

CLIP embedding analysis

Semantic extraction and
synthesis



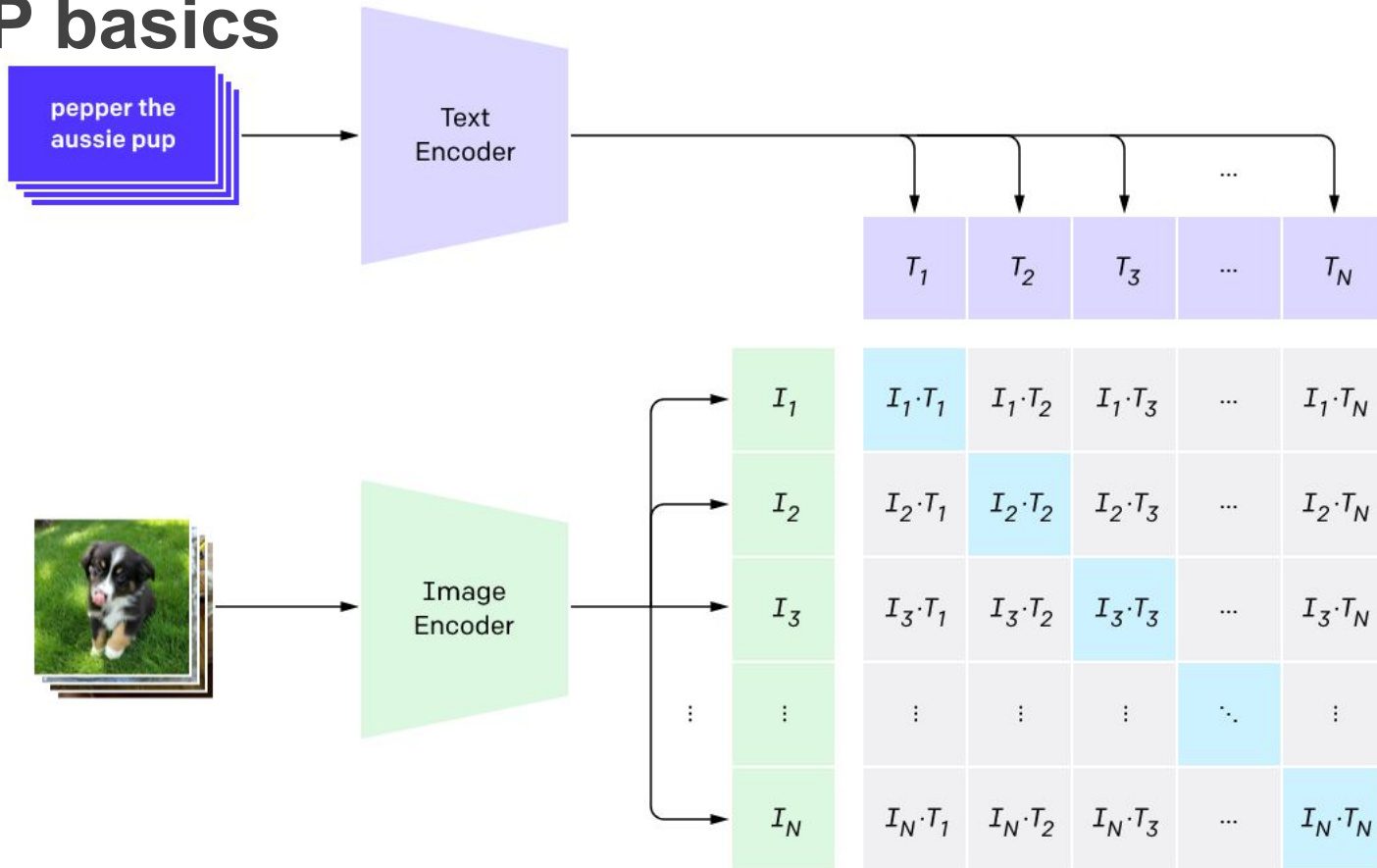
Motivation

- Multi-modality approaches are of big interest of the SOTA research.
- Dimensionality reduction is important task in ML/DL.
- Managed synthesis is key issue in generative models applications.

