Monday, 19 July 2021

Περιγραφή Papers που έχω διαβάσει

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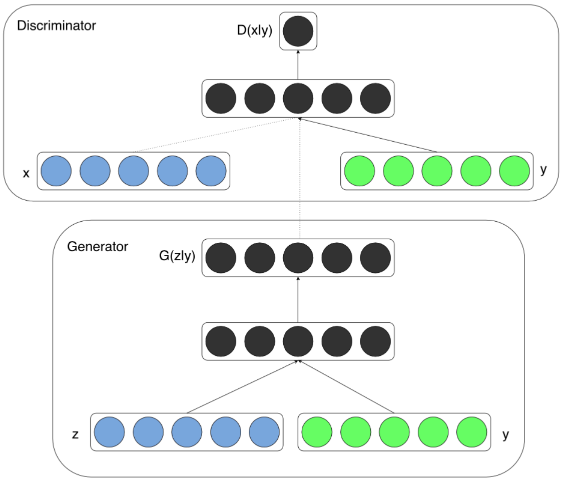
1. **Conditional GANs:**

   - Classic GAN, with added y auxiliary information (alongside hidden z space, and alongside data x).
   - 

- Θα μπορούσε να δουλέψει με multi-modal δεδομένα, όπου ο Generator έχει:
  - Noise z
  - Image features y

και ο Discriminator έχει:

  - Word tags x
  - Image features y

- Ιδέα που μπορεί να αφορά εμάς: (με μετά κάτι σαν EC-GAN)
  - Generator με noise z και Genetic Data y (Could be raw or 1-hot or other form)
  - Discriminator με Image Features x (Taken from Ravens / ROI or other) και Genetic Data y (Could be raw or 1-hot or other form)

2. ClusterGAN

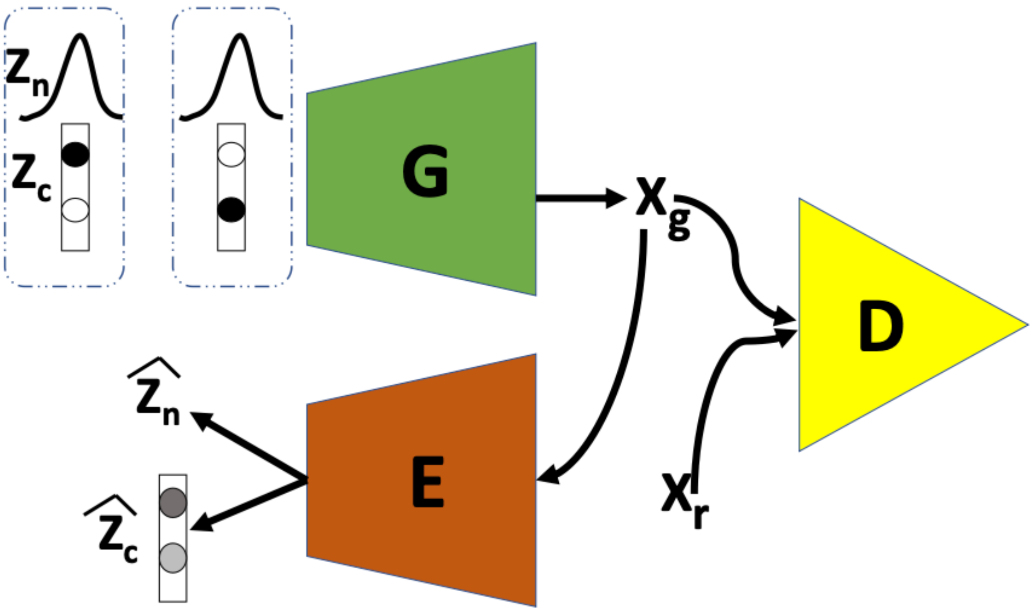
- GAN that attempts to cluster in the Latent Space
- 3 main ideas:
  - Use a mixture of discrete & continuous latent variables
  - Alter back-propagation, use inverse mapping network
  - Implement clustering-specific loss
- 

Figure 1: ClusterGAN Architecture

- Δεν ξέρω πως θα εφαρμοστεί σε εμάς

3. Deep Learning Based Multilevel Classification of Alzheimer's Disease using MRI Scans

- Uses DL to differentiate different stages of AD
- Pre-trained Architecture (VGG 16), Classification using FastAI
- Grad-CAM used to create heatmaps (hence multilevel)
- Classified MRI scans into 4 categories:
  - Non Demented
  - Very Mild Demented
  - Mild Demented
  - Moderate Demented

