LSTM: PREDICTION ERREUR

$x^{i:i+w}_{T, Cont}$ $\xrightarrow{\mathbb{1}}$ D

$x^{i:i+w}_{Cat}$ $\xrightarrow{Embed}$ D $\xrightarrow{CAT}$ W $\begin{pmatrix} T, F \\ \\ - \end{pmatrix}$ $\xrightarrow{LSTM + FC}$ D $\hat{x}^{w+1}_{T}$ $\rightarrow$ D Error

x^{w+1}_{T} ―――――――――――――――――――――――――――――――→

AE-LSTM : Reconstruction Error

$x^{i:i+w+1}_{T, Cont}$ ――――→ D

$x^{i:i+w+1}_{Cat}$ $\xrightarrow{Embed}$ D $\xrightarrow{CAT}$ $\tilde{x}^{i:i+w+1} = W+1$ $\begin{pmatrix} T, Feat \\ \\ \end{pmatrix}$ $\tilde{x}^{w+1} \rightarrow$ D Error

$\xrightarrow{LSTM\ Encoder}$ D

$W+1 \begin{pmatrix} Hidden \end{pmatrix}$ $\xrightarrow{LSTM\ Decoder}$ D
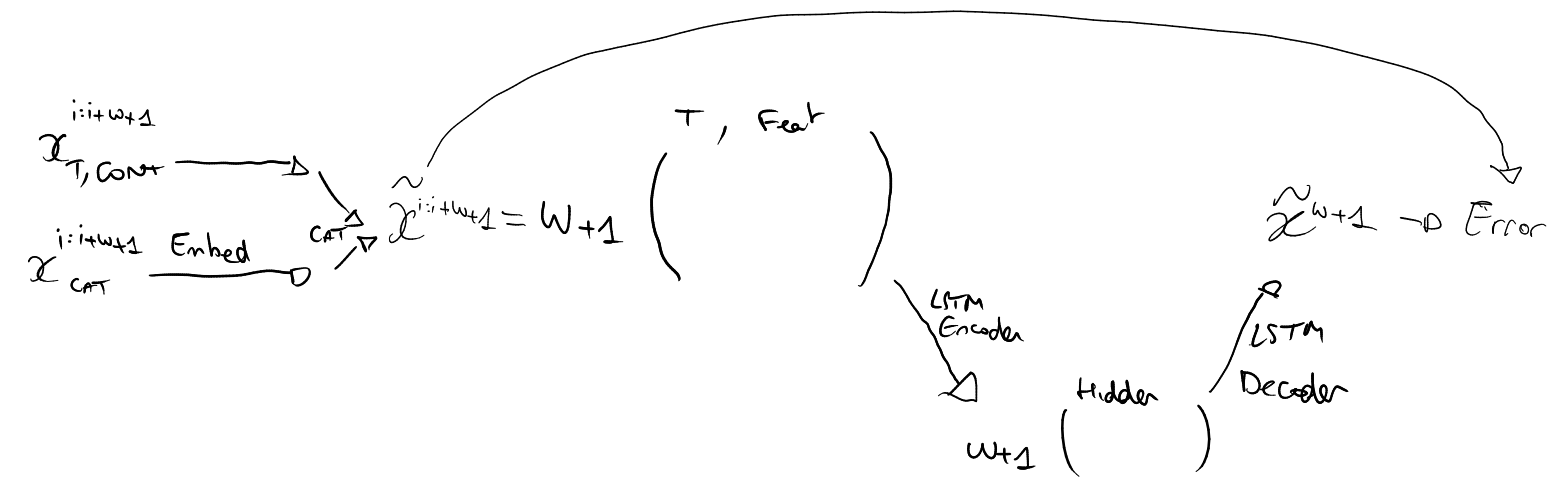
Deep One-Class Classification (DSVDD):

$x^{i:i+w+1}_{T, cont}$ ――――→ D

$x^{i:i+w+y}_{Cat}$ $\xrightarrow{Embed}$ D $\xrightarrow{CAT}$ $\tilde{x}: W+1 \begin{pmatrix} T, F \\ \\ \end{pmatrix}$ $\xrightarrow{LSTM+FC}$ $Proj(\tilde{x}^{w+1}) \rightarrow$ D Distance

Center (parameter) ――――――――――――――――――――――→

DROCC:

1) Classifier :

