Autoencdoer & matrix completion

Lecture 19

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Recap: Dimensionality reduction

Reducing # of features in data by obtaining a set of principal components

Key role: Improve generalization performance

Three prominent techniques:

1. Principal Component Analysis (**PCA**)
2. **Kernel PCA** (a non-linear version of PCA)
3. **t-SNE** (for data visualization)

Recap: Coding for dimensionality reduction

```
from sklearn.decomposition import PCA, KernelPCA
from sklearn.manifold import TSNE
from temsorflow.keras.datasets import  mnist

(X_train, y_train), (X_test, y_test) = mnist.load_data()
X_train = X_train.reshape(-1, 28*28) / 255.0

pca = PCA(n_components=0.95, svd_solver='full')
X_pca = pca.fit_transform(X_train)

kpca = KernelPCA(kernel="rbf", gamma=10)
X_kpca = kpca.fit_transform(X)

tsne = TSNE(n_components=2, random_state=0)
X_tsne = tsne.fit_transform(X_train)
```

Recap: Clustering

Classifiying data points into certain groups (clusters).

Key role: Improve generalization performance

Three prominent methods:

1. K-**means** algorithm
2. K-**medoids** algorithm (robust to outliers)
3. Hierarchical clustering (agglomerative clustering)

Recap: Coding for clustering

```
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn_extra.cluster import KMedoids


kmeans = KMeans(n_clusters=10,random_state=0).fit(X_train)

kmedoids = KMedoids(n_clusters=10,random_state=0).fit(X_train)

hierachical = AgglomerativeClustering(n_clusters=10).fit(X_train)
```

Next topics?

Mentioned: Many people in Hyundai Motors are interested in:

1. Anomaly detection

2. Fusion learning

Techniques of our focus

Mentioned: Many people in Hyundai Motors are interested in:

1. Anomaly detection

⇨ **autoencoder**

2. Fusion learning

⇨ **matrix completion**

Outline of today's lecture

Will explore autoencoder & matrix completion in depth:

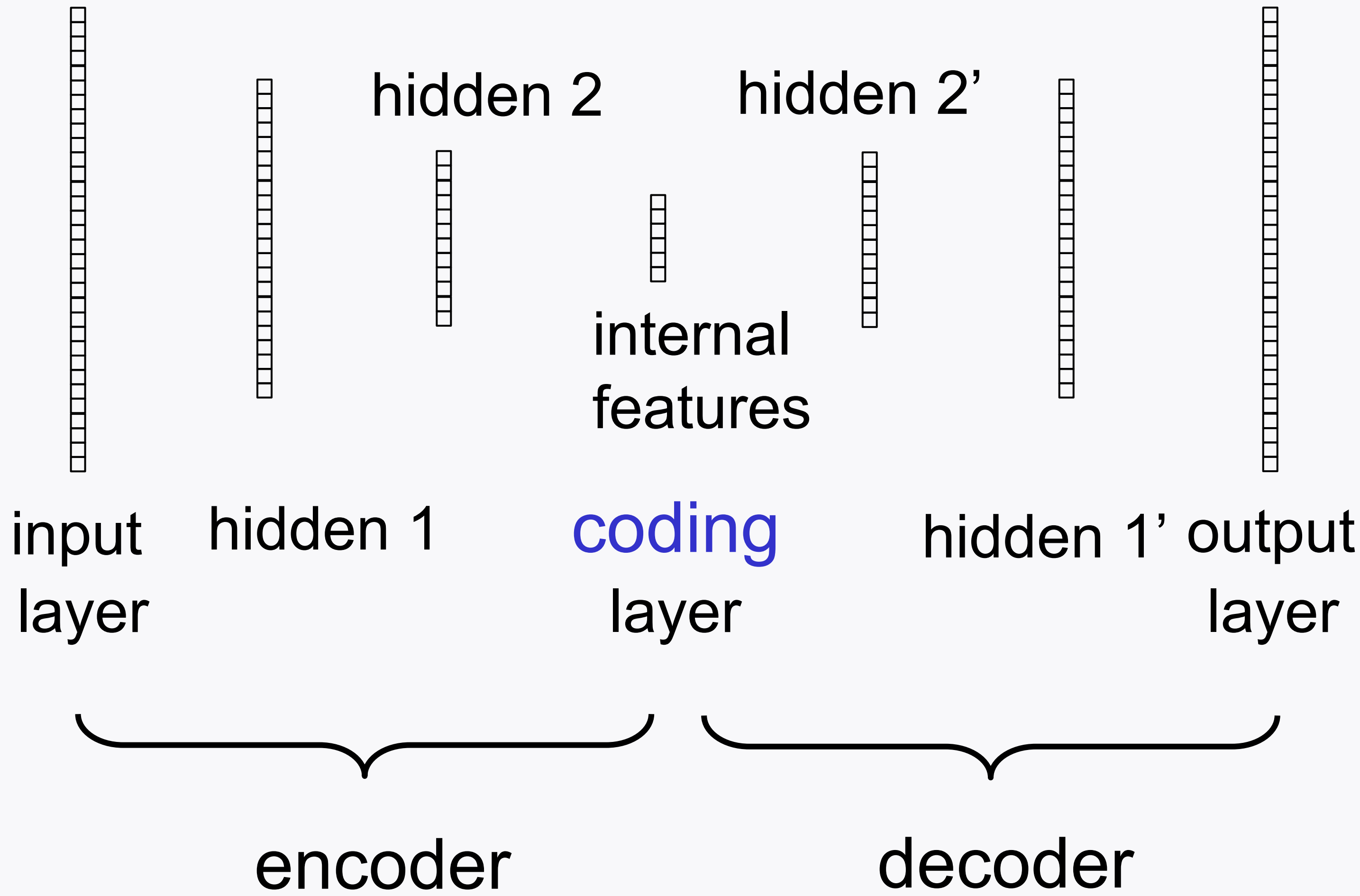
1. Investigate the architecture of autoencoder and training methods.
2. Discuss several roles of autoencoder.
3. Explore how to use autoencoder for anomaly detect.
4. Figure out what matrix completion (MC) is.
5. Figure out its relevance to fusion learning.
6. Study one recent MC technique which leverages autoencoder.

