

6/3/2020

Transfer learning: Implementing feature extraction from successful models and reusing the dense/fully-connected layer.

Dataset similarity

<u>Similar</u>	<u>Different</u>
Data set size <small>large</small> <small>small</small>	Fine-tune (2) <hr/> Fine-tune / retrain (3) <small>Start of convnet (4)</small>

Cases:

1. Adjust end of CONVNET

◦ ~~freeze and replace nodes~~ → ~~remove~~ ~~add~~ ^{new} ^{old} Dense layers (add) (not remove dense)

- Randomize dense layer weights → update weights

- freeze weights in pretrained network - don't update weight
 ↳ prevent overfitting

Forward Pass Propagation: All data travels forward through nodes to calculate the NN output

o ^{Hidden} _{are} Input Layer: Preprocessing ^{are} non-linearity

- Equation:

$$\begin{aligned} * \text{input: } x \cdot w &\xrightarrow{\text{data}} \text{weight input to hidden} \\ * \text{output: activation function(input)} &\xrightarrow{\text{sigmoid } \delta = \frac{e^x}{1+e^x}} \end{aligned}$$

o ^{Hidden} _{are} Layer: non-linearity / Linear

- Equ:

$$\begin{aligned} * \text{input: hidden output} \cdot w &\xrightarrow{\text{output from hidden layer}} \text{weights from hidden to output layer} \\ * \text{output: activation/} i \cdot \text{input} &\xleftarrow{\text{or}} \end{aligned}$$

Back propagation: data travels in opposite direction to fix/adjust weights & bias

o Output layer:

Equ input:

$$\text{Output error: } (y - \hat{y}) \xleftarrow{\text{target}} \text{output/prediction} \quad | \quad \text{label - prediction}$$

$$\text{Output error term: } (y - \hat{y}) f'(a_k) \quad | \quad \begin{array}{l} \text{label - prediction} \\ \text{(error)} \end{array} \quad | \quad \begin{array}{l} \text{derivative of} \\ \text{activation function} \\ \text{of output} \end{array} \quad | \quad \text{(gradient)}$$

hidden layer:

$$\text{hidden error: } w_{jk} \delta_k \xrightarrow{\text{weight}} \text{hidden error} \quad | \quad \begin{array}{l} \text{output layer term} \\ \text{weights hidden to output} \end{array}$$

$$\text{hidden error term: } \sum [w_{jk} \delta_k] f'(h_j) \quad | \quad \begin{array}{l} \text{hidden layer error} \cdot \text{derivative of} \\ \text{activation function} \\ \text{of hidden output} \\ \text{(error)} \end{array} \quad | \quad \text{(gradient)}$$

