异常检测，GAN如何gan？

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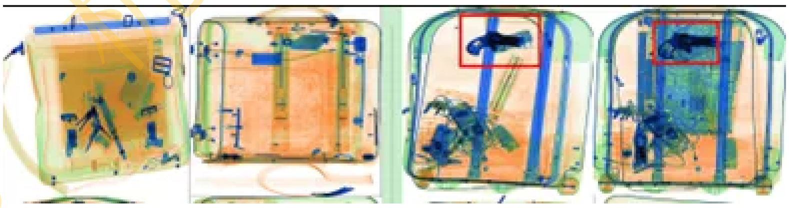
今天记录一下、一些用**GAN**来做**异常检测**的论文！

异常检测(Anomaly detection)，一个很常见的问题。

在图像方面，比如每天出入地铁安检，常常看到小姐姐小哥哥们坐在那盯着你的行李过检图像，类似如下（图来自GANomaly论文）：



又比如在一些医学图像分析上，源自健康人的影像也许是比较容易获取的，并且图像的“模式”往往固定或者不多变的，而病变的图像数量是很少、很难获取，或者病变区域多变、甚至未知的，此时异常检测就面临着正样本/异常图像很少，而相对地，正常图像更容易获得的情况。这种情况其实在很多场景下有所体现，比如工业视觉检测等等。

对于已知类别、数量较多情况下，不管异常与否，我们也许可以通过训练一个分类模型就能解决。但面对也许未知、多变的情况，要想用一个多分类模型分辨出来似乎很难。如果是想仅仅分辨出是不是异常，那也许可以做一个单分类器即可。

我们尽可能地去让模型充分学习正常数据的分布长什么样子，一旦来了异常图像，它即便不知道这是啥新的分布，但依旧可以自信地告诉你：这玩意儿没见过，此乃异类也！

用GAN一些网络怎么做呢？大体思想是：

在仅有负样本（正常数据）或者少量正样本情况下：

训练阶段：

可以通过网络仅仅学习负样本（正常数据）的数据分布，得到的模型G只能生成或者重建正常数据。

测试阶段：

使用测试样本输入训练好的模型G，如果G经过重建后输出和输入一样或者接近，表明测试的是正常数据，否则是异常数据。

模型G的选择：

一个重建能力或者学习数据分布能力较好的**生成模型**，例如GAN或者VAE，甚至encoder-decoder。

下面速览几篇论文、看看GAN是如何做异常检测的（数据主要为图像形式）：

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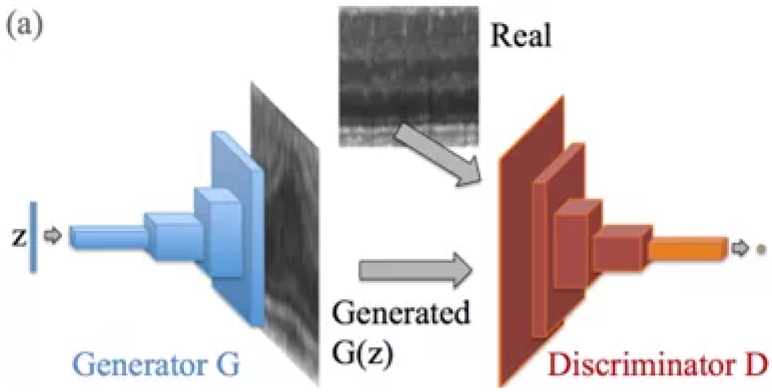
1. IPMI 2017 AnoGAN (Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery)

思路：通过一个GAN的生成器G来学习正常数据的分布，测试时图像通过学习到的G找到它应该的正常图的样子，再通过对比来找到异常与否的情况。



如上图所示，AnoGAN论文中采用的是DCGAN，一种较简单的GAN架构。

训练阶段：

对抗训练，从一个噪声向量Z通过几层反卷积搭建的生成器G学习生成正常数据图像。

测试阶段：

随机采样一个高斯噪声向量z，想要通过已经训练好的G生成一幅和测试图像x对应的正常图像G(z)。G的参数是固定的，它只能生成落在正常数据分布的图像。但此时仍需进行训练，把z看成待更新的参数，通过比较G(z)和x的差异去更新，从而生成一个与x尽可能相似、理想对应的正常图像。

