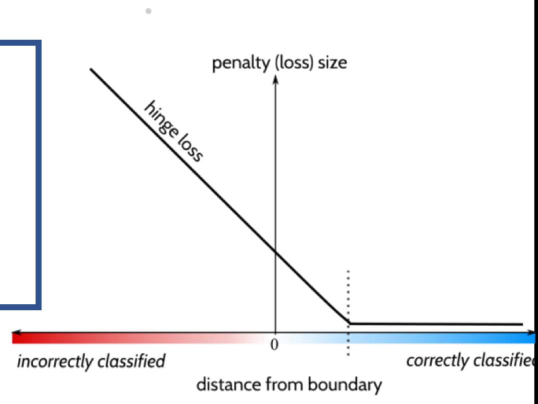
Object Recognition in Neuromorphic images using Spiking SVM

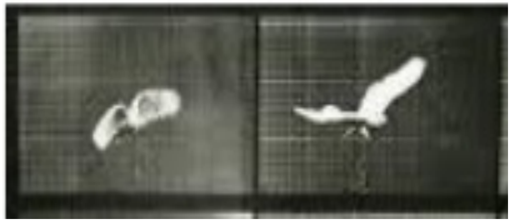
Aim :
To study object recognition in neuromorphic images with spiking SVM

$$J(\mathbf{w}, b, \alpha) = \frac{1}{2}\mathbf{w}^T\mathbf{w} - \underbrace{\sum_{i=1}^{N} \alpha_i[d_i(\mathbf{w}^T\mathbf{x}_i + b) - 1]}_{g(x)}$$

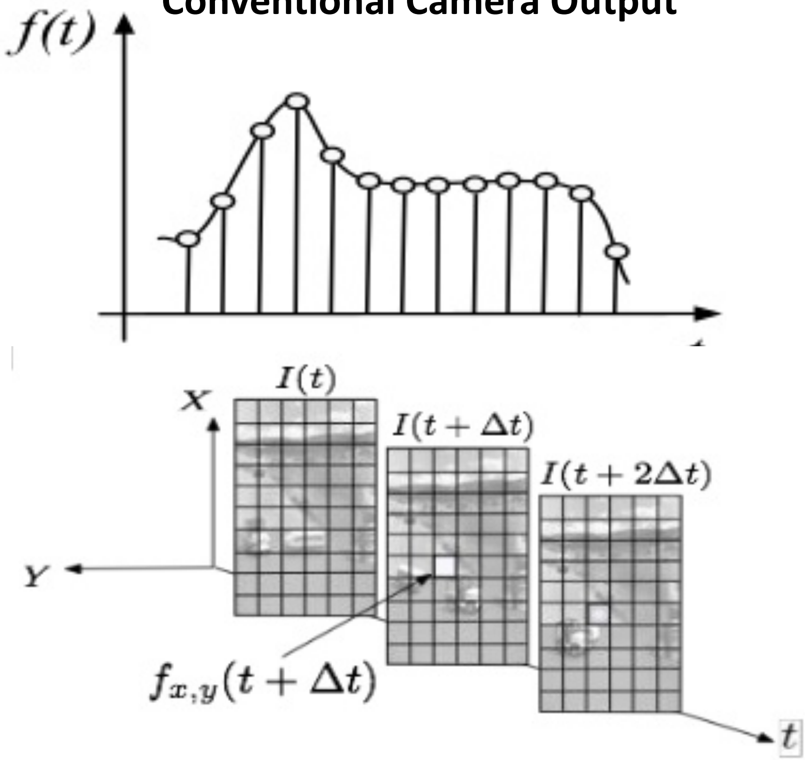
Spiking SVM has modified loss to generate spikes