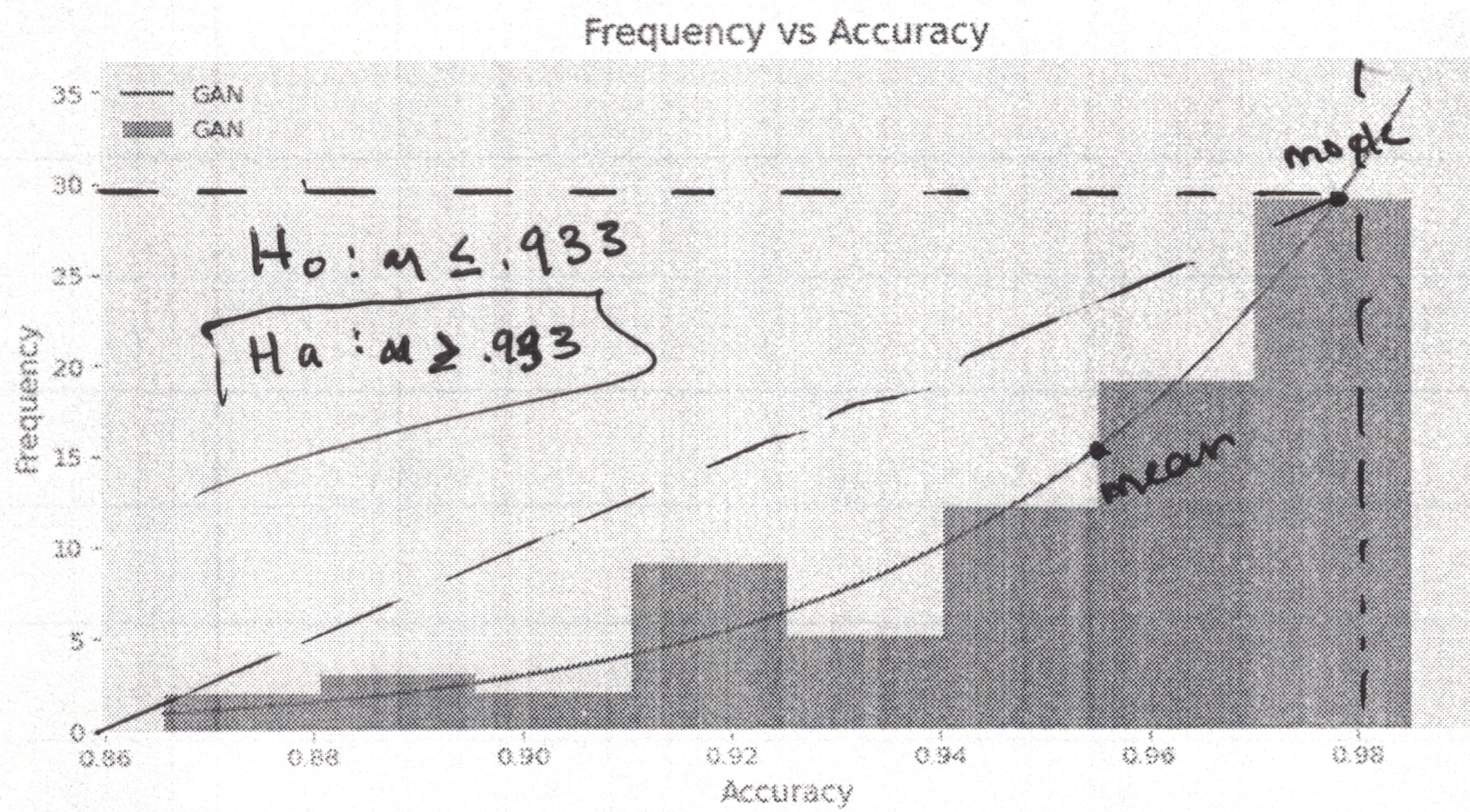
1/16/21

$$\bar{X} = 0.9498$$

$$\sigma_x = 0.0293$$

$$t = \frac{0.9498 - 0.933}{\frac{0.0293}{\sqrt{141}}} = 7.022$$

$$P = 1.08 e^{-10}$$



The distributions are skewed to the left, could mean that it is stable in performance.