如果x是正常的图像，那么x和G(z)应该是一样的。

如果x异常，通过更新z，可以认为重建出了异常区域的理想的正常情况，这样两图一对比不仅仅可以认定异常情况，同时还可以找到异常区域。

为了比较G(z)和x差异去更新z：

一是通过计算G(z)和x的图像层面的L1 loss：

Residual Loss The *residual loss* measures the visual dissimilarity between query image $\mathbf{x}$ and generated image $G(\mathbf{z})$ in the image space and is defined by

$$\mathcal{L}_R(\mathbf{z}) = \sum |\mathbf{x} - G(\mathbf{z})|. \qquad (3)$$

Under the assumption of a perfect generator G and a perfect mapping to latent space, for an ideal normal query case, images $\mathbf{x}$ and $G(\mathbf{z})$ are identical. In this case, the *residual loss* is zero.

二是利用到训练好的判别器D，取G(z)和x在判别器D的中间层的特征层面的loss：

a richer intermediate feature representation of the discriminator and define the *discrimination loss* as follows:

$$\mathcal{L}_D(\mathbf{z}\ ) = \sum |\mathbf{f}(\mathbf{x}) - \mathbf{f}(G(\mathbf{z}\ ))|, \tag{4}$$

where the output of an intermediate layer $f(\cdot)$ of the discriminator is used to specify the statistics of an input image. Based on this new loss term, the adaptation of the coordinates of $\mathbf{z}$ does not only rely on a hard decision of the trained discriminator, whether or not a generated image $G(\mathbf{z}\ )$ fits the learned distribution of normal images, but instead takes the rich information of the feature representation, which is learned by the discriminator during adversarial training, into account. In this sense, our approach utilizes the trained discriminator not as classifier but as a feature extractor.

两者综合：

For the mapping to the latent space, we define the overall loss as weighted sum of both components:

$$\mathcal{L}(\mathbf{z}_\gamma) = (1-\lambda) \cdot \mathcal{L}_R(\mathbf{z}_\gamma) + \lambda \cdot \mathcal{L}_D(\mathbf{z}_\gamma). \tag{5}$$

Only the coefficients of $\mathbf{z}$ are adapted via backpropagation. The trained parameters of the generator and discriminator are kept fixed.

另外，异常分数计算方法：

2.3 Detection of Anomalies

During anomaly identification in new data we evaluate the new query image $\mathbf{x}$ as being a normal or anomalous image. Our loss function (Eq. (5)), used for mapping to the latent space, evaluates in every update iteration γ the compatibility of generated images $G(\mathbf{z}_\gamma)$ with images, seen during adversarial training. Thus, an *anomaly score*, which expresses the fit of a query image $\mathbf{x}$ to the model of normal images, can be directly derived from the mapping loss function (Eq. (5)):

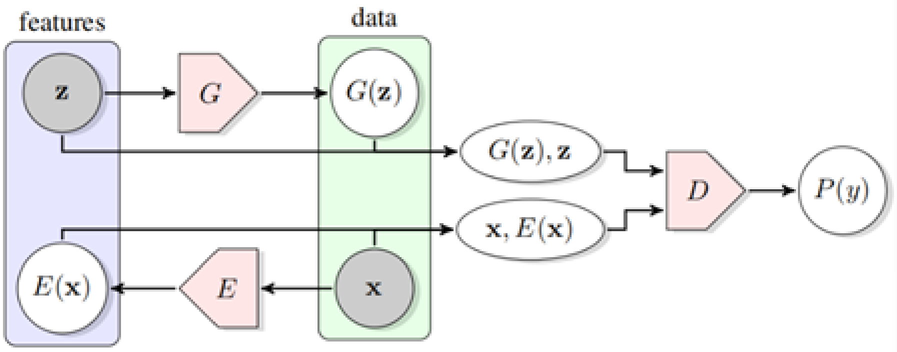
$$A(\mathbf{x}) = (1-\lambda) \cdot R(\mathbf{x}) + \lambda \cdot D(\mathbf{x}), \tag{6}$$