Focus of Lecture 19

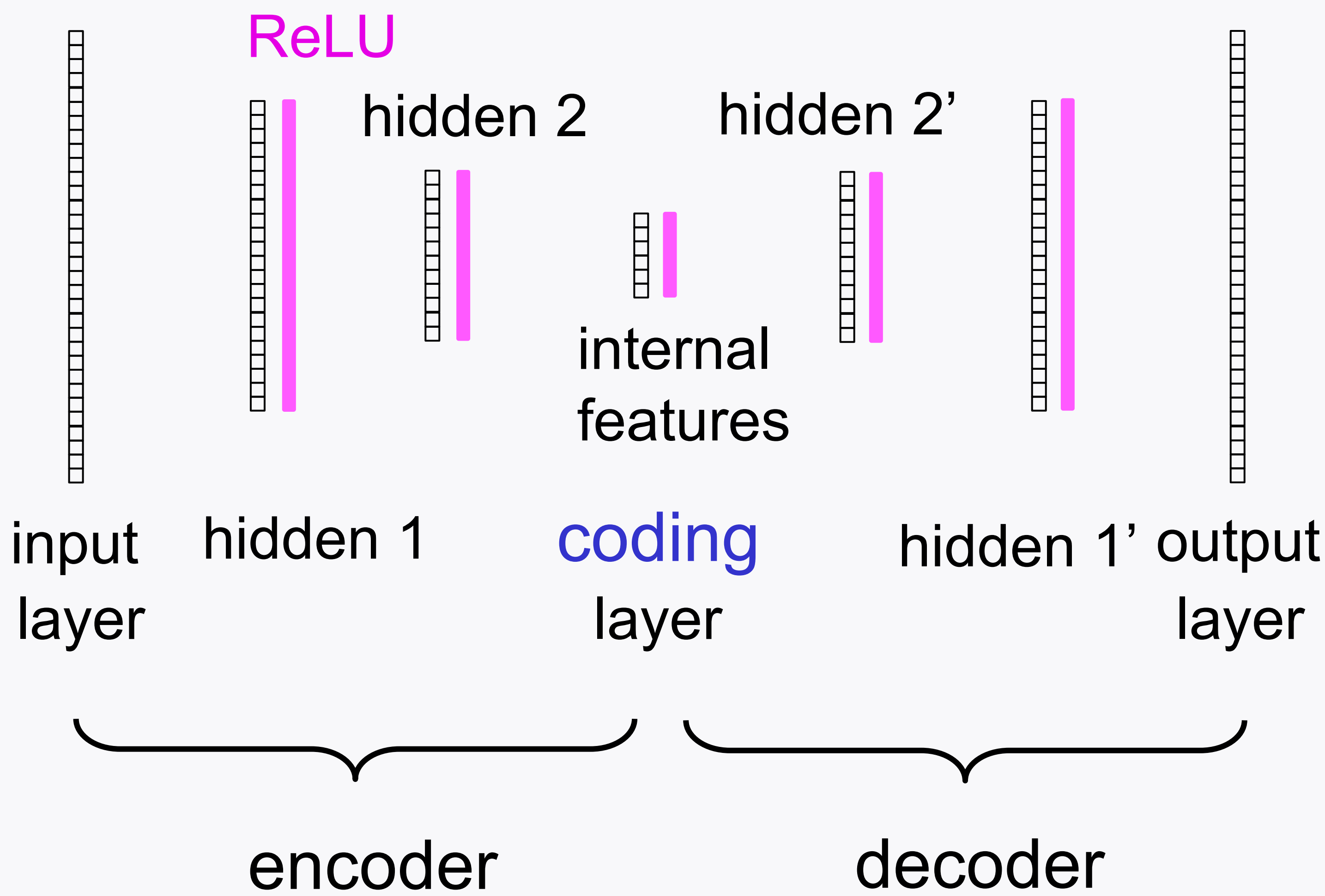
Will explore autoencoder & matrix completion in depth:

1. Investigate the architecture of autoencoder and training methods.
2. Discuss several roles of autoencoder.
3. Explore how to use autoencoder for anomaly detect.
4. Figure out what matrix completion (MC) is.
5. Figure out its relevance to fusion learning.
6. Study one recent MC technique which leverages autoencoder.

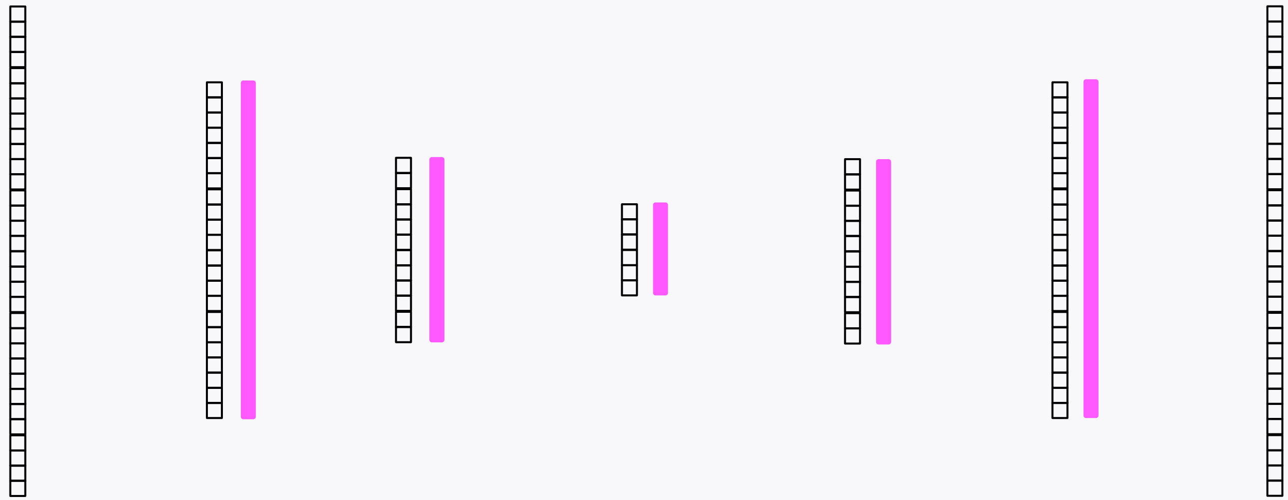
Autoencoder architecture



