1. binary masking technique 真的准确吗？灰度阈值的设定可否一成不变？
2. binary grayscale-based masking会保留大部分信息，但是可能会忽略边际上的某些信息或者产生噪声，FCN的目的是为了捕捉全局规律，从而滤除噪声或是对边际误差进行补全
3. 数据归类方法K-means 超参数调优可能不精确
4. Kmeans就分两类？？？kmeans效果 两个很相似的类，聚类中心在外头（聚类为数据均衡化的手段）
5. 已成规模的方法中，三人的方法我都认为存在一定程度上的局限。

* Sun的方法中，他尝试使用Kmeans进行聚类从而进行样本平衡，之后再使用XGBoost进行Void类别判断。问题在于：1、Kmeans所基于的分类标准必须基于卷积核能否成功区分二者的边界情况，此后是否还需要使用灰度binary musking等类似手段进行label的区分在文中尚未体现，只能假设卷积核已经成功分离了Background与void的特征类似性，后续的算法效果将极大依赖于此处数据的可靠性。2、由于数据本身的高稀疏性，在全局范围上的Void与background的分布可能较为均匀，这可能导致最终二类的聚类中心均相对重合于图像中心，最终的聚类效果可能与未聚类的效果相差无多，关于这点在文中也并未见明确解释。3、输入XGBoost的数据不明确，XGBoost所预测的label源自于1中卷积核的输出，而其所使用的Feature也同样来自于多个卷积核的特征提取，整个模型的应用更倾向于单个数据集中的映射关系，而不是原始数据上的分类，因此我对最终模型所取得的效果存疑。并且对于另一类background类而言，如果在2的处理正确，则这一XGBoost所最终展示的物理意义很可能是将所有数据向Background的方向预测，也就是这部分相较于原数据可能呈现更大的数据不平衡性，因此我认为这部分不应作为结果之一进行展现。
* 使用SVM进行高维非线性分割对核函数选择存在较大的要求，使用以LSTM为代表的一系列时序模型的应用则有着更大的局限性，即无法捕捉非平稳数据，而存在极大空间不确定性的该数据更是难以捕捉规律，因此这二人的思路我认为很难实现。

我的想法：使用卷积核进行边界锐化与分割的思路我认为极具参考意义，但是基于卷积核的特征抽取显然会遗漏较多其他细节。下一阶段，我认为基于密度的聚类算法，DBSCAN会有更好的效果，这一聚类算法无需设定初始簇类，而是可以根据密度找到连通区域，并且可以很方便的将离散噪声点删除，从而达到样本平衡。我认为分类器应当使用一个较为完善的分类器在平衡样本上进行训练（XGBoost已经是一个强大的分类手段，理应可以完成任务），并在真实全局数据上完成性能测试，从而得到更为准确的分类结果。

思路2：可采用多维度数据进行处理。目前的多份研究中均只使用到了单一图片，尝试进行Void与背景的多分类任务。但事实上，Void的存在并不应该反映在单独的二维平面，同一个Void空腔很可能在此平面的前后多张CT中均会出现，但是背景却很难会如此连续出现，因此想法是可以使用3-5张连续CT作为数据来源，分析数据上存在的数据异同性，从而提高初始Label的标注精度。

思路3：在思路2的基础上，可以考虑使用多通道（3-5通道）的卷积核的CNN网络进行提取，此时考虑到数据的立体特征，此时的CNN应该会较先前的实验有着更多的提升空间，捕捉更多的空间特征数据。

思路补充，单一的图像维度数据有时可能不足以充分反映数据分布规律，如果在条件允许的情况下，可以考虑介入材料的其他物理属性，如应力或温度等数据。

Hello guys，my name is Tianyao Majoring in Computer Science and Artificial Intelligence, and you can call me Alan. Now I’m gonna to share something about my opinion on this topic.

So, in previous study, many drawbacks exist that lead to trouble in accurate detection of Voids in COSB. Neural networks are struggling to capture the extremely complexity of data, KNN has achieved a good performance, but it still needs lot of human label, which is quite time consuming. SVM can be powerful in linear segmentation but must use kernel functions to process nonlinear data, which can be quite hard to select. LSTM can be even harder to implement, because the data input into LSTM should be stationary, too much uncertainty may make LSTM learn Nothing.

In recent work, Sun has provided a Great overview of this topic, but after I delve into his passage, I still found something hard to explain and can be modified maybe in somedays. So first, many parts of data used in his experiment is produced by many convolution kernels, and the experiment is greatly dependent on the performance of these convolution kernels. And the selections of such kernels are based mostly on tests and lack of enough logical explanations, which may lead to trouble in future study.

What’s more, using K-means to make balance datasets is reasonable, but may not be workable. As you can see voids and backgrounds can be distributed almost anywhere and pretty evenly due to high sparsity of these data, So the centers we get may finally be nearly both on the center of the image, in other words, overlap with each other. And those beyond the certain cluster would be only even more imbalanced! Because of the decrease in the density of Voids.

Also, I think the data input into local XGBoost can be a problem. Indeed, adding features produced by Convolution kernel and label also produced by Convolution kernel is just like mapping the data to themselves, which leads to my confusion about his result.

So, my suggestion is, we can use the combination of several convolution kernels, instead of one single filter shown in Sun’s Paper, these data can be sent together into XGBoost for predictions.

Also, I think another clustering algorithm, DBSCAN, can be more suitable. This algorithm is based on the density of data, and we do not need to set the number of cluster center beforehand, and it’s easy to remove those noise points to maintain data balance.

And just as I said before, the prediction on background dataset can be meaningless, so only a powerful classifier can be enough, because the data is much more important than what model you use.

And in my opinion, multiple continuous images can be used at a time instead of a single input in previous study. Because Voids can appear much continuously, but background would not. So, it’s important to use the 3-dimensional nature of these images

Furthermore, a more complex convolution kernel with multiple channels can be use to extract features from a group of images. We can now try again to use CNN, and I think it will achieve a good result.

By the way, using 3-dimensional kernels may also succeed in extracting totally 3D data in the future. What we need to do is just delve into more images in the same 2D areas, however, all these approaches should be based on the continuous CT data, without which, everything would be over.

And if conditions permit, we can even consider using some physical data, like the press or temperature, which have been proved to have an impact on the voids of COSB

So, this is all what I want to share with you, thanks for your patience and time.