where the *residual score* $R(x)$ and the *discrimination score* $D(x)$ are defined by the *residual loss* $\mathcal{L}_R(\mathbf{z}_\Gamma)$ and the *discrimination loss* $\mathcal{L}_D(\mathbf{z}_\Gamma)$ at the last (Γ^{th}) update iteration of the mapping procedure to the latent space, respectively. The model yields a large *anomaly score* $A(\mathbf{x})$ for anomalous images, whereas a small *anomaly score* means that a very similar image was already seen during training. We use the *anomaly score* $A(\mathbf{x})$ for image based anomaly detection. Additionally, the residual image $\mathbf{x}_R = |\mathbf{x} - G(\mathbf{z}_\Gamma)|$ is used for the identification of anomalous regions within an image. For purposes of comparison, we additionally define a *reference anomaly score* $\hat{A}(\mathbf{x}) = (1-\lambda) \cdot R(\mathbf{x}) + \lambda \cdot \hat{D}(\mathbf{x})$, where $\hat{D}(\mathbf{x}) = \mathcal{L}_{\hat{D}}(\mathbf{z}_\Gamma)$ is the *reference discrimination score* used by Yeh et al. [13].

2. 2018-02 EFFICIENT GAN-BASED ANOMALY DETECTION

针对AnoGAN测试阶段仍然需要更新参数的缺陷，此方法提出一种基于BiGAN可快百倍的方法。

训练时，同时学习将输入样本x映射到潜在表示z的编码器E，以及生成器G和判别器D：



$\min_{G,E} \max_D V(D,E,G)$, with $V(D,E,G)$ defined as

$$V(D,E,G) = \mathbb{E}_{x\sim p_X}\left[\mathbb{E}_{z\sim p_E(\cdot|x)}\left[\log D(x,z)\right]\right] + \mathbb{E}_{z\sim p_Z}\left[\mathbb{E}_{x\sim p_G(\cdot|z)}\left[1-\log D(x,z)\right]\right].$$

Here, $p_X(x)$ is the distribution over the data, $p_Z(z)$ the distribution over the latent representation, and $p_E(z|x)$ and $p_G(x|z)$ the distributions induced by the encoder and generator respectively.

如此可避免测试仍需要“找到z”那个耗时的步骤。与常规GAN中的D仅考虑输入（实际的或生成的）图像不同，而还考虑了潜在表示z(作为输入)。

测试时，判断图像的异常与否的分值计算方法，可选择可AnoGAN基本一样的方法。

Having trained a model on the normal data to yield G, D and E, we then define a score function $A(x)$ (as in Schlegl et al. (2017)) that measures how anomalous an example x is, based on a convex combination of a reconstruction loss L_G and a discriminator-based loss L_D:

$$A(x) = \alpha L_G(x) + (1-\alpha)L_D(x)$$

where $L_G(x) = ||x - G(E(x))||_1$ and $L_D(x)$ can be defined in two ways. First, using the cross-entropy loss σ from the discriminator of x being a real example (class 1): $L_D(x) = \sigma(D(x,E(x)),1)$, which captures the discriminator's confidence that a sample is derived from the real data distribution. A second way of defining the L_D is with a “feature-matching loss”$L_D(x) = ||f_D(x,E(x)) - f_D(G(E(x)),E(x))||_1$, with f_D returning the layer preceding the logits for the given inputs in the discriminator. This evaluates if the reconstructed data has similar features in the discriminator as the true sample. Samples with larger values of $A(x)$ are deemed more likely to be anomalous.