Tasks

- dimensionality reduction
- embedding clustering
- disentanglement and managed synthesis

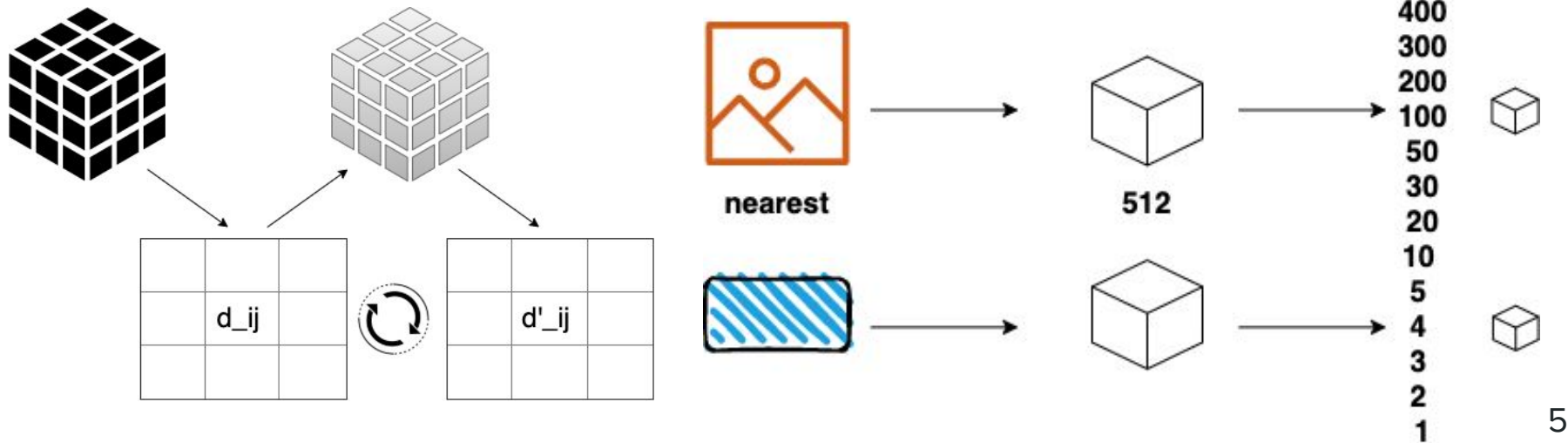
CLIP basics



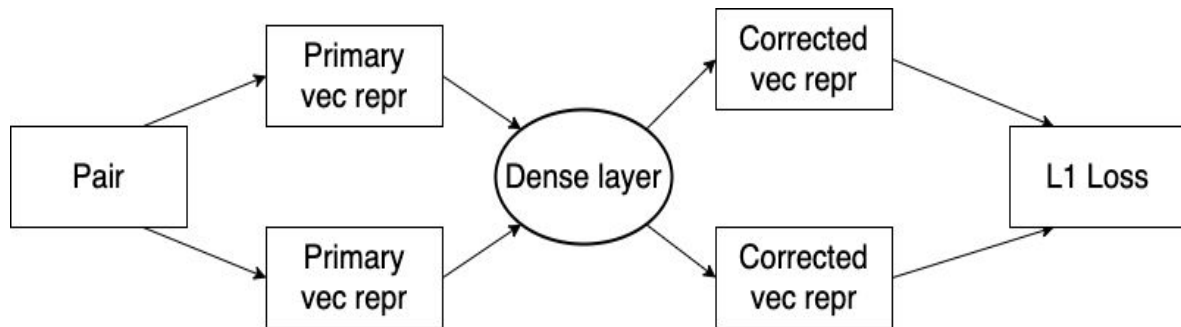
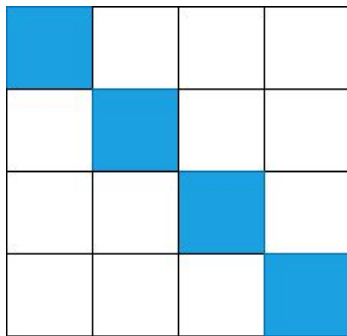
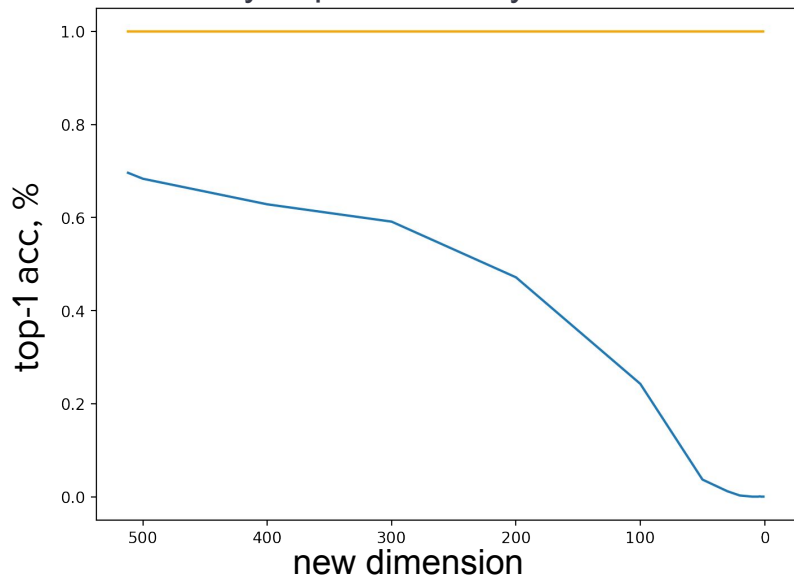
Dimensionality Reduction