Autoencoder architecture



Training methods

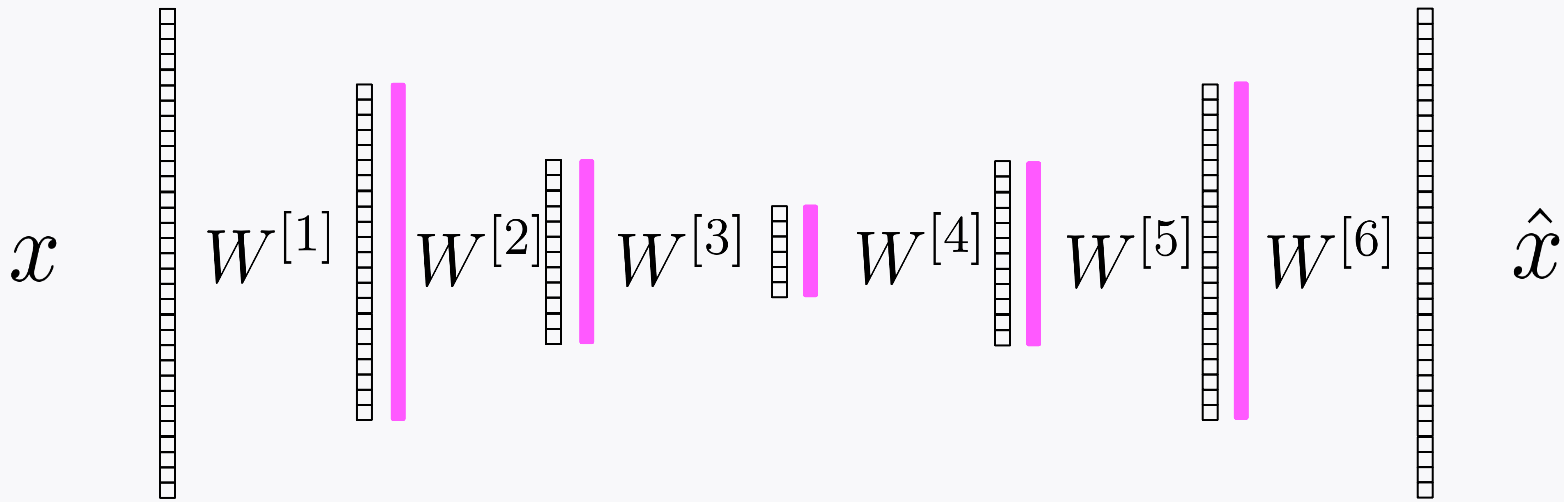


1. Naive method

2. Standard method

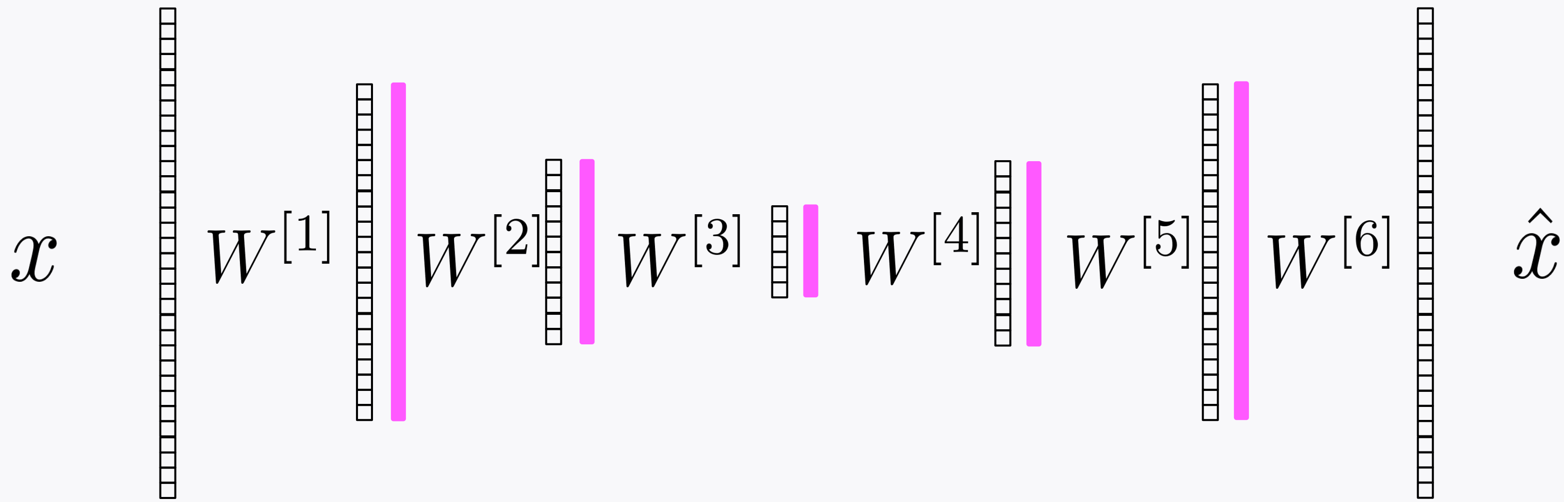
3. Standard method with tying weights

1. Naive method



$$\min_{W^{[1]},\ldots,W^{[6]}} \underbrace{\frac{1}{m}\sum_{i=1}^{m}\left(x^{(i)} - \hat{x}^{(i)}\right)^2}_{\text{reconstruction loss}}$$