3. 2018-12 Adversarially Learned Anomaly Detection

第二种方法的加强版，也是基于BiGAN,并且在稳定训练上做了些功夫。如下所示，（乖乖，搞了三个判别器 =_=

$\min_{G,E} \max_{D_{xz},D_{xx},D_{zz}} V(D_{xz}, D_{xx}, D_{zz}, E, G)$, with $V(D_{xz}, D_{xx}, D_{zz}, E, G)$ defined as

$$V(D_{xz}, D_{xx}, D_{zz}, E, G) = V(D_{xz}, E, G) + V(D_{xx}, E, G) + V(D_{zz}, E, G).$$

A schematic of this final GAN model is shown in Figure 1.

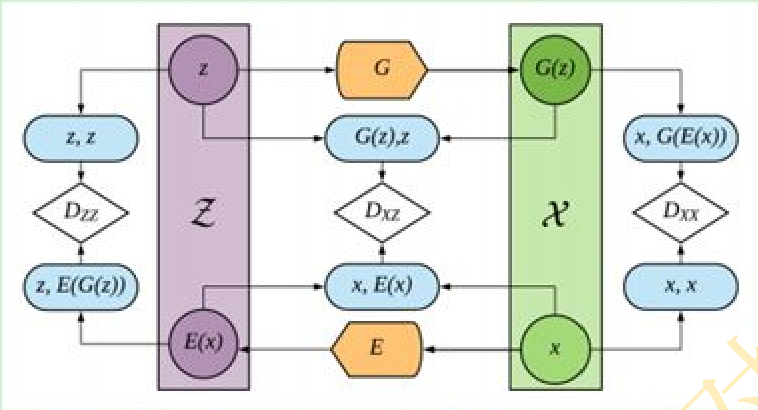


Figure 1. The GAN used in Adversarially Learned Anomaly Detection. D_{zz}, D_{xz} and D_{xx} denote discriminators (white), G the generator (orange), and E the encoder (orange); these networks are simultaneously learned during training.

检测时的计算方法：

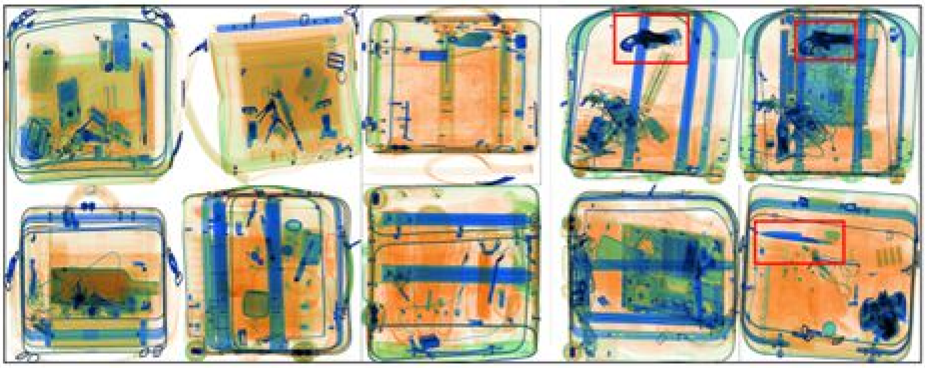
Algorithm 1 Adversarially Learned Anomaly Detection

Input $\boldsymbol{x}, \sim p_{X_{Test}}(x), E, G, f_{xx}$ where f_{xx} is the feature layer of D_{xx}

Output $A(\boldsymbol{x})$, where A is the anomaly score

```
procedure INFERENCE
    z̃ ← E(x)                          ▷ Encode samples
    x̂ ← G(z̃),                         ▷ Reconstruct samples
    f_δ ← f_xx(x, x̂)
    f_α ← f_xx(x, x)
    return ||f_δ − f_α||_1
end procedure
```

4. 2018-11-13 GANomaly: Semi-Supervised Anomaly Detection via Adversarial Training



(a) Normal Data (X-ray Scans) (b) Normal + Abnormal Data (X-ray Scans)