$$\bar{X} = 0.9030$$

$$\sigma_x = 0.0547$$

$$t = \frac{0.903 - 0.933}{\frac{0.0547}{\sqrt{141}}} = -6.69$$

$$P = 1.05 e^{-10}$$

Sensitive is Maximized

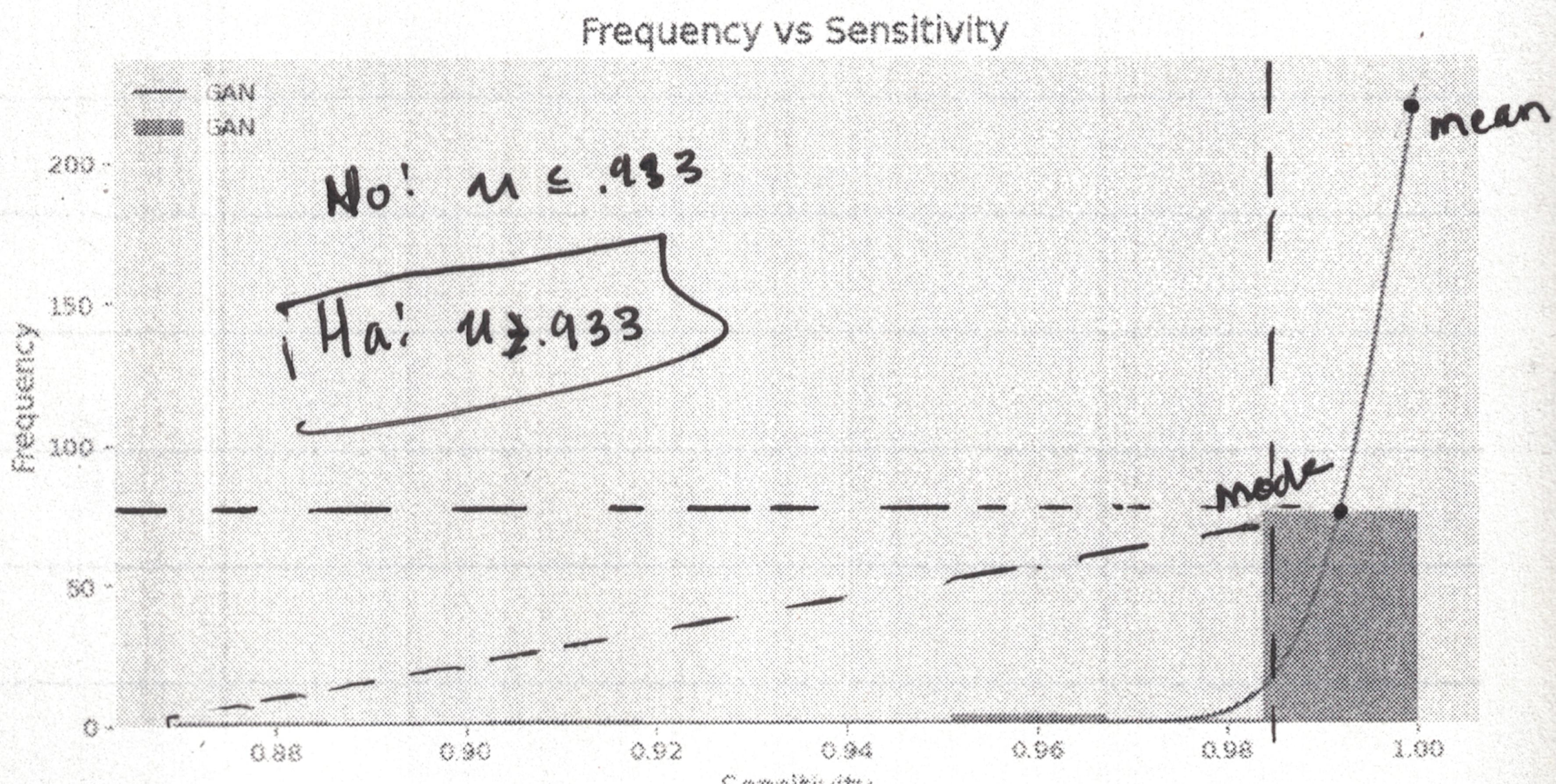
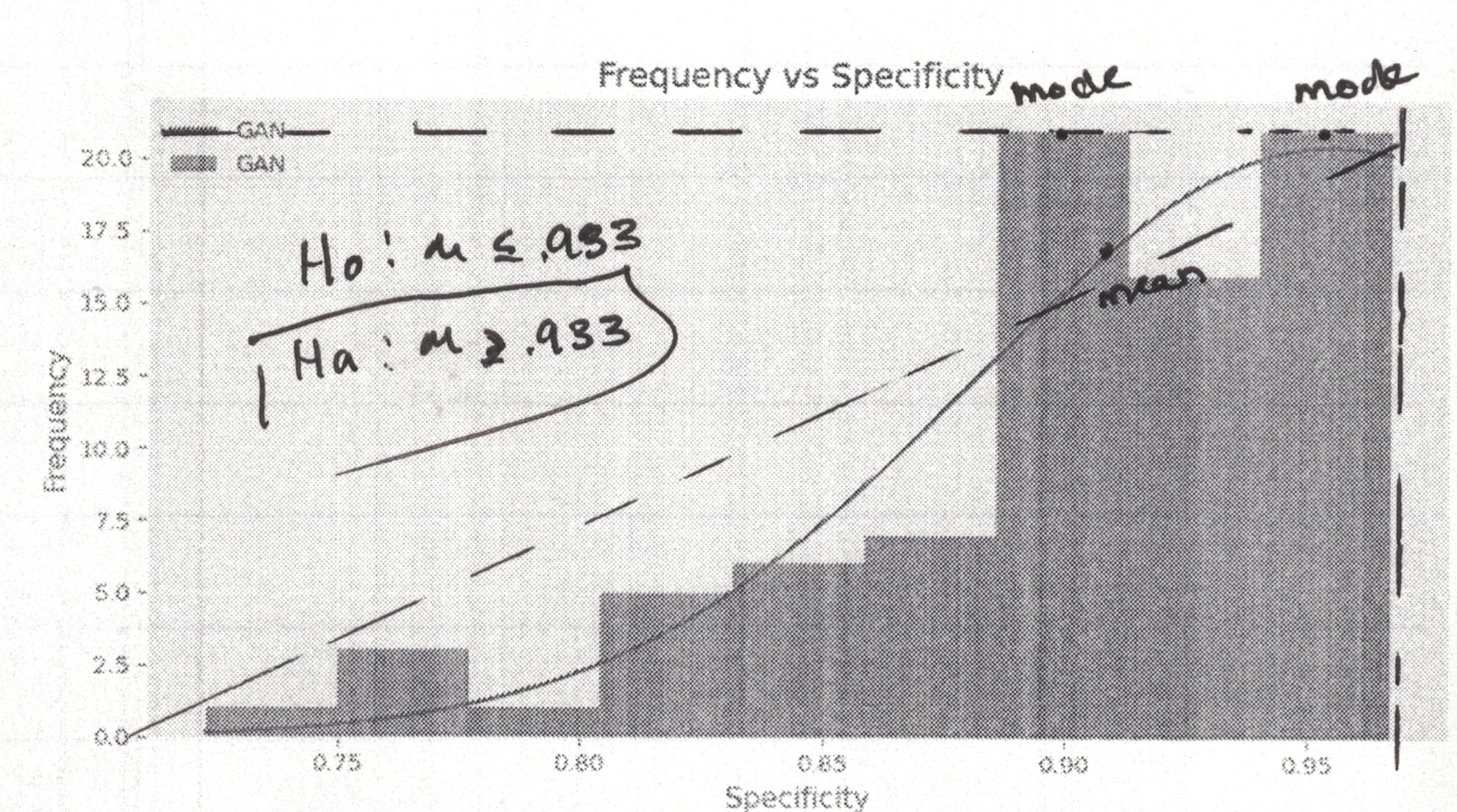
b/c we want to have all potential anomalies detected

