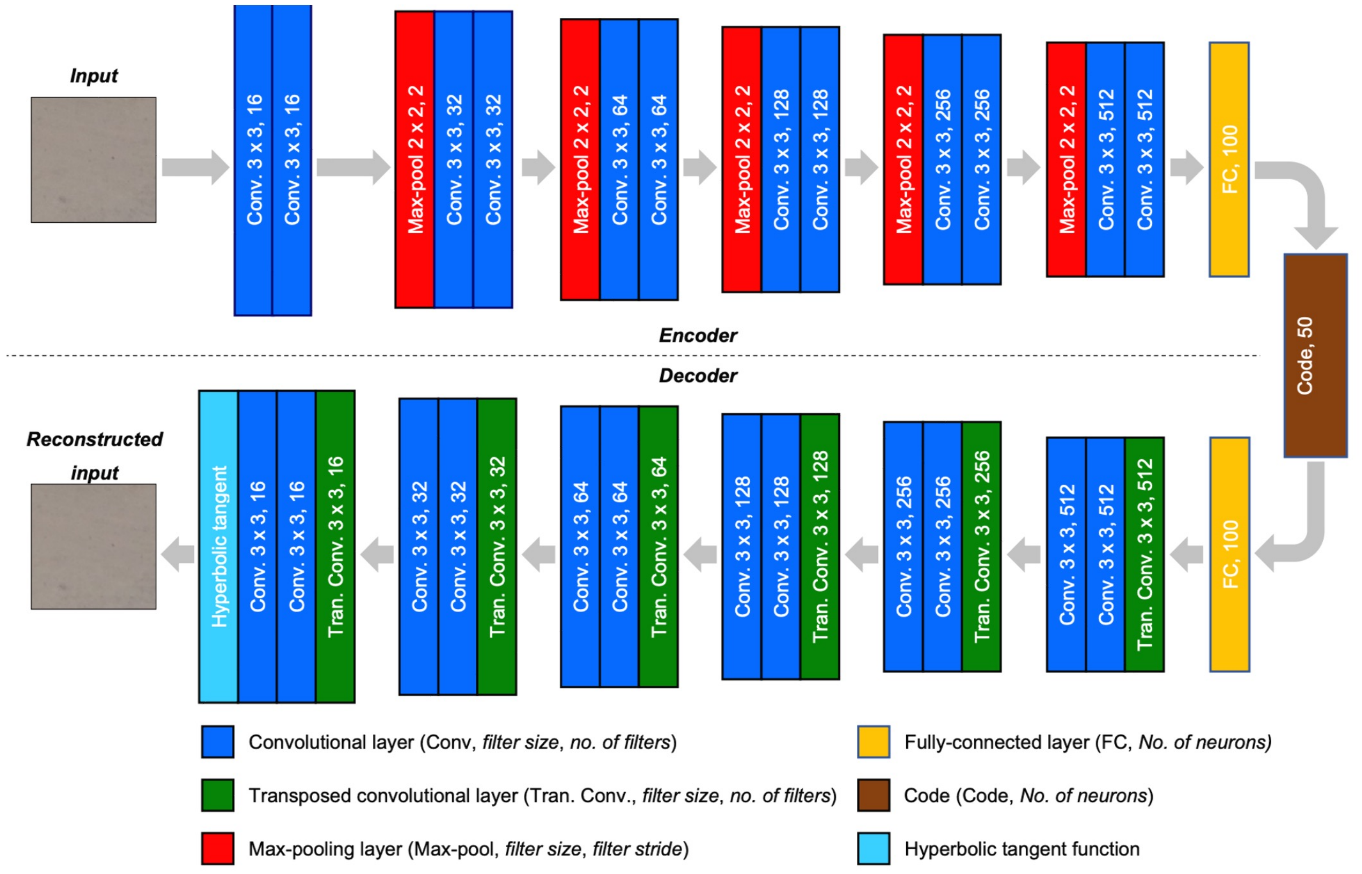


Fig. 4. Network architecture of the convolutional autoencoder proposed for the unsupervised anomaly detection in this study.

Reference: Chow, J. K., Su, Z., Wu, J., Tan, P. S., Mao, X., & Wang, Y. H. (2020). Anomaly detection of defects on concrete structures with the convolutional autoencoder. Advanced Engineering Informatics, 45, 101105. doi:10.1016/j.aei.2020.101105