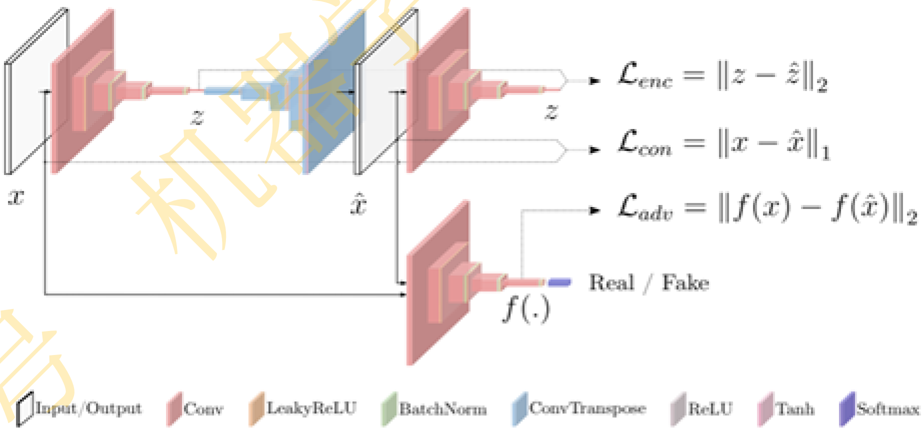
Fig. 1. Overview of our anomaly detection approach within the context of an X-ray security screening problem. Our model is trained on normal samples (a), and tested on normal and abnormal samples (b). Anomalies are detected when the output of the model is greater than a certain threshold $\mathcal{A}(x) > \phi$.

原理：

训练时，约束正常的数据编码得到潜在空间表示z1，和对z1解码、再编码得到的z2，差距不会特别大，理想应该是一样的。

所以训练好后，用正常样本训练好的 G只能重建正常数据分布，一旦用于从未见过的异常样本编码、解码、再经历编码得到的潜在空间Z差距是大的。

当两次编码得到的潜在空间差距大于一定阈值的时候，就判定样本是异常样本。



5. 2019-01-25 Skip-GANomaly: Skip Connected and Adversarially Trained Encoder-Decoder Anomaly Detection

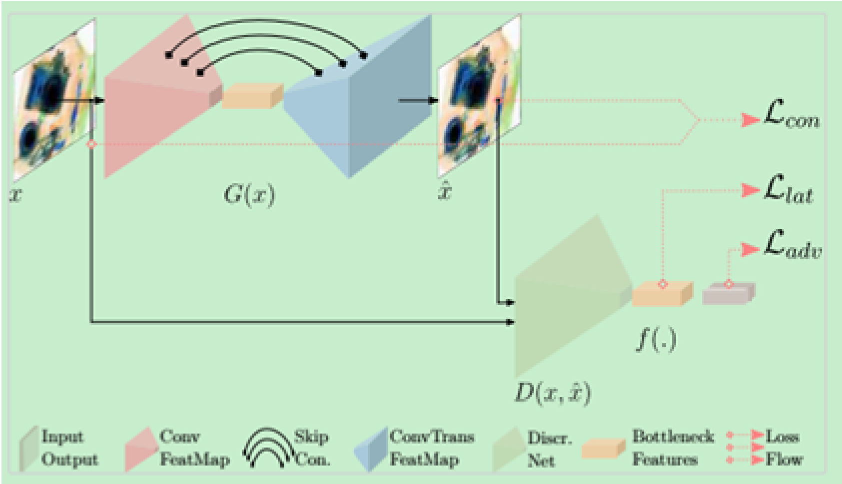
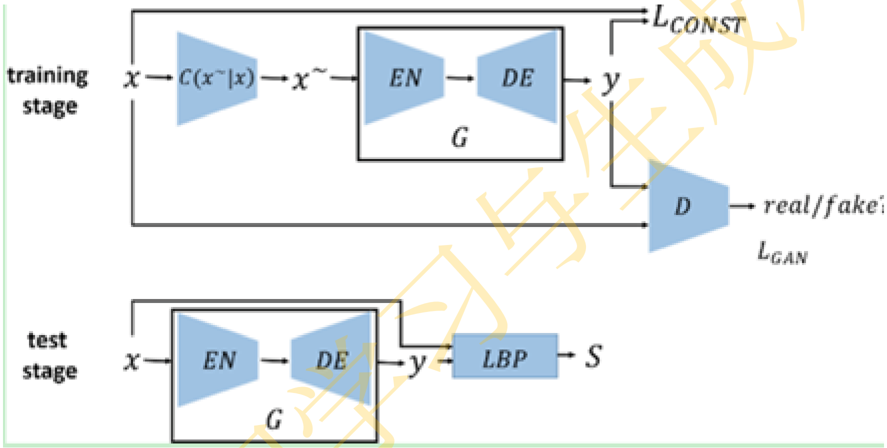