$x^{i:i+w+1}_{T, cont}$ ――――→ D

the model also output this

$x^{i:i+w+y}_{Cat}$ $\xrightarrow{Embed}$ D $\xrightarrow{CAT}$ $\tilde{x}: W+1 \begin{pmatrix} T, F \\ \\ \end{pmatrix}$ $\xrightarrow{LSTM+FC}$ $proba(\tilde{x}^{w+1})$ est normal.
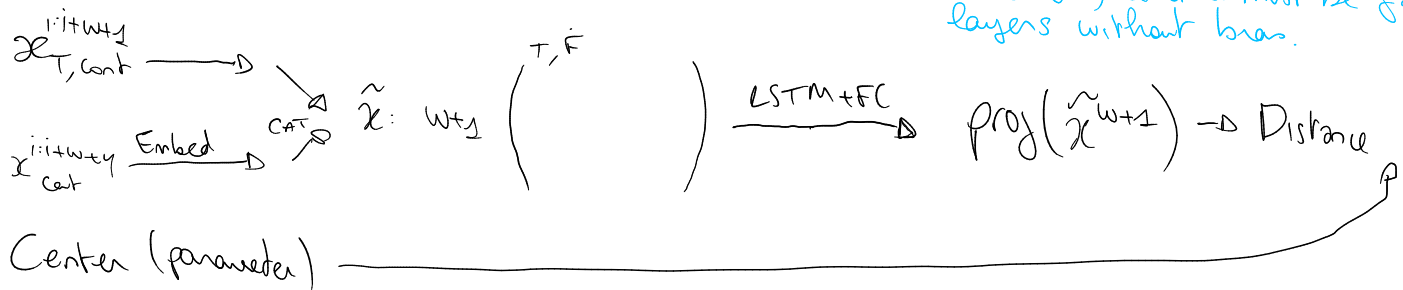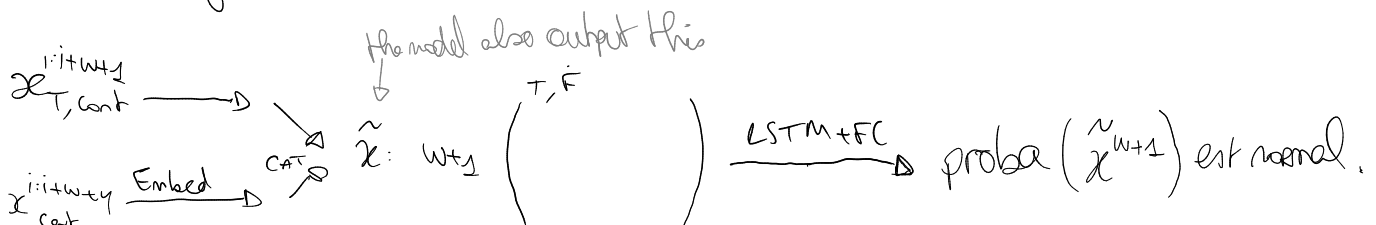
Pb : We do unsupervised learning so we have only 1 class.

→ During training, we will generate fakes samples.

2) TRAINING:

for each epoch:

   normal pred, $\tilde{x}$ = model (normal data)

   normal loss = BCE (normal pred, 1)

   anormal = generate anormale that fools the model ie. BCE (anormal, 0) >> 0
       using G.D. (anormal must lives in a disc around the normal)
       they are generated using $\tilde{x}$.

   pred anormal = model (anormal)

   loss anormal = BCE (pred anormal, 0)

   loss = loss anormal + loss normal

   G.D. w.r.t. loss.

$$Score = model(x^{test}) = normal\ proba\ given\ the\ model.$$

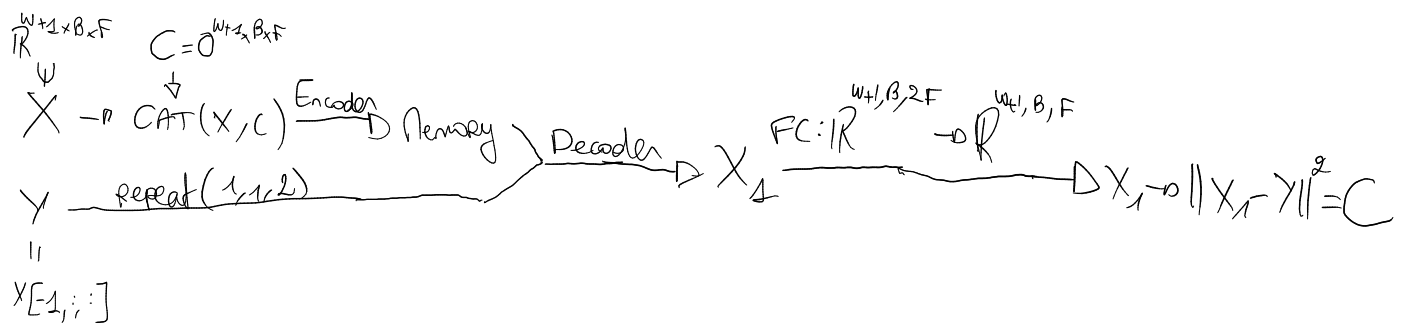Uses encoder and decoder with past memory and error knowledge.