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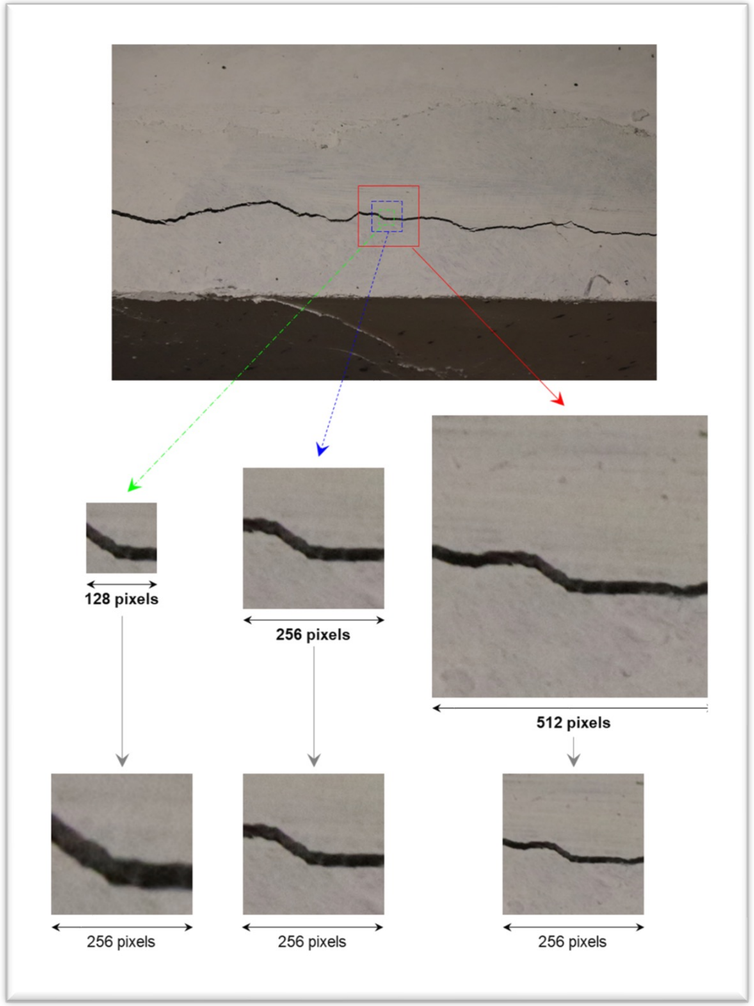

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Applications

- **IMAGE DENOISING**
  - ↘ using small sample size, denoising autoencoders constructed using convolutional layers can be used for efficient denoising of medical images

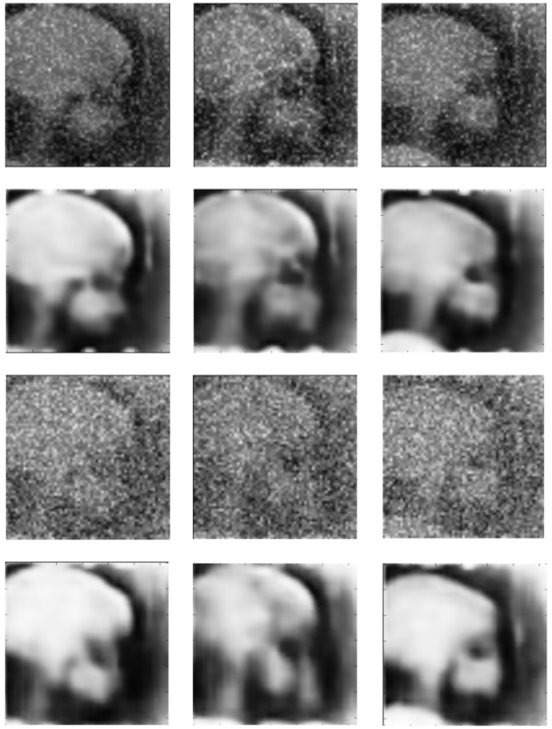

Fig. 10. CNN DAE performance on Poisson corrupted images. Top row shows images corrupted with $p = 0.2, \lambda = 1$ with second row showing denoised results using CNN DAE. Third and fourth rows show noisy and denoised images corrupted with $p = 0.2, \lambda = 5$.

Reference: Gondara, L. (2016). Medical Image Denoising Using Convolutional Denoising Autoencoders. 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW). doi:10.1109/icdmw.2016.0041

Applications

- **GENERATIVE MODELING**
  - ↘ Oversampling images to balance an imbalanced dataset

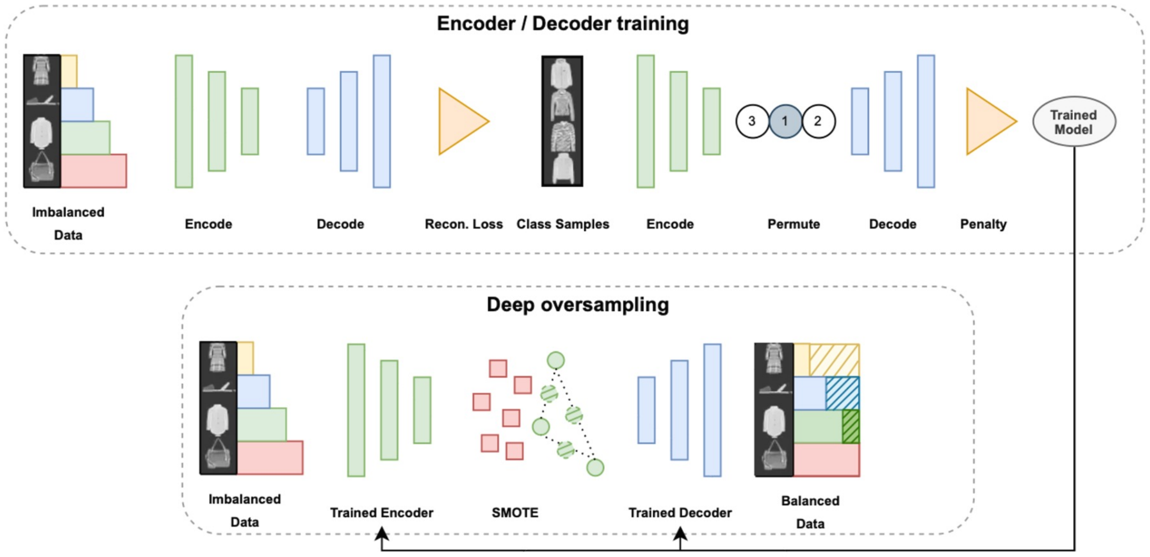

Fig. 1: Illustration of DeepSMOTE implementation. The encoder / decoder structure is trained with imbalanced data and a reconstruction and penalty loss. During training, data is sampled, encoded and the order of examples are permuted before decoding. The trained encoder and decoder are then combined with SMOTE to produce oversampled data.