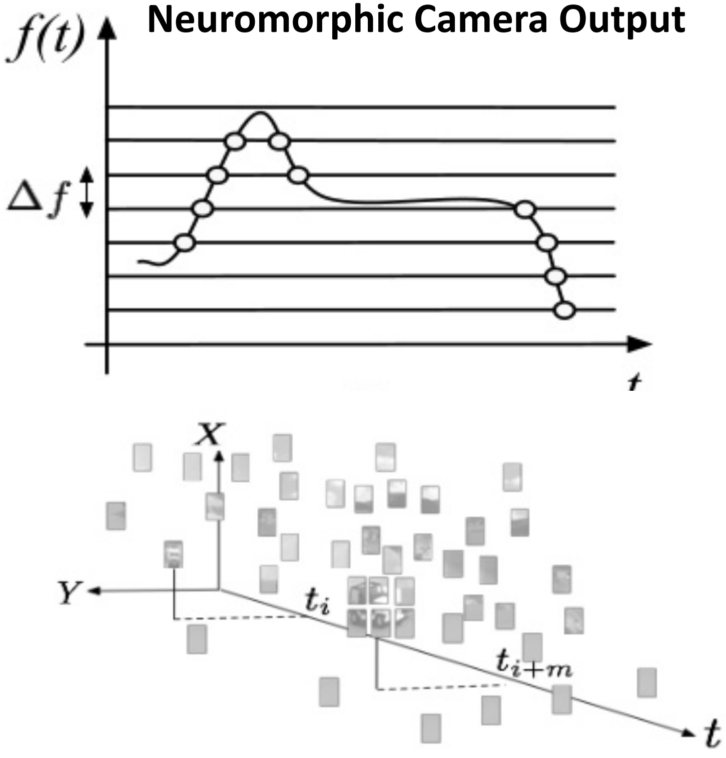
Input Scene



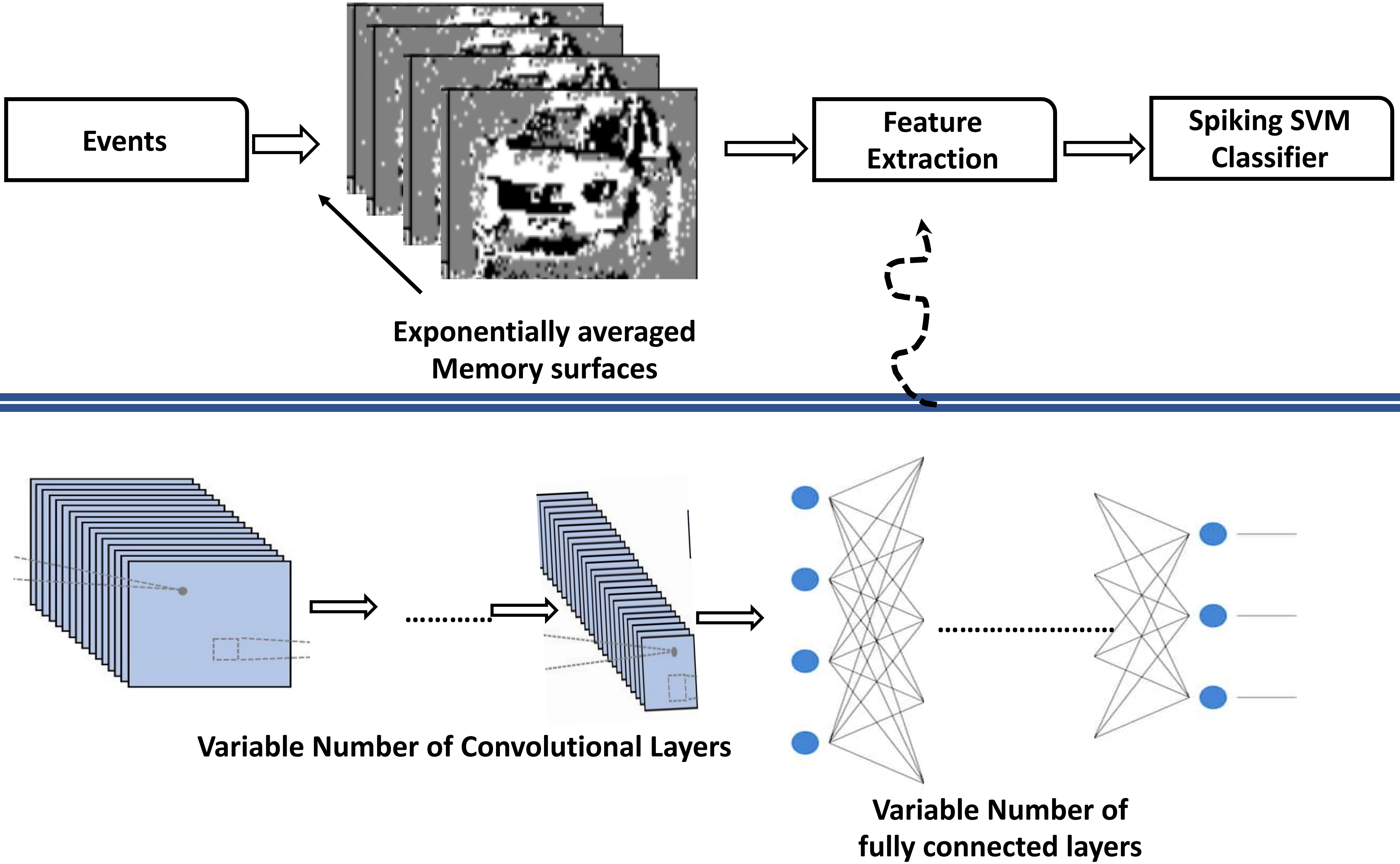
Conventional Camera Output



Neuromorphic Camera Output



Algorithm


Events
Feature Extraction
Spiking SVM Classifier
Exponentially averaged Memory surfaces
Variable Number of Convolutional Layers
Variable Number of fully connected layers

SVM and Growth Transform potential function

Primal Loss Function

$$P = \frac{1}{2}\|w\|^2 + C\sum_i g\left(z_i\right)$$

Constraint: $g\left(z_i\right)$

$$z_i = y_i\left(wx_i + b\right).$$

g can be Hinge Loss

Differentiating with respect to w and b:

$$\partial \mathcal{P}/\partial \mathbf{w} = \mathbf{w} + C\sum_i g'(z_i) y_i \mathbf{x}_i = 0$$

$$\partial \mathcal{P}/\partial b = C\sum_i g'(z_i) y_i = 0$$

$$\mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i . \qquad \sum_{i=1}^{N} \alpha_i y_i = 0.$$

Where, $\alpha_i = -Cg'(z_i)$

Substituting for w in alpha equation:

$$g'^{-1}\left(-\alpha_i/C\right) = y_i\left[\sum_j \alpha_j y_j K\left(x_j, x_i\right)\right]$$