Alexey Kolosov, Ekaterina Orlova

Task: Investigate dimensionality reduction methods and show that for the presented data there exist such embedding dimensionality $D' < D$ which doesn't decrease embeddings correspondence quality (top-1 accuracy).



Quality dependence by new dimension



Neural MDS

Alexey Kolosov

Problems statements

1. COCO, isometric, val
2. COCO, isotonic, val

$$d(i, j) = e(g(i), g(j))$$

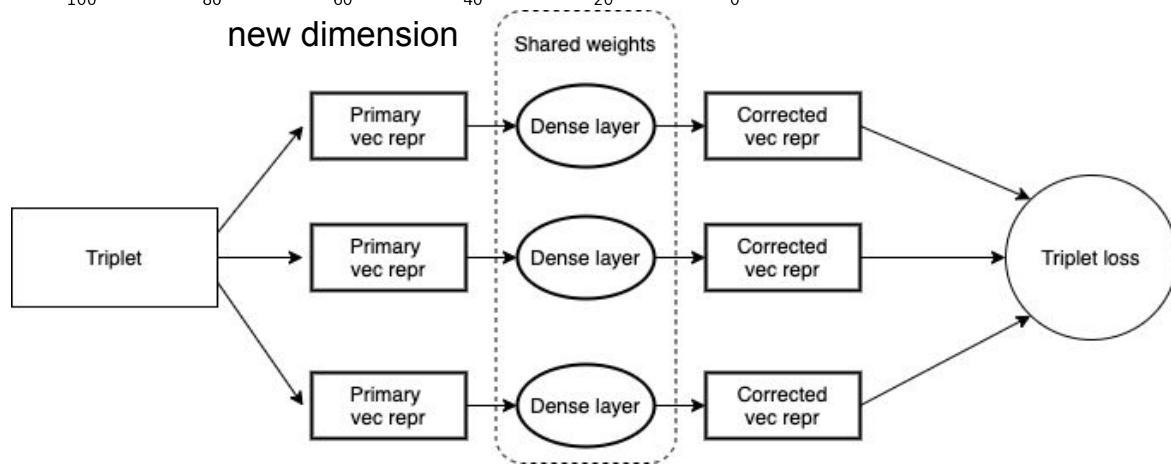
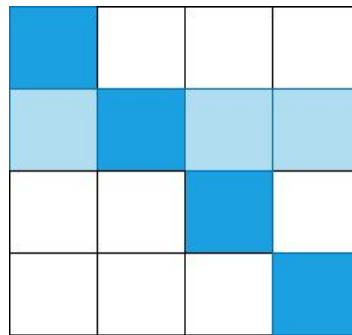
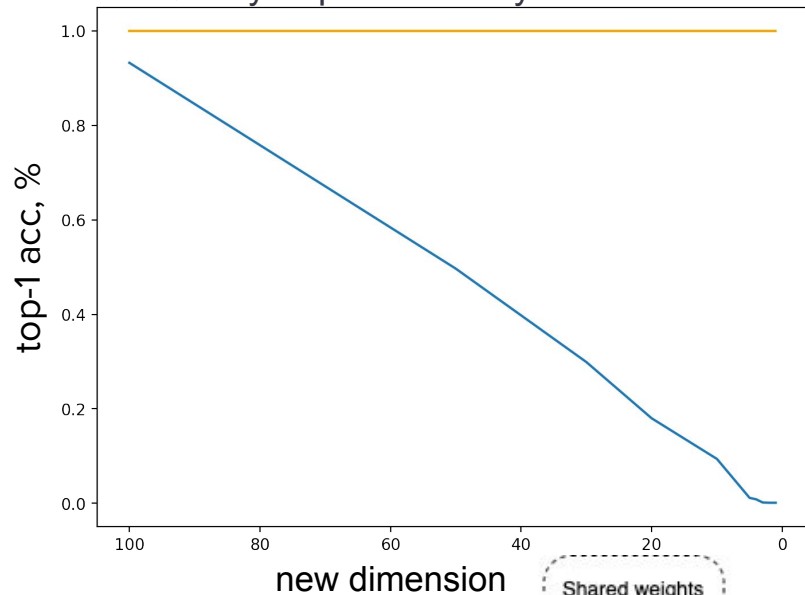
Top-1 accuracy