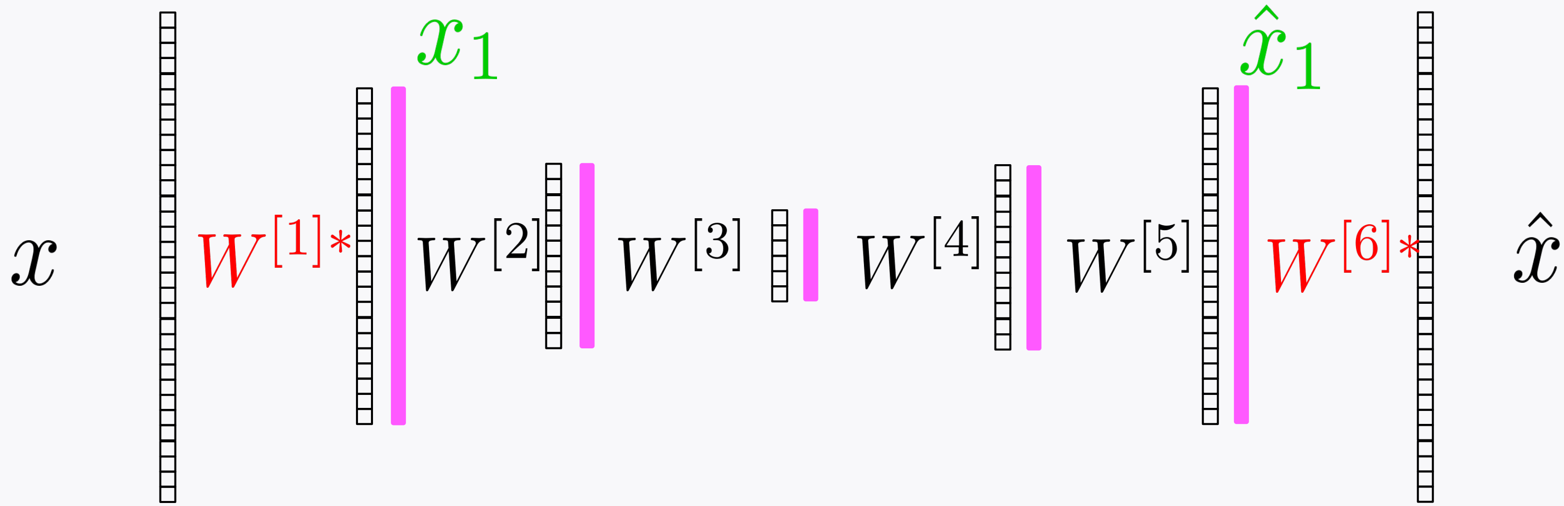
2. Standard method



Step 1: Find $(W^{[1]*}, W^{[6]*})$ while ingoring others.

$$\min_{W^{[1]}, W^{[6]}} \frac{1}{m} \sum_{i=1}^{m} (x^{(i)} - \hat{x}^{(i)})^2$$