1) Encoder:

$$x \to Att(x,x,x) \xrightarrow[D]{DP} \oplus \xrightarrow[D]{\overset{+DP}{FC(\sigma(FC))}} \oplus \to OUTPUT$$

2) Decoder:

$$\left\{ \begin{array}{l} x \to Att(x,x,x) \xrightarrow[D]{DP} \oplus \to \tilde{x} \to Att(\tilde{x}, memory, memory) \xrightarrow[D]{DP} \oplus \xrightarrow[D]{\overset{+DP}{FC(\sigma(FC))}} \oplus \to OUTPUT. \\ memory \end{array} \right.$$

3) The Whole Architecture:

Phase 1:

$$\mathbb{R}^{W+1 \times B \times F} \quad C = 0^{W+1 \times B \times F}$$

$$X \xrightarrow{\Psi} CAT(X, C) \xrightarrow{Encoder} Memory \rangle Decoder \Rightarrow X_1 \xrightarrow{FC: \mathbb{R}^{W+1, B, 2F} \to \mathbb{R}^{W+1, B, F}} X_1 \to \|X_1 - Y\|^2 = C$$

$$Y \xrightarrow{repeat(1,1,2)}$$

$$Y = X[-1, :, :]$$

Phase 2:

$$\mathbb{R}^{W+1 \times B \times F} \quad C = \|X_1 - Y\|^2$$

$$X \xrightarrow{\Psi} CAT(X, C) \xrightarrow{Encoder} Memory \rangle Decoder \Rightarrow X_2 \xrightarrow{FC: \mathbb{R}^{W+1, B, 2F} \to \mathbb{R}^{W+1, B, F}} X_2$$

$$Y \xrightarrow{repeat(1,1,2)}$$

$$Y = X[-1, :, :]$$
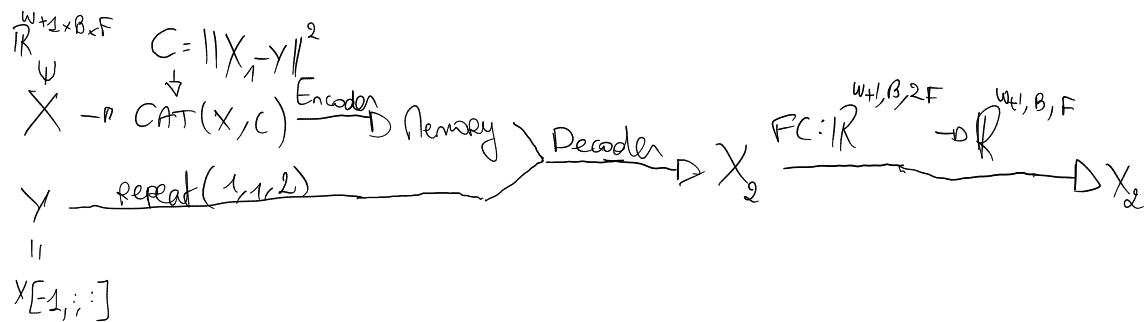
$$\text{Train loss} = \lambda_1 \|X_1 - Y\|^2 + \lambda_2 \|X_2 - Y\|^2$$

$$\text{Anomaly Score} = -\|X_2 - Y\|^2$$

MAD-GAN:

1) LSTM - Generator: $Z \in \mathbb{R}^{W+1, B, H} \xrightarrow{LSTM + FC} \tilde{x} \in \mathbb{R}^{W+1, B, F}$

2) LSTM - Discriminator: $x \in \mathbb{R}^{W+1, B, F} \xrightarrow{LSTM + FC + Sigmoid} P \in \mathbb{R}^{1, B, 1}$

3) Best latent Representation:

$x \in \mathbb{R}^{W+1, B, F}$:   1) $Z \in \mathbb{R}^{W+1, B, H}$ Random

2) GD:
     i) rec = gen(z)
     2) loss = $\|rec - x\|^2$
     3) update z

3) return z

Train the GAN (Gen + Disc) Normally

$\sqrt{x}_{test}$

2) z_{test} = get best latent representation (x_{test})

3) $rec_{test} = gen (z_{test})$

4) prob rec = $disc (Rec_{test})$

5) rec loss = $\| rec_{test} - x_{test} \|^2$

6) disc loss = $disc (rec test)$

7) anomaly score = $\lambda_1 (disc loss) - \lambda_2 (Rec loss)$