Dual Function

$$\frac{1}{2}\sum_{ij}\alpha_i\alpha_j y_i y_j K\left(x_i, x_j\right) - C\sum_i \phi\left(\alpha_i\right)$$

Dual Potential function:

$$\Phi(a) = \int_0^a g'^{-1}(-v/C)dv$$

(2017) **Extended Polynomial Growth Transforms for Design and Training of Generalized Support Vector Machines**, IEEE Transactions on Neural Network and Learning Systems

Spiking SVM

Primal Loss Function

$$P = \frac{1}{2}\sum_{k=1}^{2} \|w_k\|^2 + \sum_{i=1}^{N}\sum_{k=1}^{2} g\left(z_{ik}\right)$$

Constraint: $g\left(z_i\right)$

$$z_{ik} = w_k x_i + b_{ik}$$

g can be Hinge Loss

Defining a function for differentiation of loss function:

$$\frac{d}{dz_{ik}} g(z_{ik}) = \psi(z_{ik}) = p_{ik}$$

Substituting for w:

$$\psi^{-1}(p_{ik}) = z_{ik}$$

$$\Psi^{-1}(p_{ik}) = (\sum_j \mathbf{x}_j p_{jk}).\mathbf{x}_i + b_{ik}$$

Dual Function

$$\sum_{k=1}^{2}\left[\sum_{i=1}^{N}\sum_{j=1}^{N}(K_{ij}p_{jk} - b_{ik})(K_{ij}p_{jk} - b_i k) - \sum_{i=1}^{N}\phi\left(p_{ik}\right)\right]$$