2. Standard method

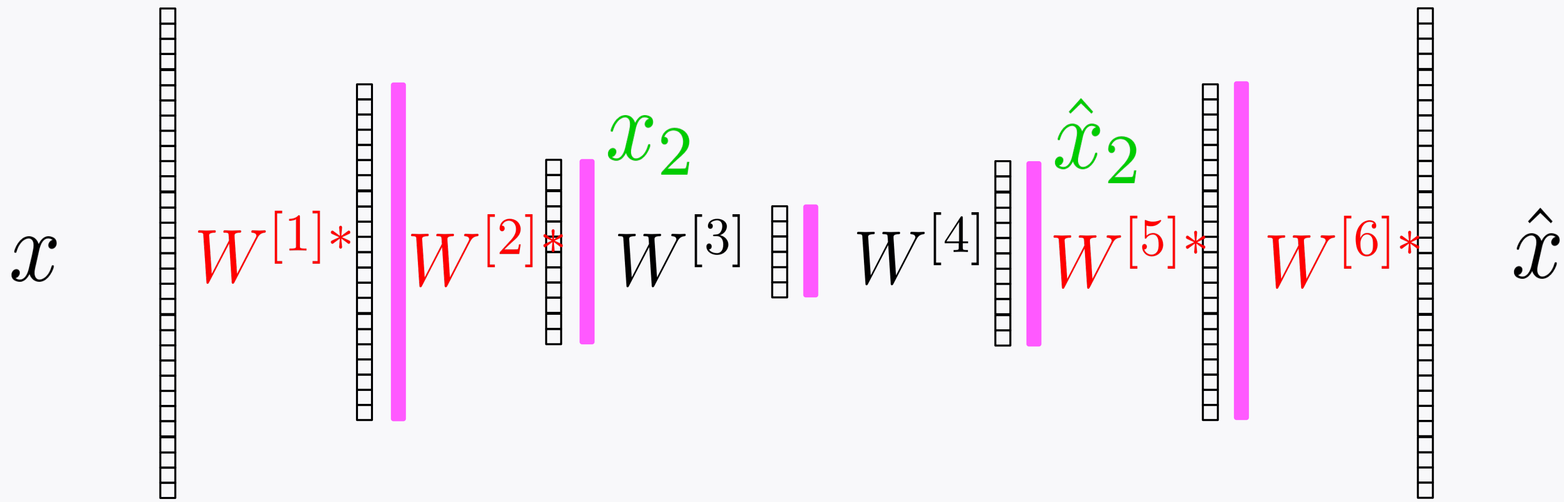


Step 2: Freezing $(W^{[1]*}, W^{[6]*})$:

find $(W^{[2]*}, W^{[5]*})$ while inside layers.

$$\min_{W^{[2]}, W^{[5]}} \frac{1}{m} \sum_{i=1}^{m} (x_1^{(i)} - \hat{x}_1^{(i)})^2$$

2. Standard method

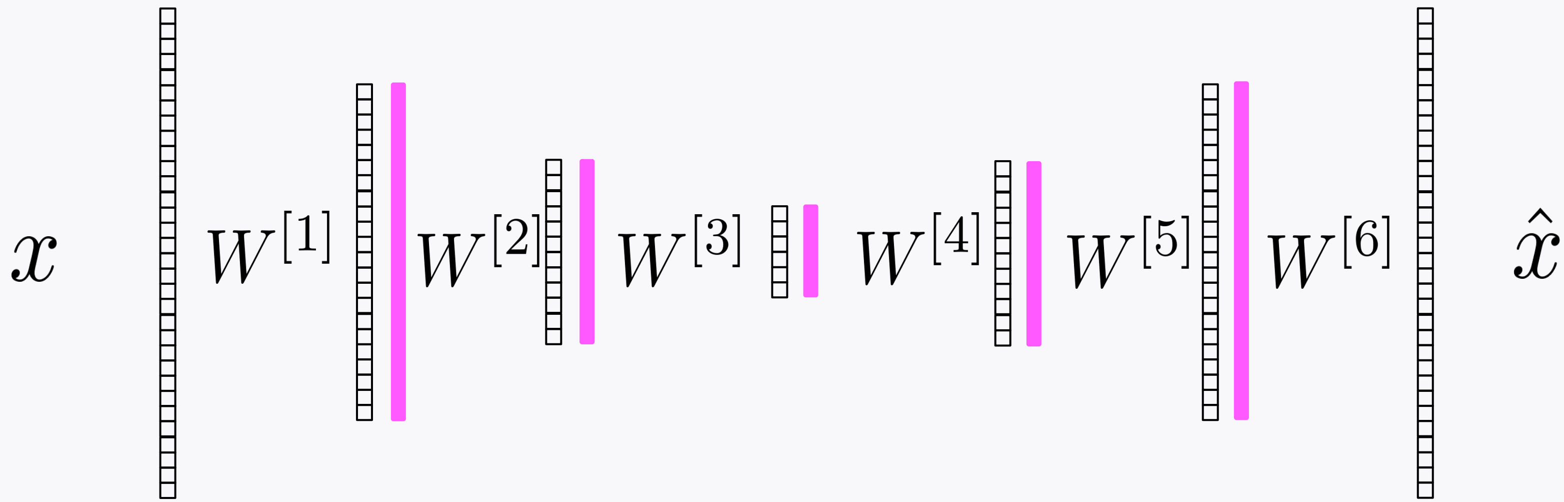


Step 3: Freezing $(W^{[1]*}, W^{[6]*}, W^{[2]*}, W^{[5]*})$:

find $(W^{[3]*}, W^{[4]*})$

$$\min_{W^{[3]}, W^{[4]}} \frac{1}{m} \sum_{i=1}^{m} (x_2^{(i)} - \hat{x}_2^{(i)})^2$$