COCO, isometric, val

5000 pairs, 200 epochs

for 512 dim - 1639 pairs

Quality dependence by new dimension



Neural MDS

Alexey Kolosov

Isotonic problem result

$$d(i, j) < d(k, l) \Rightarrow e(g(i), g(j)) < e(g(k), g(l))$$

Top-1 accuracy

COCO, isotonic, val

8000000 quads, 200 epochs

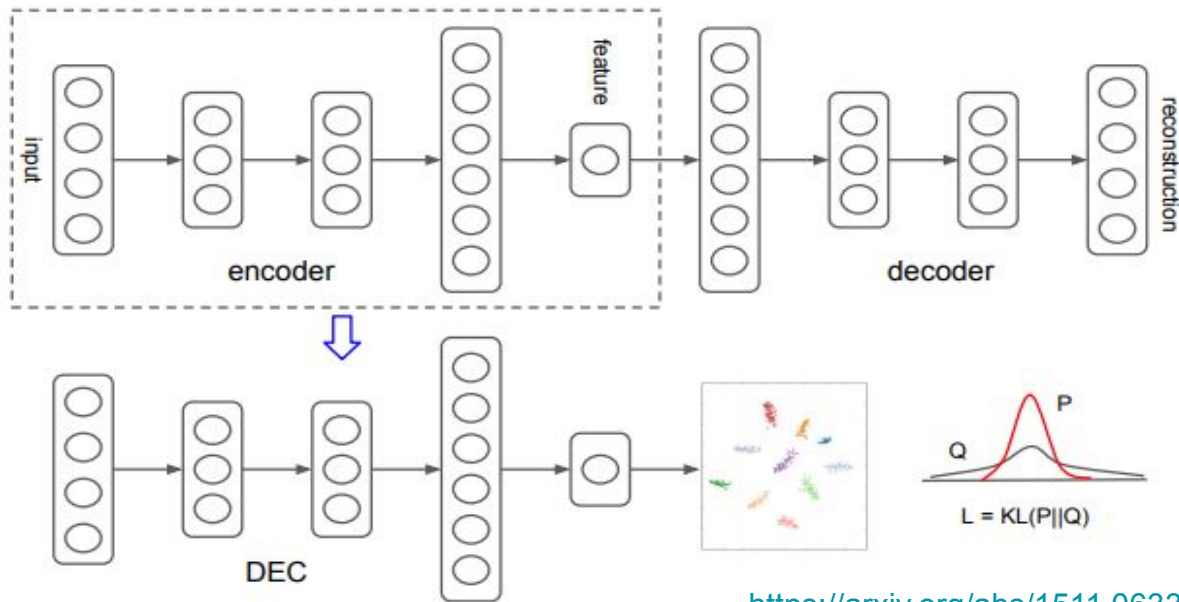
for 512 dim - 1639 pairs

Embeddings clusterization

Abdullaeva Uma, Anna Dmitrienko, Sergey Skorik, Anna Rudenko

Task: Investigate the clusterization methods and show that there exist clusters in the embeddings data. Perform the visualization of these data clusters.