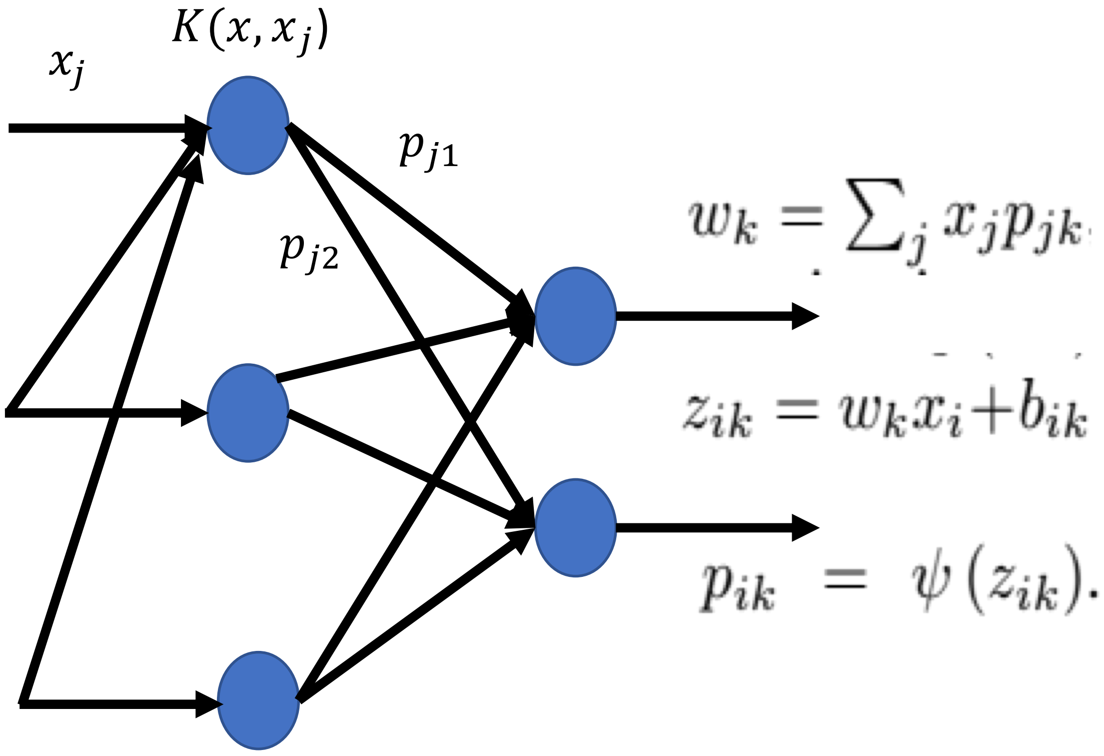
Dual Potential function:

$$\phi\left(p_{ik}\right) = \int \psi^{-1}\left(p_{ik}\right) dp_{ik}$$

Ahana Gangopadhyay and Shantanu Chakrabartty (2018), **Spiking, Bursting and Population Dynamics in a Network of Growth Transform Neurons**