2. Standard method

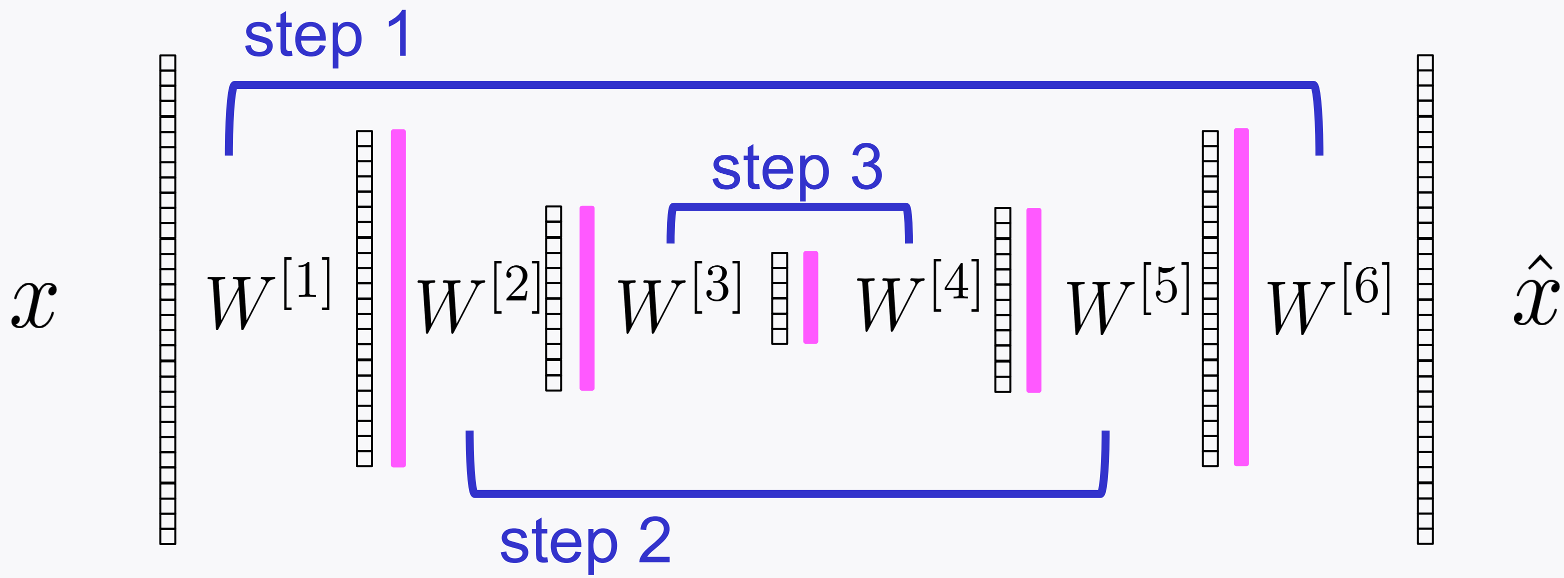


Step 4: With initial weights $(W^{[1]*}, W^{[6]*}, W^{[2]*}, W^{[5]*}, W^{[3]*}, W^{[4]*})$:

fine-tune $(W^{[1]}, \ldots, W^{[6]})$

$$\min_{W^{[1]},\ldots,W^{[6]}} \frac{1}{m} \sum_{i=1}^{m} (x^{(i)} - \hat{x}^{(i)})^2$$