Reference: Dablain, D. & Krawczyk, B. (2021). DeepSMOTE: Fusing Deep Learning and SMOTE for Imbalanced Data. Retrieved from https://arxiv.org/pdf/2105.02340.pdf

Applications

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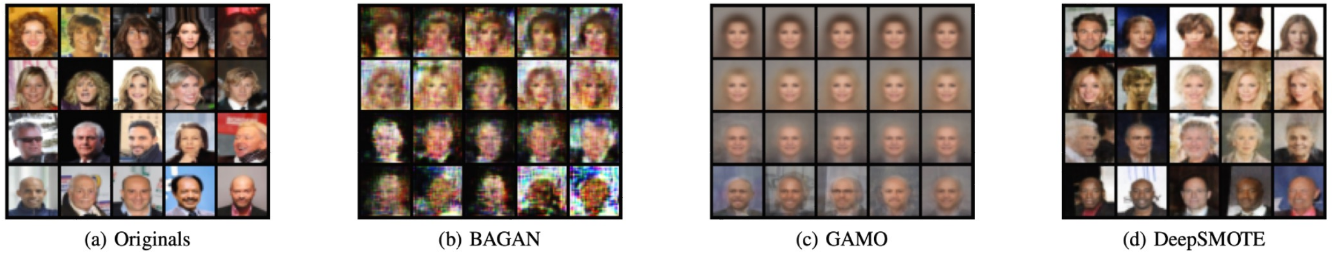

Fig. 7: CELEBA minority class images: brown hair / blond hair / gray hair / bald

Reference: Dablain, D. & Krawczyk, B. (2021). DeepSMOTE: Fusing Deep Learning and SMOTE for Imbalanced Data. Retrieved from https://arxiv.org/pdf/2105.02340.pdf

Applications

- **FEATURE LEARNING**
  - ↘ Used the features in the bottleneck layer as inputs to a deep neural network recommender system

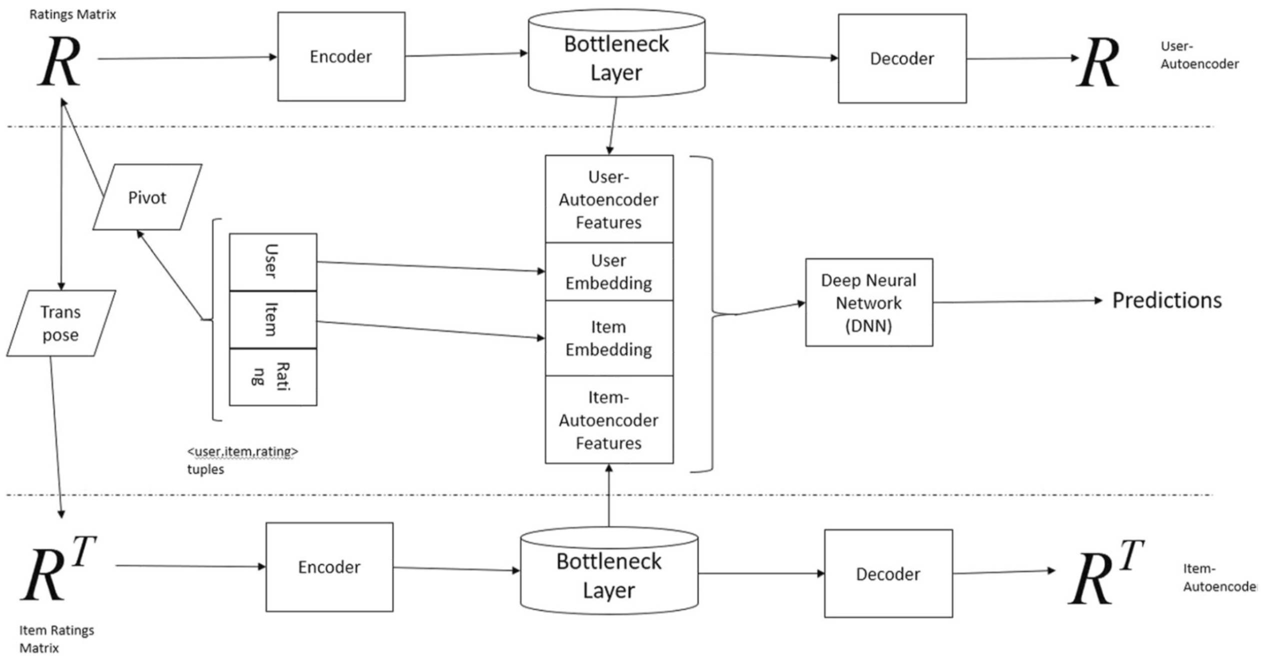

Fig. 4 DAFERec overall flow: proposed solution

Reference: Rama, K., Kumar, P., & Bhasker, B. (2021). Deep autoencoders for feature learning with embeddings for recommendations: a novel recommender system solution. Neural Computing and Applications. doi:10.1007/s00521-021-06065-9