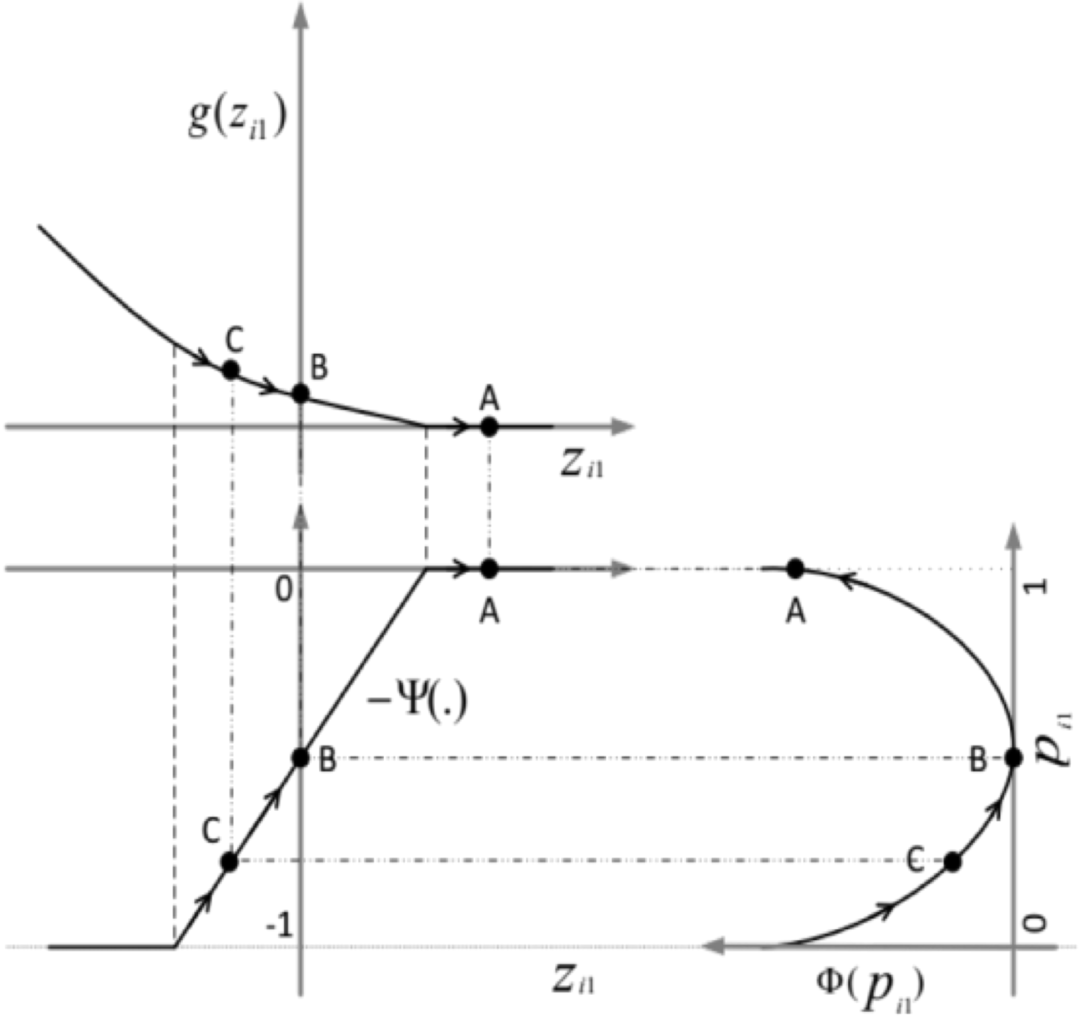
Spiking SVM

Spiking SVM Architecture:

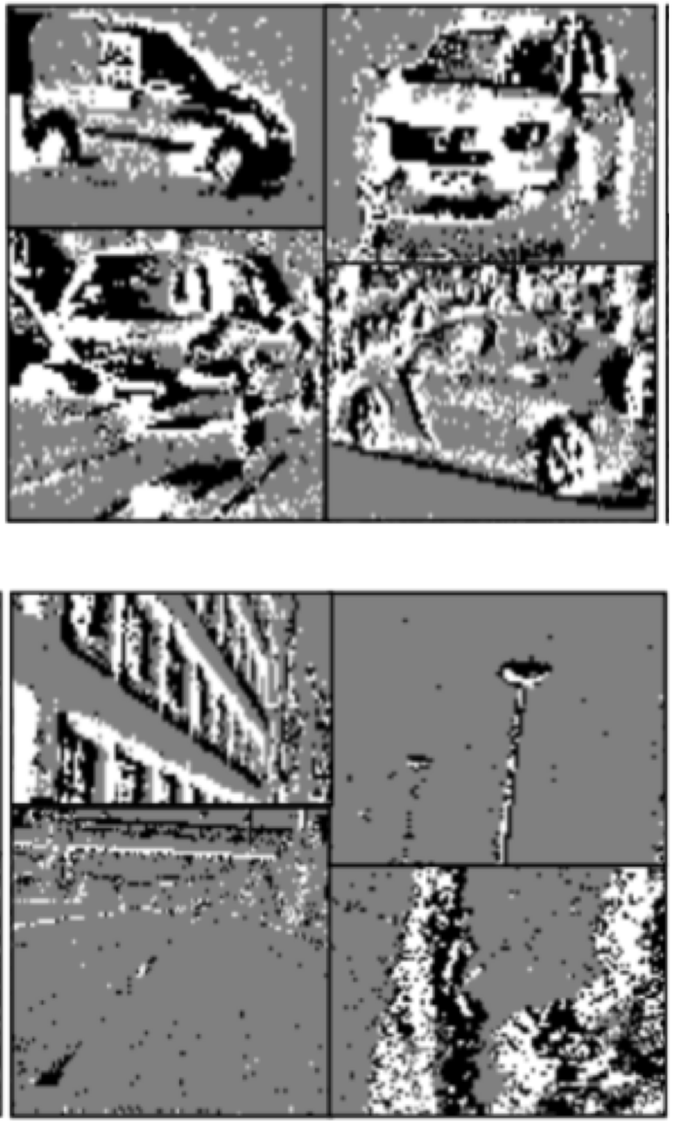


Spikes and Dual Potential function:

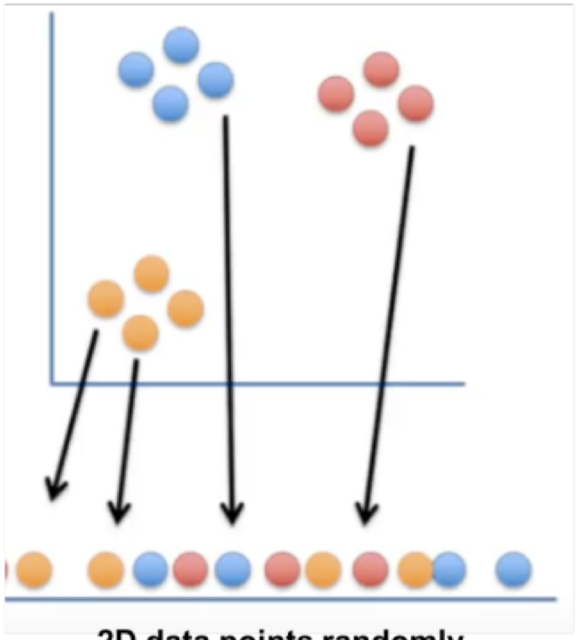
Differentiation of Dual potential function of Data points (B) on the boundary shows oscillating behavior



Results (2D plot of CNN features)

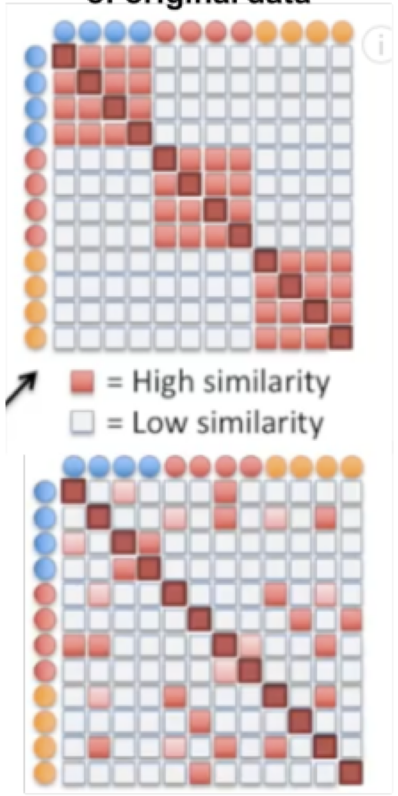


Projection of High dimensional data onto Low Dimension:



2D data points randomly projected onto 1D

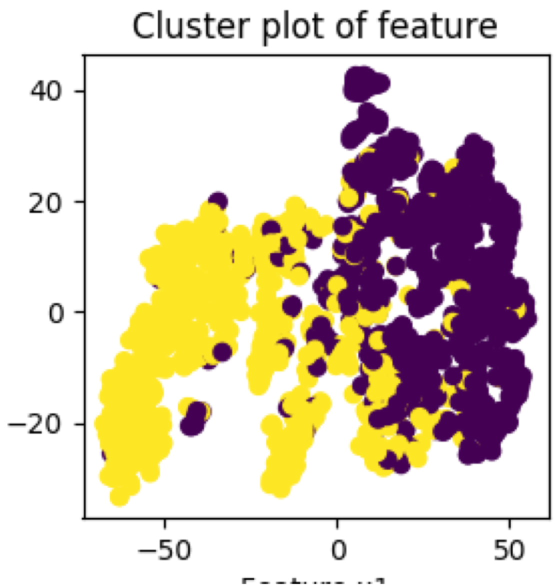
Similarity Matrix of original data



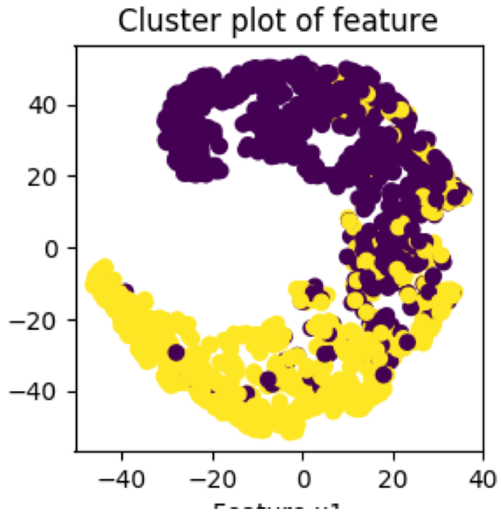
Similarity Matrix of randomly projected data

Randomly projected points are moved till the similarity matrices of original data and projected data becomes equal