Fig. 2: Overview of the proposed adversarial training procedure.

6. PRICAI 2018 A Surface Defect Detection Method Based on Positive Samples



原理：

C（x~|x）是人工缺陷制造模块。X~是模拟缺陷的样本，经过EN-DE编码解码器后重建正常样本Y。

测试阶段，X输入EN-DE后得到理想正常样本y，使用LBP对Y和X逐像素特征比较，相差大则有缺陷。

7. MIDL 2018 Unsupervised Detection of Lesions in Brain MRI using constrained adversarial auto-encoders

使用的是AAE来学习建模正常数据分布。有时，对于在正常分布的的两个数据之间的距离，比一个正常和一个异常之间的距离还大，所以提出在隐空间也加一个约束。

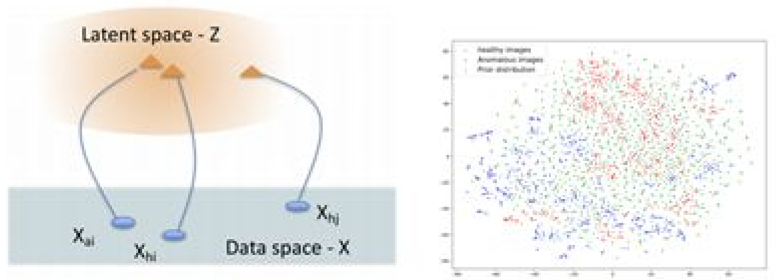


Figure 1: Encoding input data into latent representation. Left: Illustration shows the encoding of VAE/AAE model. Data samples (blue circles) are encoded into latent representation (orange triangles). Difference between two 'healthy' images X_{hi} and X_{hj} might be larger than the distance between an image with an abnormal lesion X_{ai} and its 'healthy' version X_{hi}. Latent representation of these images may also satisfy the same relationship. As a result, images with abnormalities may not lie separate than normal images. Right: Image shows TSNE embeddings of healthy images (red) and lesion images (blue) from the BRATS dataset. We also show samples from the prior distribution in green. Healthy images and abnormal images can be mapped close in the latent space, the latent representations of the abnormal images also lie in the prior distribution together with the representations of healthy images, making them indistinguishable in the latent space.

暂时先写到这吧。

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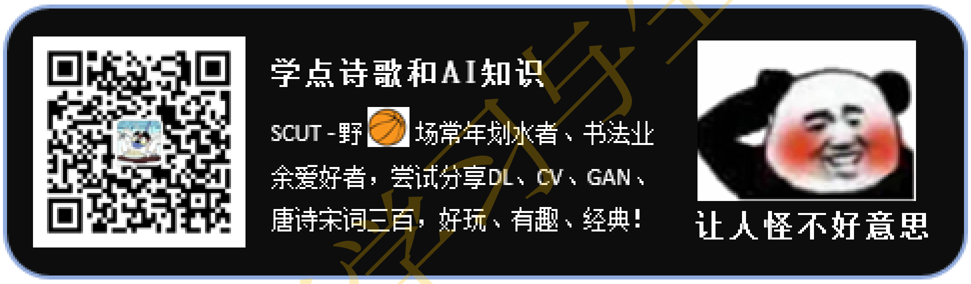

最后的最后，再来发一波、到**目前为止**、**部分**、用 **GAN** 做**异常检测**的基本相关（**直接用“adversarial anomaly detection”在arxiv上爬下来的，不一定相关！2333**）论文供参考！！！

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