Applications

- **CLUSTERING**
  - ↘ learns good features with local structure preserved by using convolutional autoencoders and manipulates feature space by incorporating a clustering-oriented loss

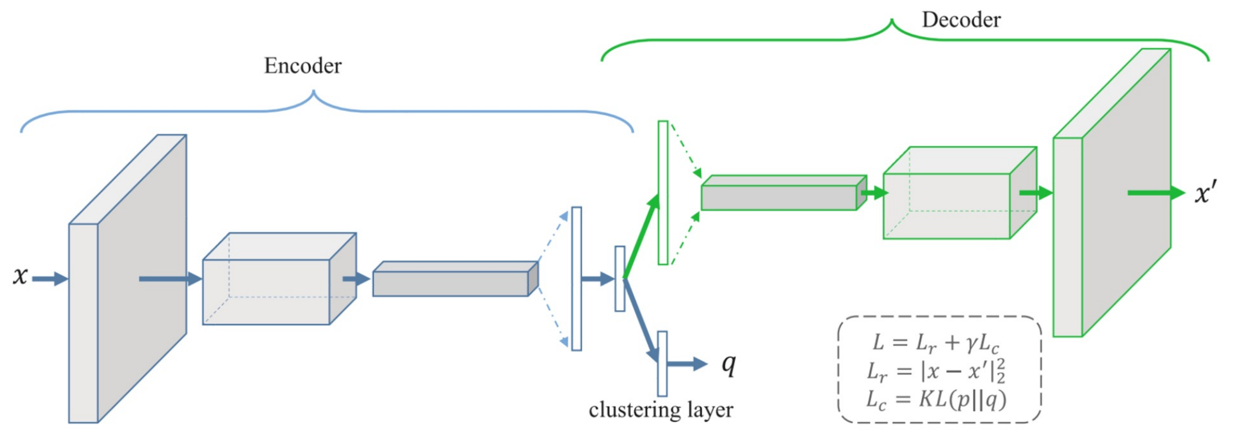

Fig. 2. The structure of deep convolutional embedded clustering (DCEC). It is composed of a convolutional autoencoders and a clustering layer connected to embedded layer of autoencoders.

Reference: Guo, X., Liu, X., Zhu, E., & Yin, J. (2017). Deep Clustering with Convolutional Autoencoders. Lecture Notes in Computer Science, 373–382. doi:10.1007/978-3-319-70096-0_39

Applications

- **FORECASTING**
  - ↘ Time series prediction with uncertainty estimation

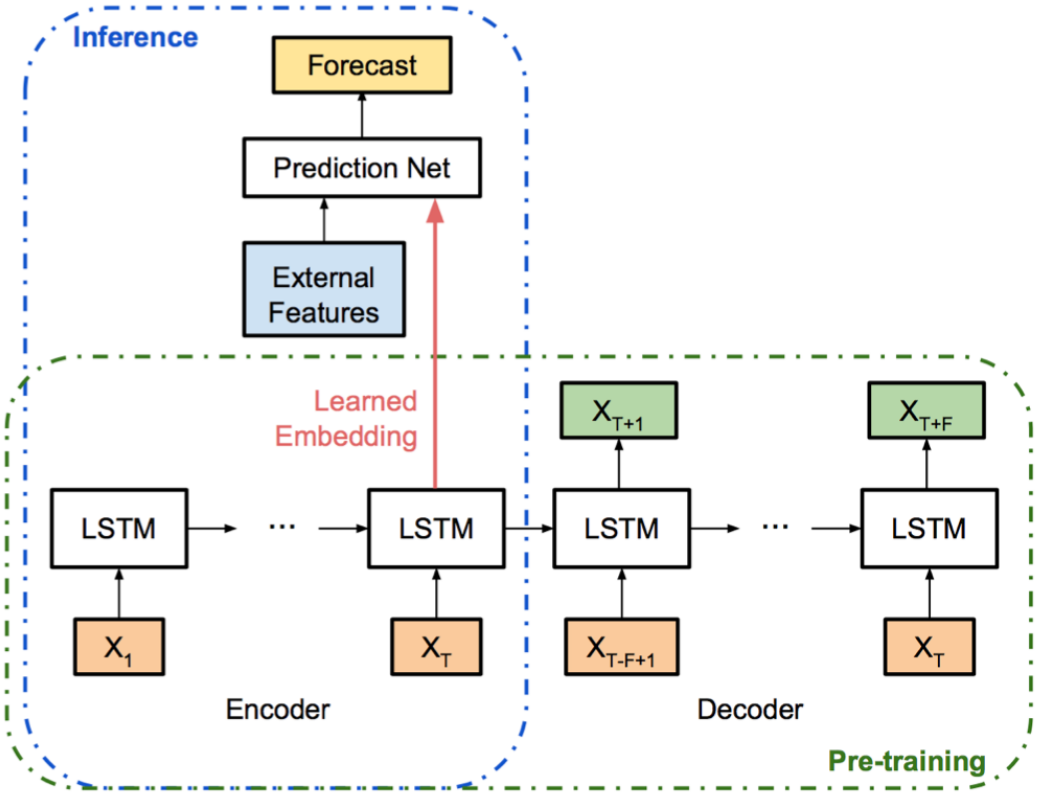

Figure 1. Neural network architecture, with a pre-training phase using a LSTM encoder-decoder, followed by a prediction network, with input being the learned embedding concatenated with external features.