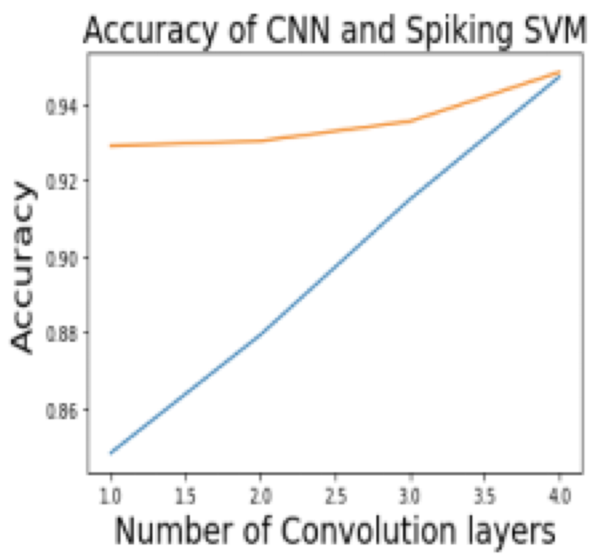
Single CNN layer:

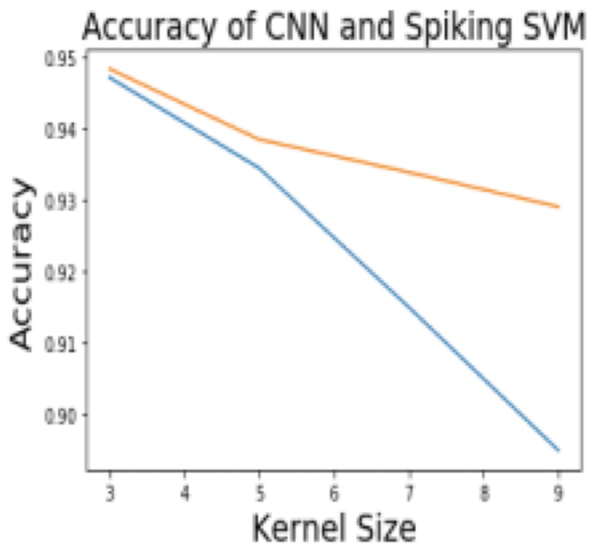


Multiple CNN layer:

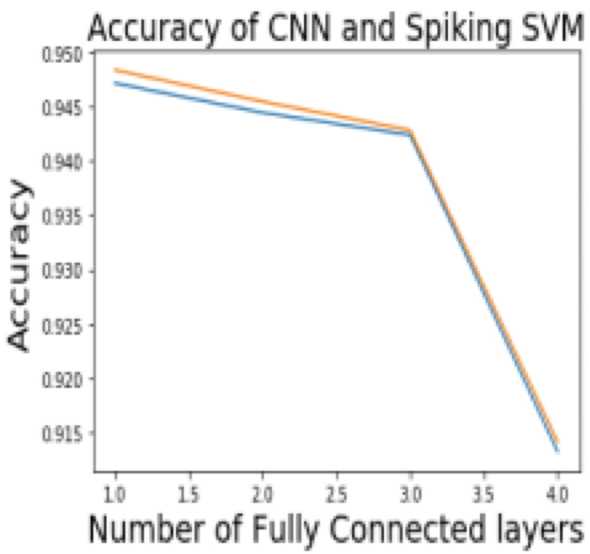


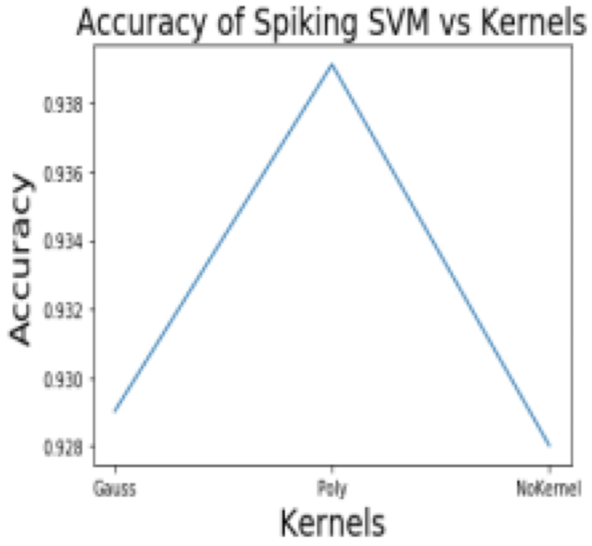
Result (Spiking SVM performance)