Deep embedded
clustering (DEC)
model



Let "S"- set of n element

$X = \{X_1, X_2, \dots, X_n\}$ – the division into classes

$Y = \{Y_1, Y_2, \dots, Y_n\}$ - the resulting division into clusters

$X \backslash Y$	Y_1	Y_2	...	Y_s	Sums
X_1	n_{11}	n_{12}	...	n_{1s}	a_1
X_2	n_{21}	n_{22}	...	n_{2s}	a_2
\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
X_r	n_{r1}	n_{r2}	...	n_{rs}	a_r
Sums	b_1	b_2	...	b_s	n

$$p_{ij} = \frac{n_{ij}}{n}, p_i = \frac{a_i}{n}, p_j = \frac{b_j}{n}$$

Metrics

$$\overbrace{\text{Adjusted Index}}^{\text{ARI}} = \frac{\overbrace{\sum_{ij} \binom{n_{ij}}{2}}^{\text{Index}} - \underbrace{[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}]}_{\text{Expected Index}} \mathcal{V} \binom{n}{2}}{\underbrace{\frac{1}{2} [\sum_i \binom{a_i}{2} + \sum_j \binom{b_j}{2}]}_{\text{Max Index}} - \underbrace{[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}]}_{\text{Expected Index}} \mathcal{V} \binom{n}{2}}$$

$$\text{ARI} = \frac{\text{RI} - E[\text{RI}]}{\max(\text{RI}) - E[\text{RI}]} \quad \text{RI} = \frac{a + b}{C_2^{n_{\text{samples}}}}$$