Reference: Zhu, L. & Laptev, N. (2017). Deep and confident prediction for time series at Uber. *2017 IEEE International Conference on Data Mining Workshops*. Retrieved from https://arxiv.org/pdf/1709.01907.pdf

General Architecture

References: Hinton, GE, & Salakhutdinov (2006). Reducing the dimensionality of data with neural networks. *Science, 313 (5786)*, 504-507.
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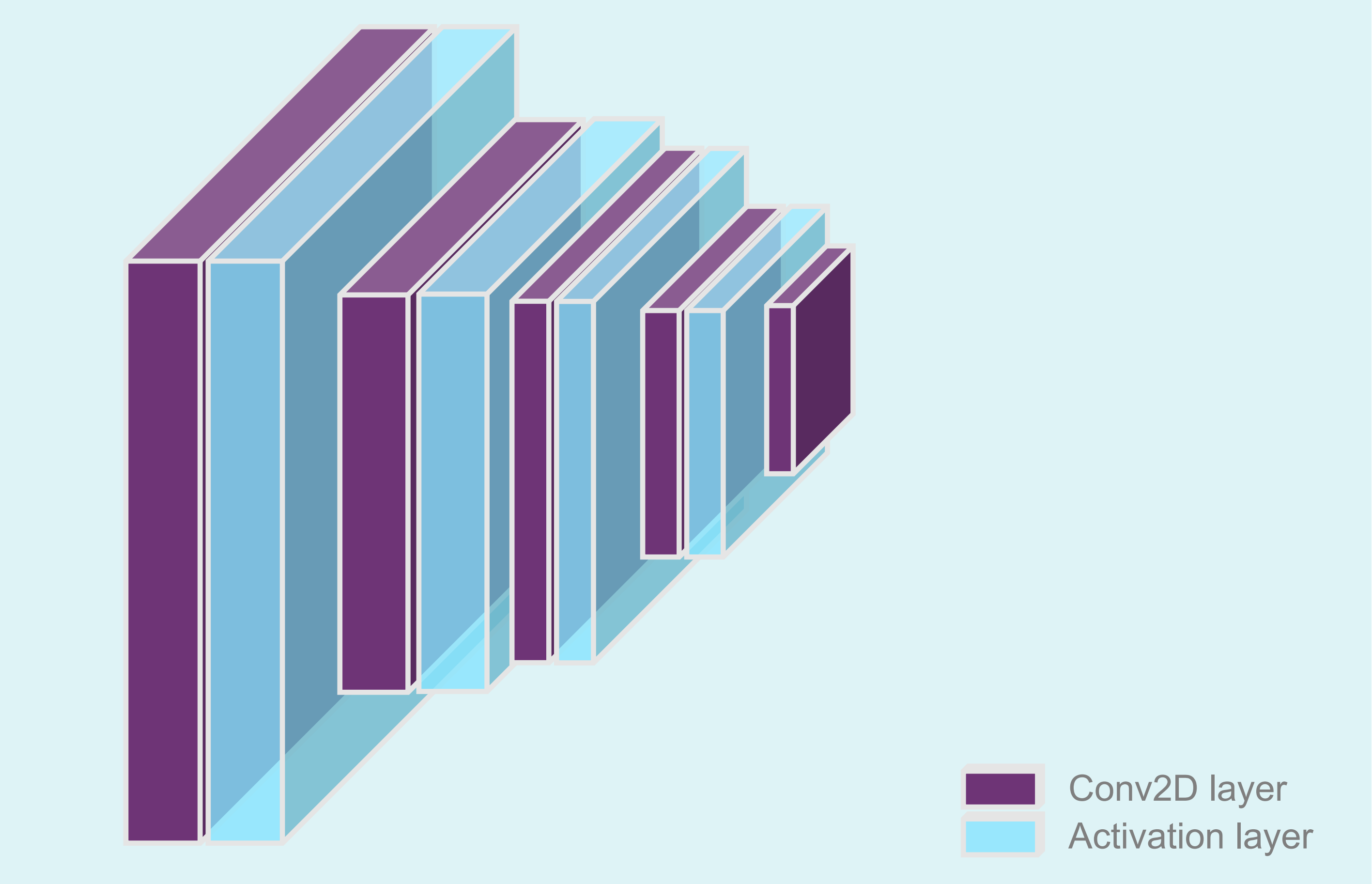
encoder