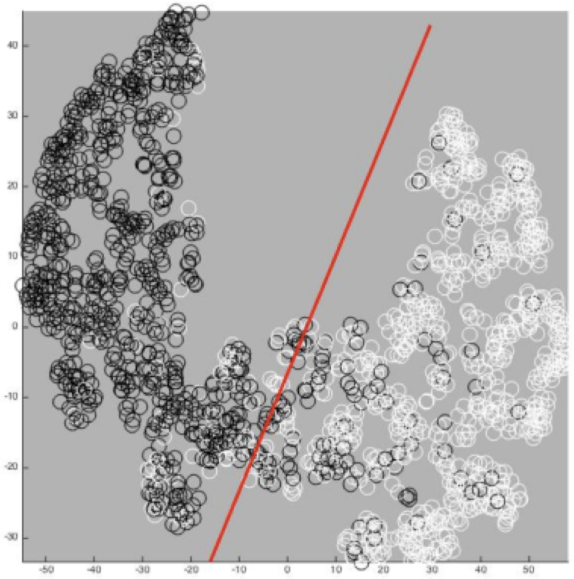
Blue: Only CNN
Red: CNN+ Spiking SVM

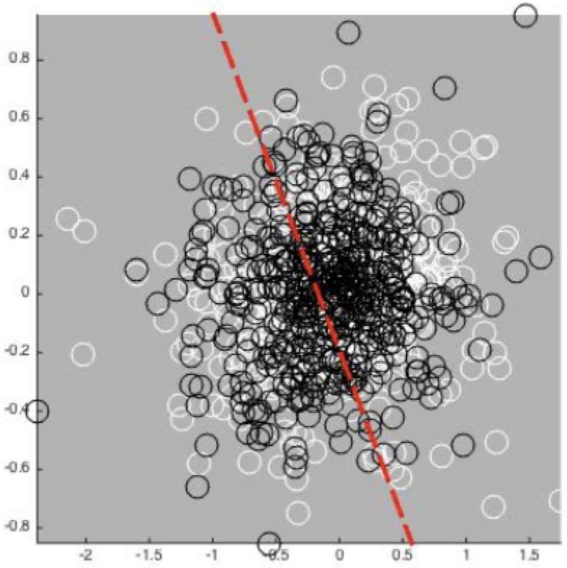




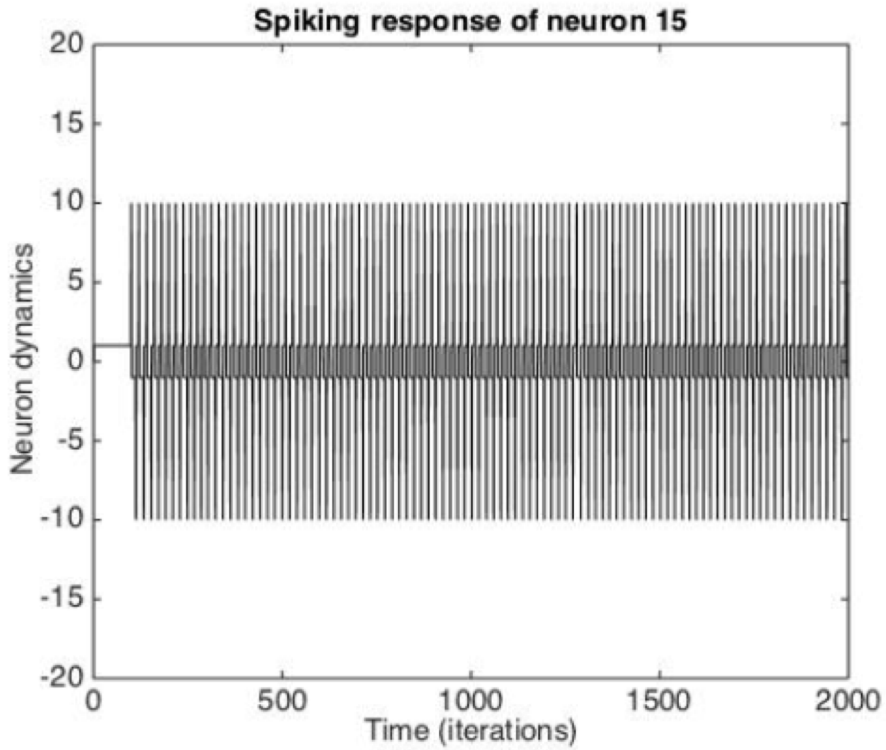
Classification Boundary and Spiking Nature

Classification on CNN features in 2 Dimension





Spiking Nature of Support Vector



Thank You