$$\text{NMI}(U, V) = \frac{\text{MI}(U, V)}{\text{mean}(H(U), H(V))}$$

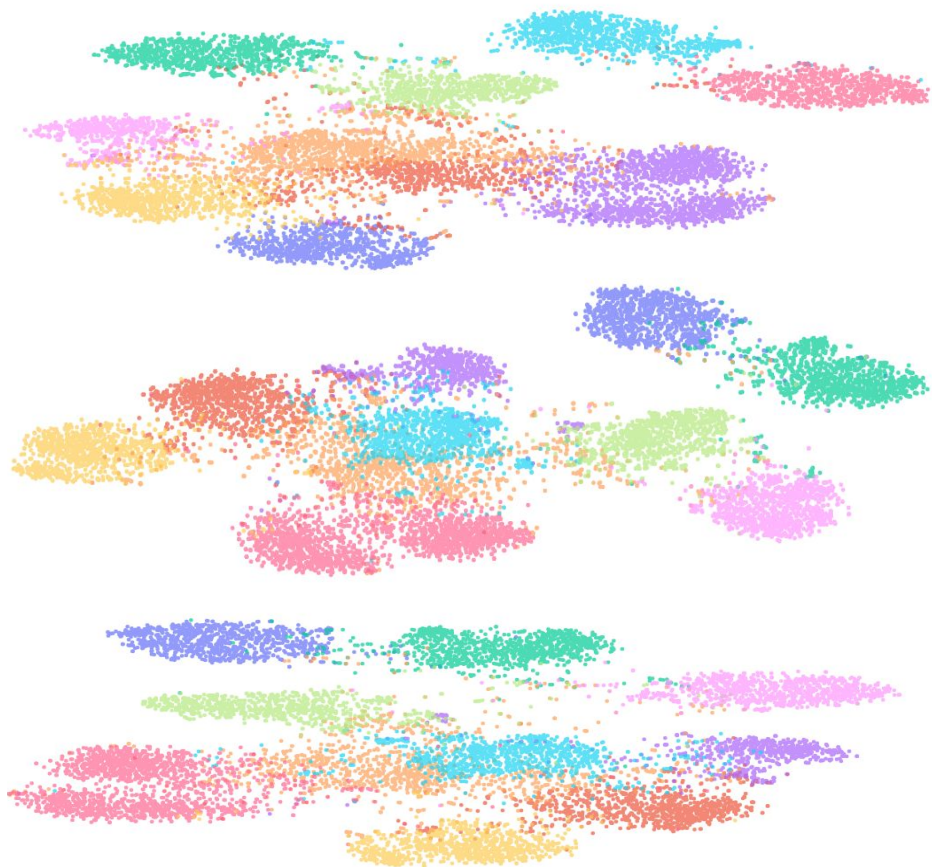
Results

	AMI	ARI	FMI	NMI
K-Means	0.72	0.63	0.67	0.72

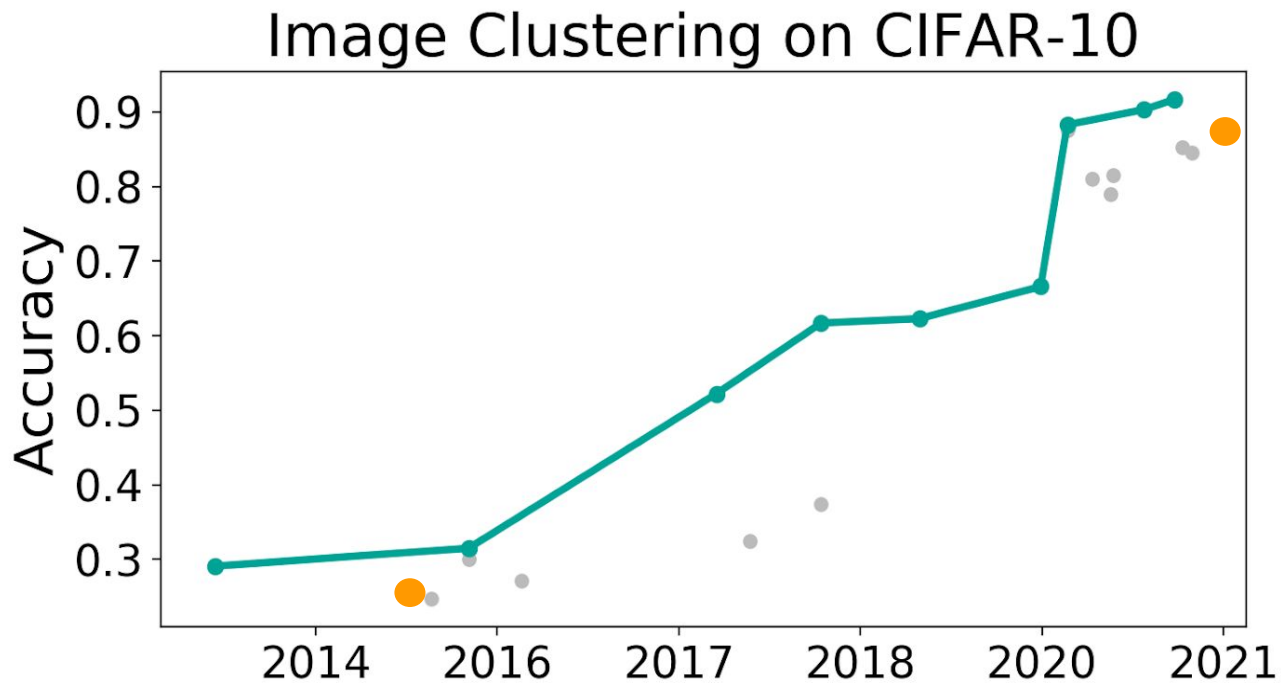
Auto - encoder	0.74	0.67	0.70	0.76
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DEC	0.82	0.77	0.79	0.82
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Visualizing clusters using T-SNE