Sample architecture



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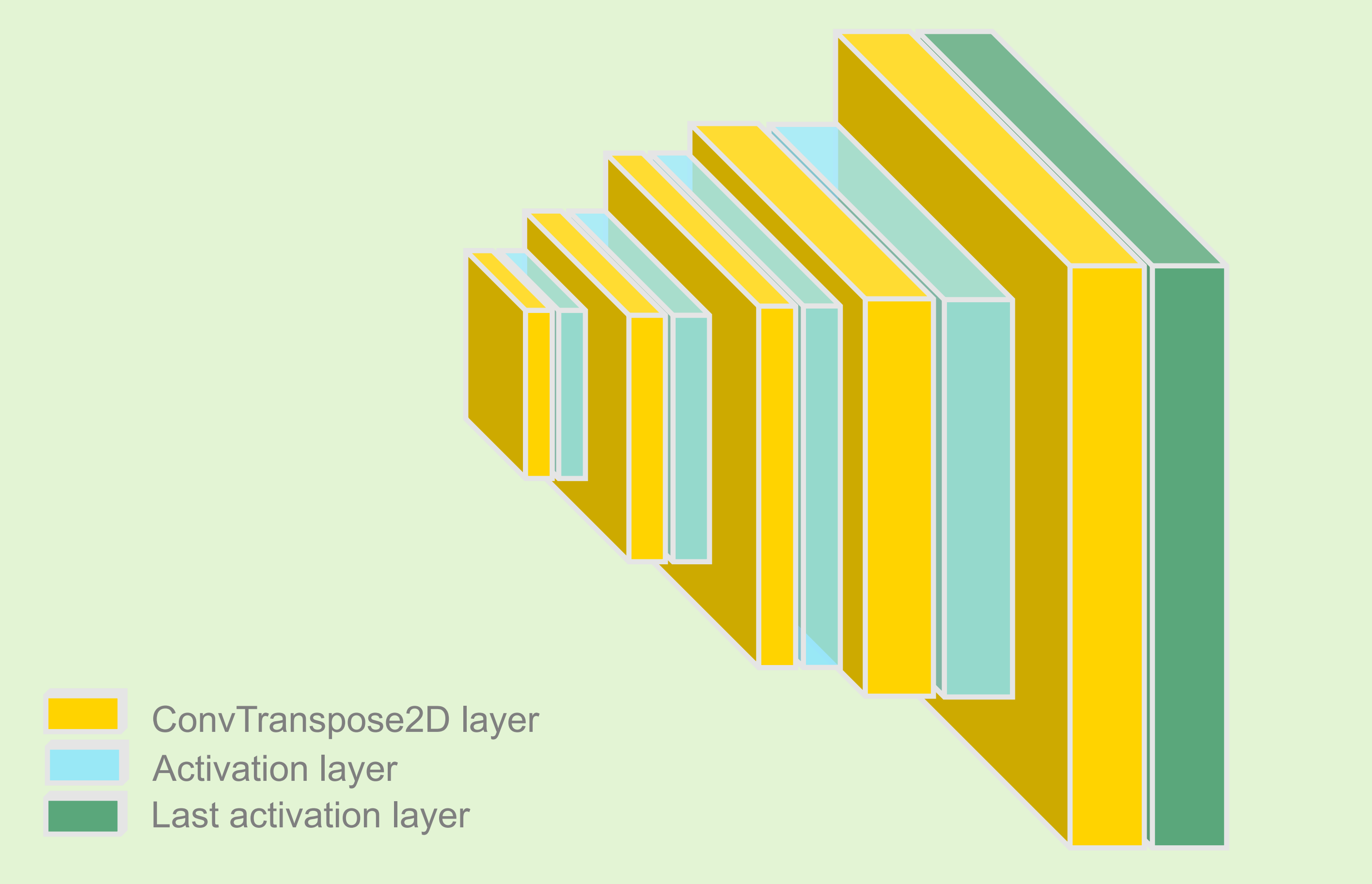

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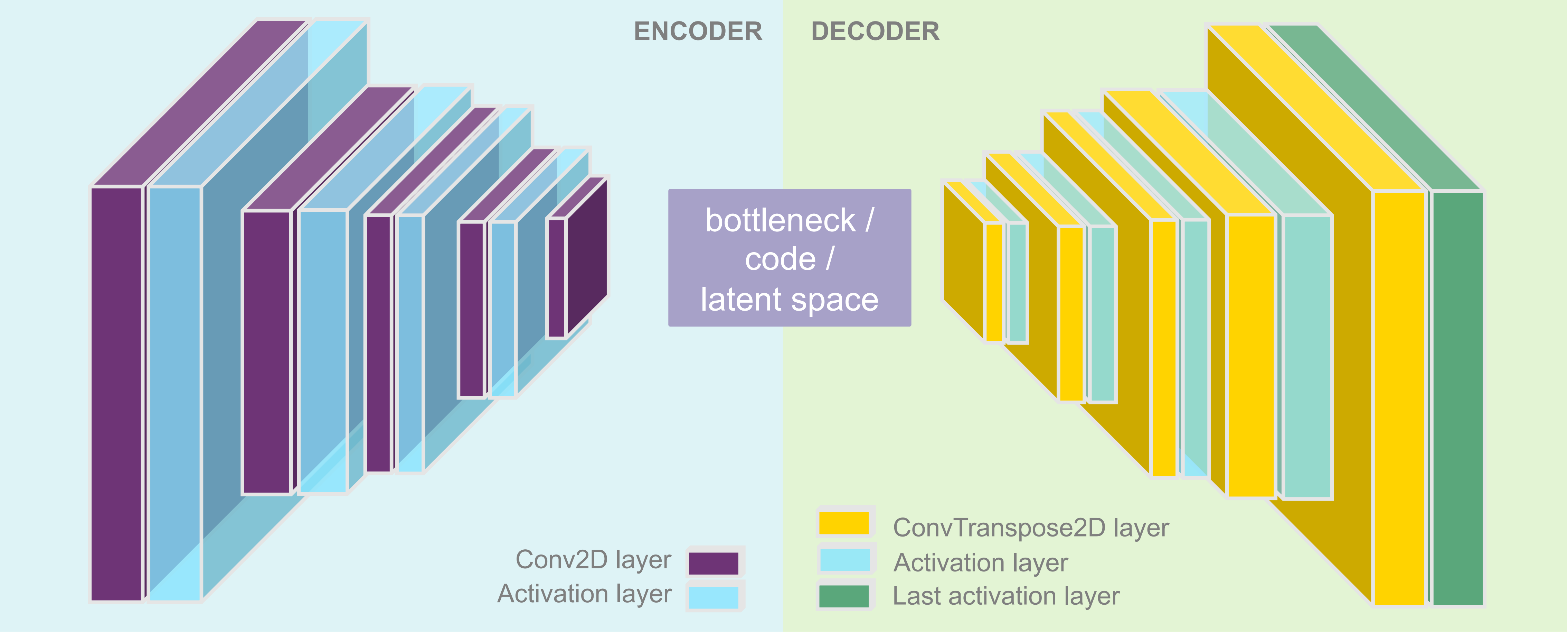