$$\bar{X} = 0.9952$$

$$\sigma_x = 0.0197$$

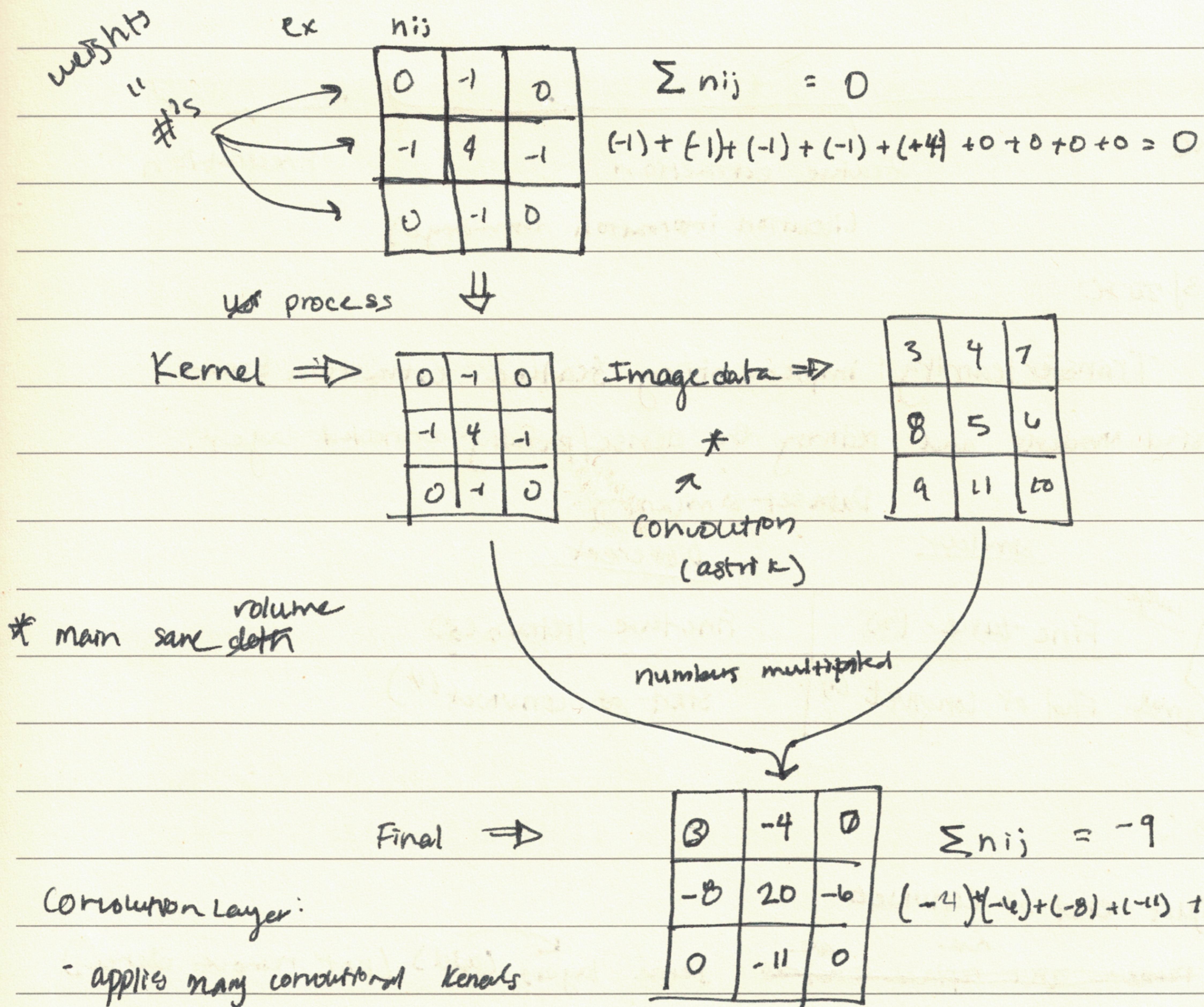
$$t = \frac{0.9952 - 0.933}{\frac{0.0197}{\sqrt{141}}} = 38.5$$

$$P = 1.54 e^{-11}$$



Filters & Edges in CNNs:

- low pass filters : block high frequencies (vice versa)
- using high pass filters - can block low pass freqs in image
 - o used for edge detection
- convolutional kernel : edge detection filter



- applies many convolutional kernels

- shrink the distance from pixel to pixel

- -9 becomes center pixel value (5) in data image

Max pooling - used for decreasing complexity & to overfitting

Avg Pooling

Capsel Network