Benchmark

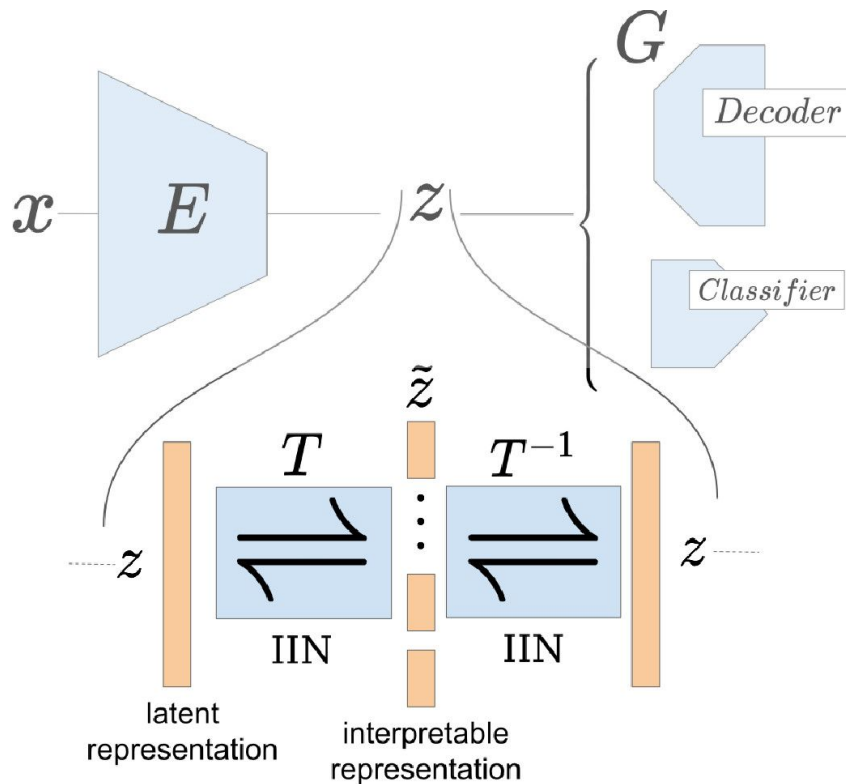


Advantages of DEC model

- DEC method is linear in the number of data points and scales gracefully to large datasets
- DEC employs deep neural networks to perform non-linear embedding that is necessary for more complex data
- CLIP + DEC show SOTA results in clustering

Disentanglement

Ekaterina Orlova, Anna Dmitrienko, Sergey Skorik, Anna Rudenko, Abdullaeva Uma



Embedding in latent space:

$$z = E(x) \in \mathbb{R}^{H \times W \times C}$$

Invertible Interpretation Network:

$$T(z) = \bar{z}$$

Modified latent vector z :

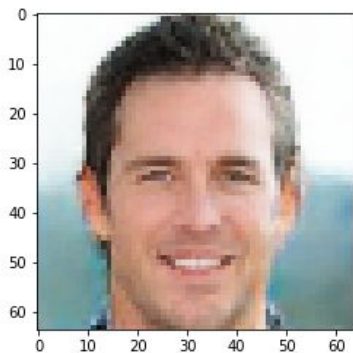
$$z \rightarrow z^* := T^{-1}(T(z)^*)$$

Loss function:

$$\mathcal{L} = \sum_{F=1}^K \mathbb{E}_{(x^a, x^b) \sim p(x^a, x^b | F)} \ell(E(x^a), E(x^b) | F),$$