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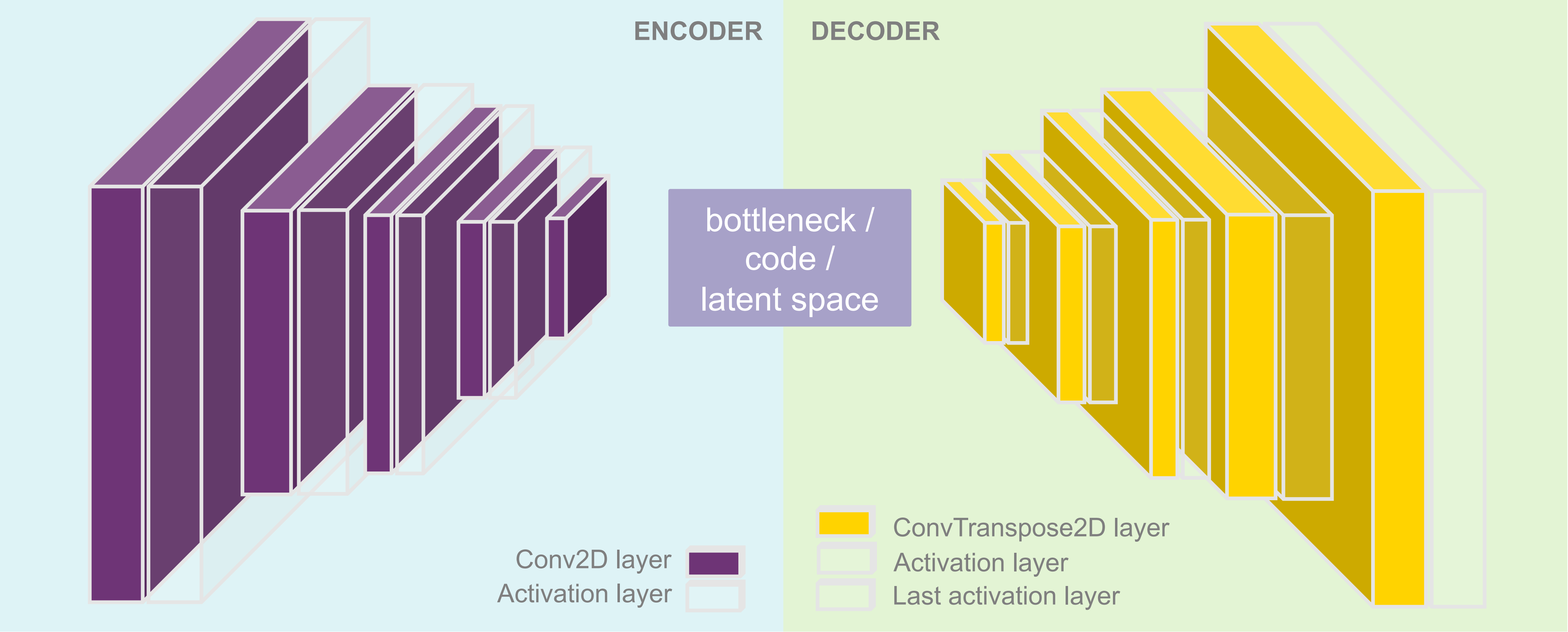