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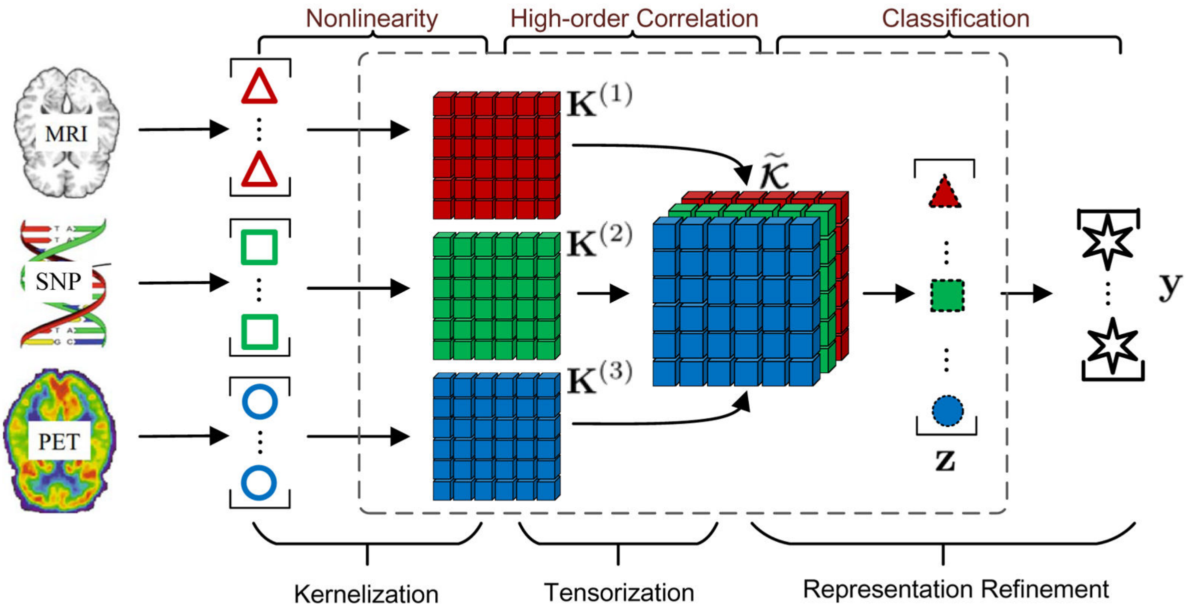
4. Multi Layer Multi View AD Diagnosis Classification

- Proposes a Multi-View to diagnose AD
- Uses Neuroimaging + genetic data



filter function

$$= \sum_{m=1}^{M} \xi_m \|\widetilde{\mathcal{K}}_{(m)}\|_*$$

nuclear norm

New Goal: $$\min_{\vec{\xi}, \vec{p}^{(v)}, \widetilde{K}^{(v)}} \Big\{ \frac{1}{2} \|P_0 (\vec{\xi}\vec{Z} - \vec{Y})\|_F^2 + a \|\widetilde{\mathcal{K}}\|_* + \frac{\beta}{2} \|\mathcal{K} - \widetilde{\mathcal{K}}\|_F^2 + \frac{\delta}{2} \sum_{v=1}^{V} \|\vec{p}^{(v)} \cdot \widetilde{\Phi(\vec{X}^{(v)})}^T\|_F^2 + \frac{\eta}{2} \|\vec{\xi}\|_F^2 \Big\}.$$

such that $\mathcal{K} = \mathcal{T}(K^{(1)}, \dots, K^{(V)})$, $\widetilde{\mathcal{K}} = \mathcal{T}(\widetilde{K}^{(1)}, \dots, \widetilde{K}^{(V)})$.

($\mathcal{T}(\cdot)$ is tensor function, constructs kernel "box").

P_0 is a function, που αν έχουμε το label για το input δίνει $1 \cdot$ input, αλλιώς αν δεν το έχουμε, $0 \cdot$ input.

TL;DR: for #categories (# of labels) << dimensions of latent representation

and #labels << # number of samples,

Optimization algorithm is $O(K^3 + N^3)$.

- Best results among methods without multi-view data, and generally is SOAT