where l – per-example loss

Process



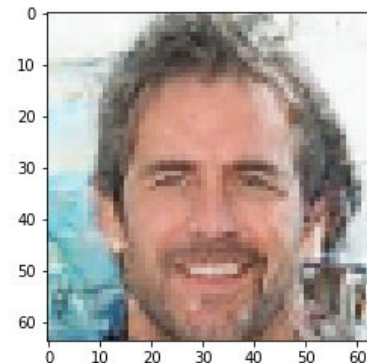
E
 T

-1,99
-1,65
1,94
-0,82
-0,82
-1,06
-1,23
1,06
0,32
2,52
-0,28
-0,40
0,18



-1,99
-1,65
1,94
-0,82
-0,82
-1,06
-1,23
1,06
0,32
2,52
-0,28
-3,00
0,18

D
 $T-1$



SelebA - Glasses

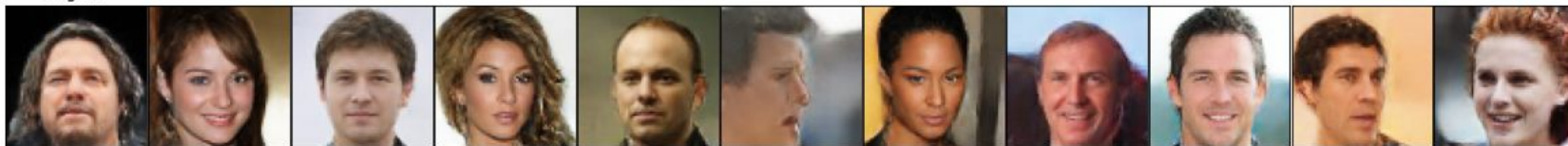


SelebA - Race



SelebA - Sex

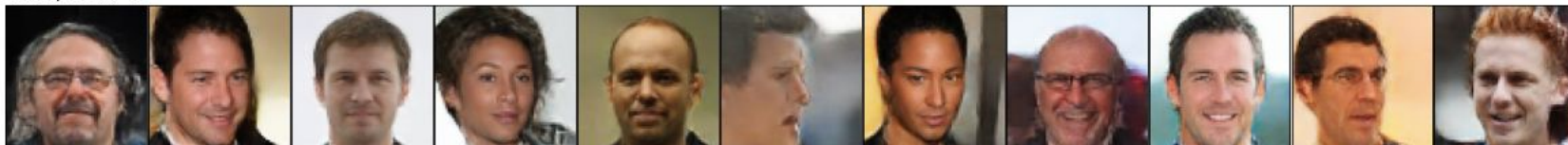
original



1 component = -3





1 component = 2

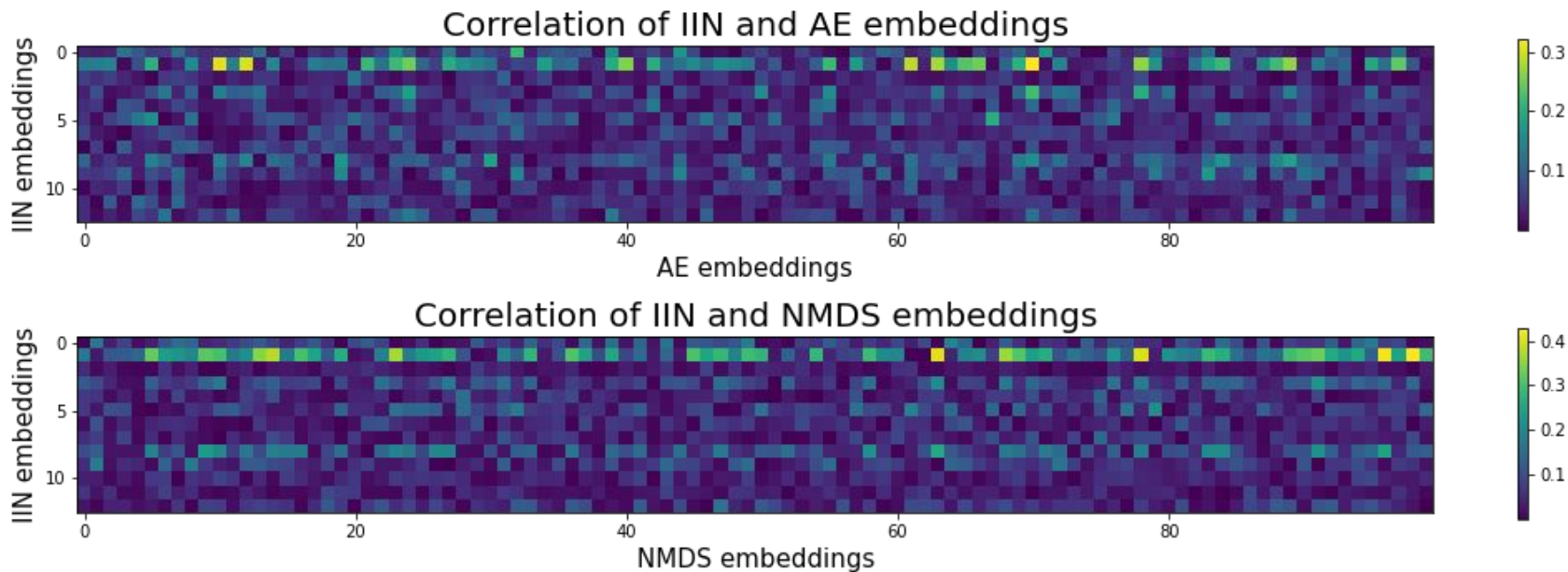


Semantic analysis by CLIP

Cosine similarity between text and image features

							
woman with red hair	0.2810	0.2089	0.2239	0.2721	0.2367	0.1793	man with hat and sunglasses
blonde woman with red lipstick	0.2429	0.2723	0.2194	0.2269	0.2520	0.1774	man with glasses turned his face
woman with sunglasses	0.2659	0.2224	0.2888	0.2005	0.2182	0.2450	woman with long hair

Correlation of semantic features and embeddings



Conclusions

- Proposed new method for **dimensionality reduction** of CLIP embeddings
- Proposed and evaluated new method for **clusterization**, close to SOTA
- Interpreted **latent representations** of various VAE

What's next?

- Automatic data augmentation with text descriptions
- Improving managed image synthesis