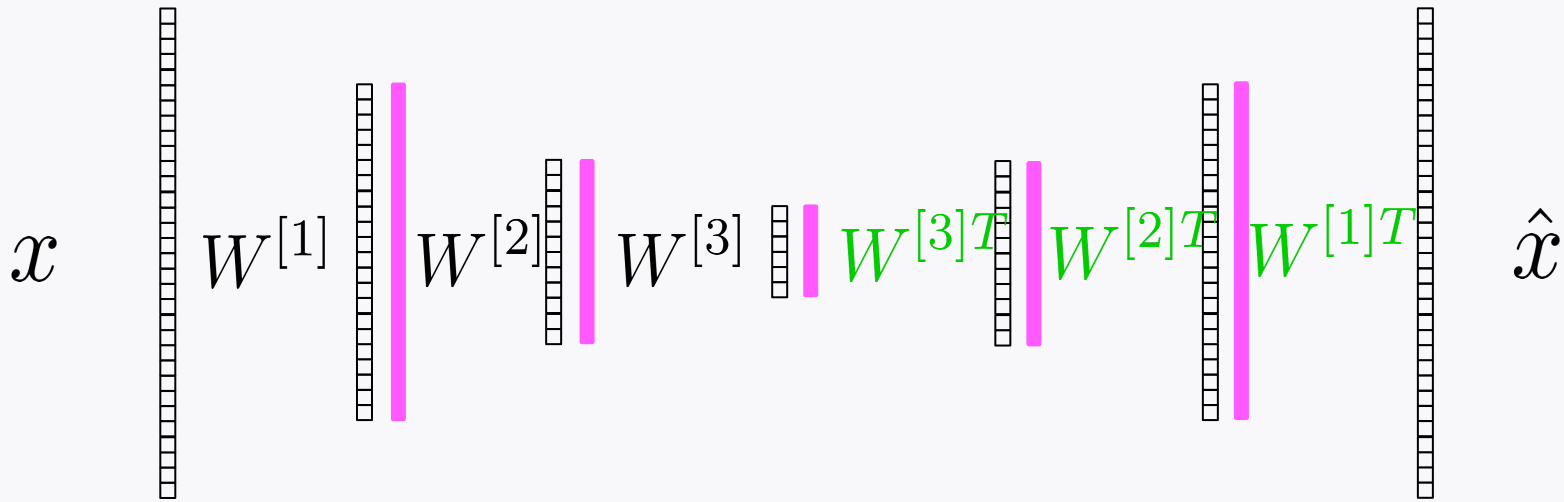
Remarks



Particularly useful for **very deep** neural networks

Easy to implement in TensorFlow

3. Standard method with tying weights

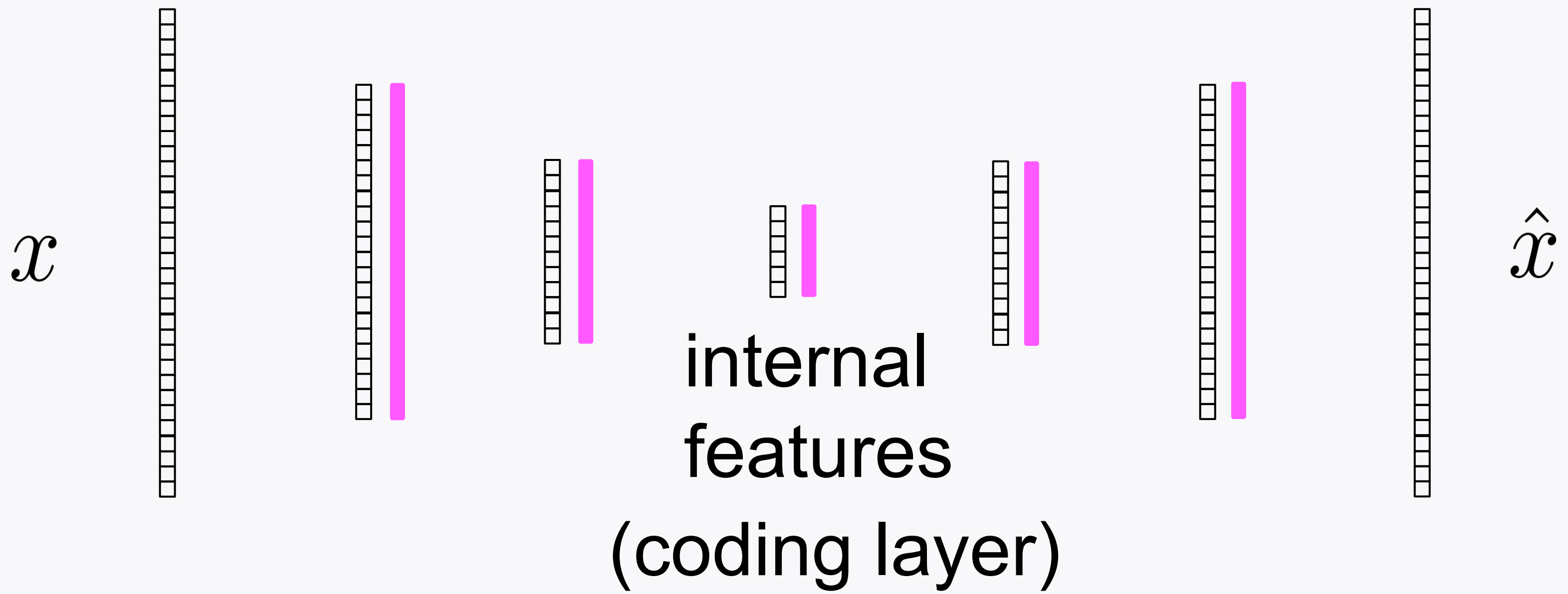


Tie 1st layer's weights to the last layer's ones.

Similarly for the other inside layers.

Except for this, the training method is the same as before.

Main role of autoencoder



Can serve as a non-linear **dimensionality reduction** technique.

Look ahead

1. Discuss other roles of autoencoder.

2. Explore how to use autoencoder for anomaly detect.