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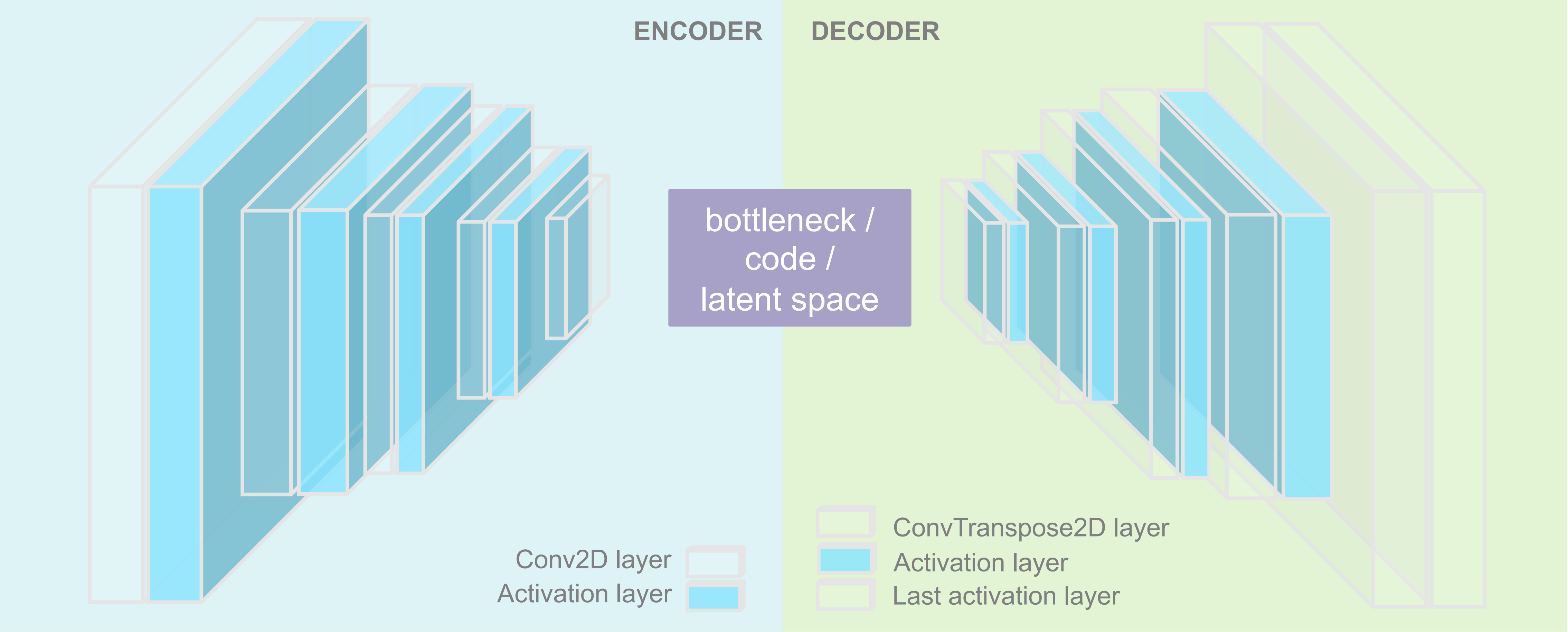

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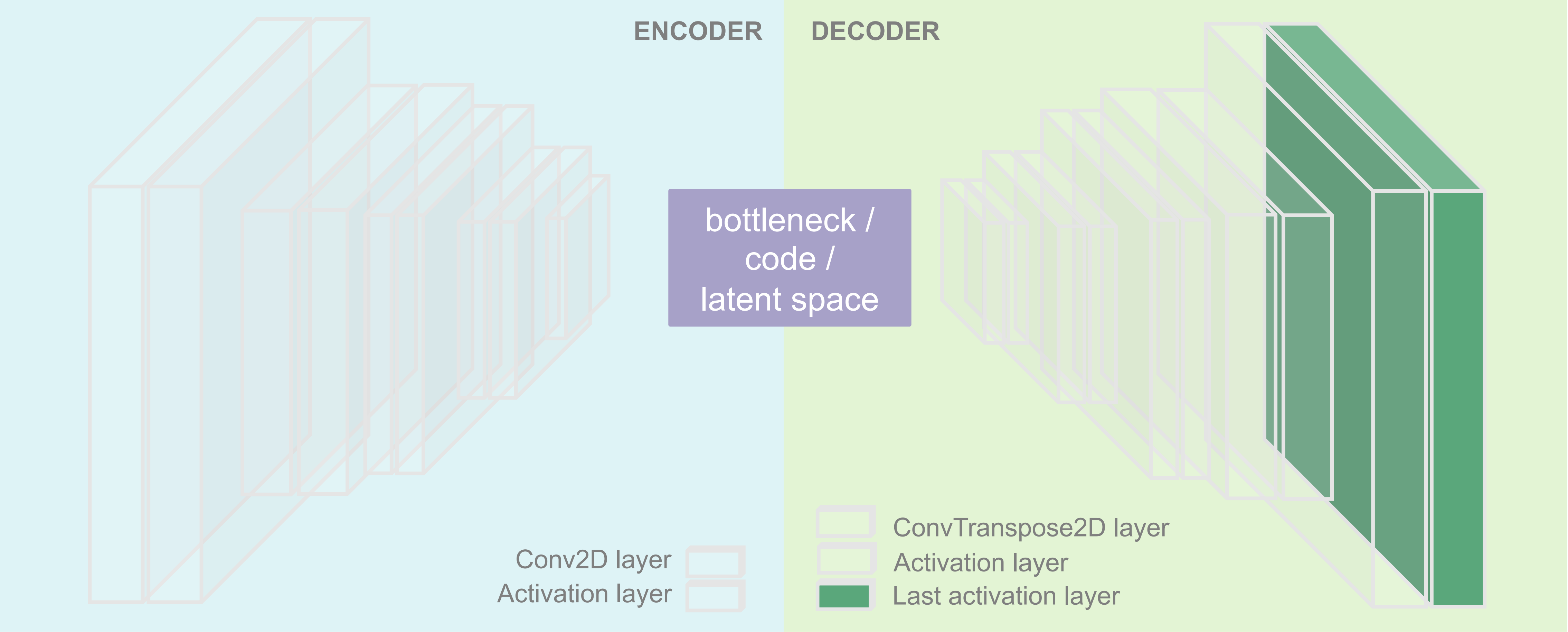

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Building a Convolutional Autoencoder using PyTorch

Training a Convolutional Autoencoder using PyTorch

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