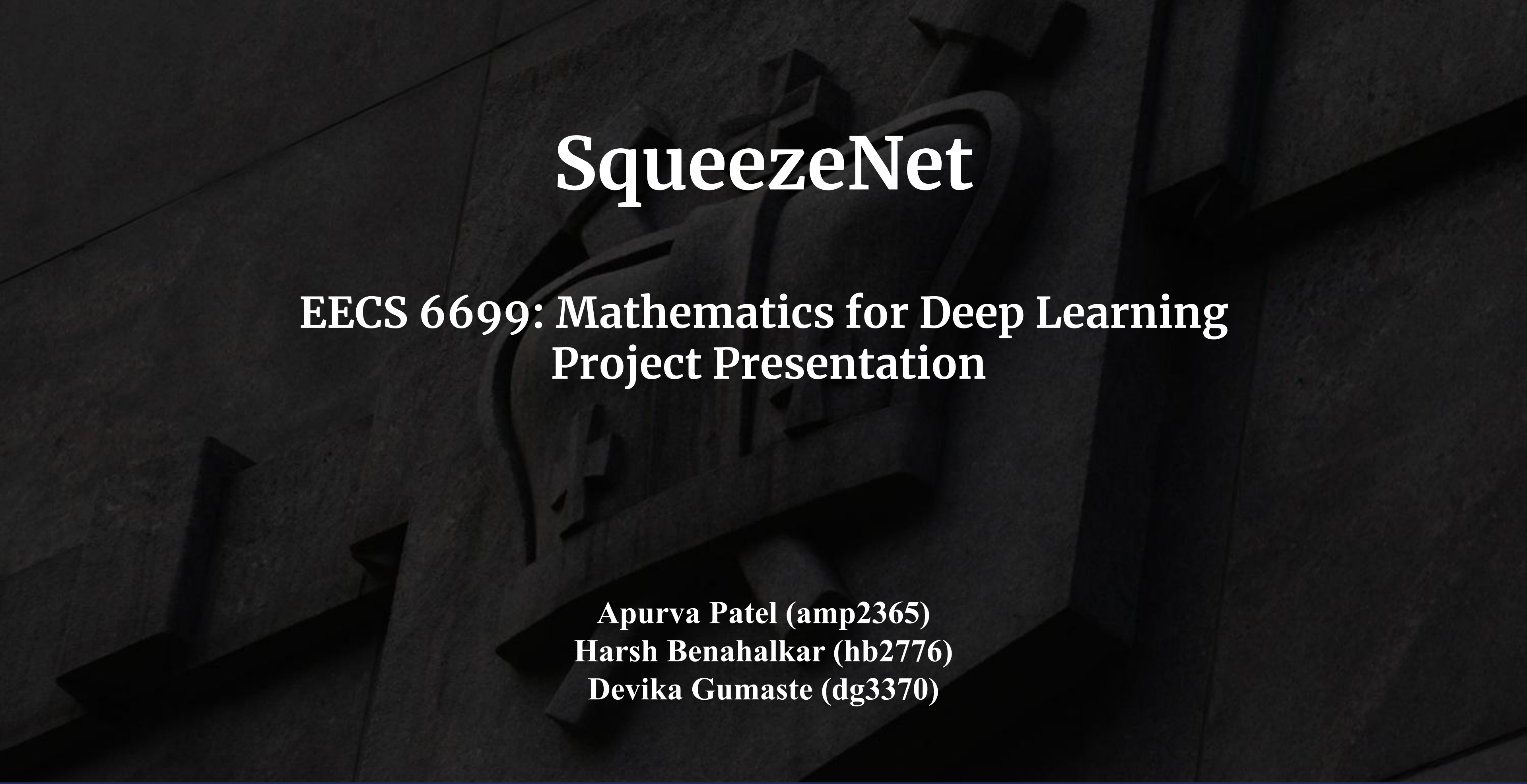

# SqueezeNet

## EECS 6699: Mathematics for Deep Learning
## Project Presentation

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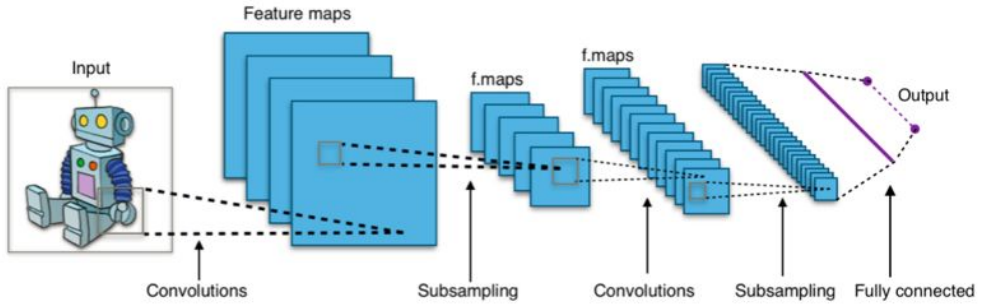
# *Traditional Convolution Neural Networks*

*(CNNs)*



- **Complex Data Processing:** CNNs are designed to handle complex data structures like images, videos, and audio, which have high-dimensional data representations.

- **Feature Extraction:** CNNs are adept at learning hierarchical patterns and features automatically from raw data. Using successive convolutional, pooling layers, and activation layers, CNNs can identify both, local-level features like edges and textures, and global-level features like shapes, objects, and semantic concepts.

- **Applications in Computer Vision:** CNNs have revolutionized the field of computer vision by enabling image tasks such as classification, detection, and segmentation with competitive accuracy.

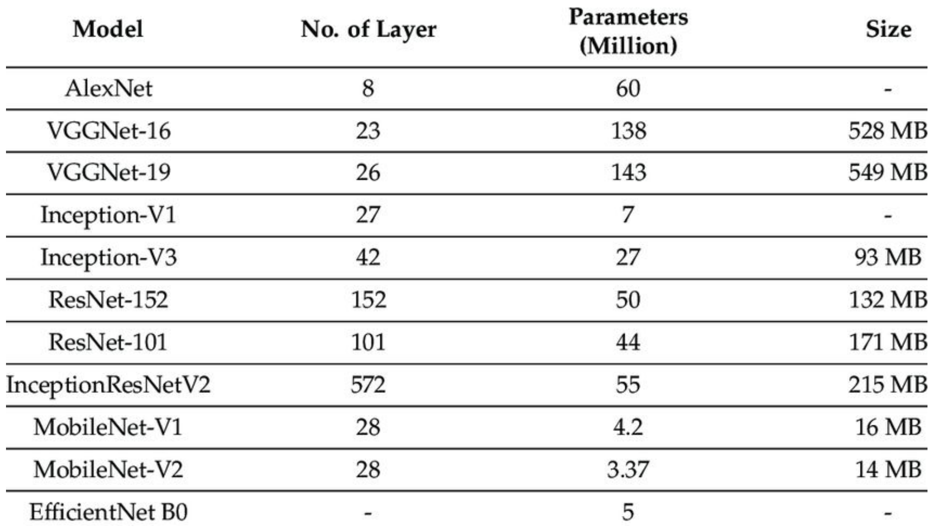
# Motivation

**Why do we need smaller models?**

- Lack of compute resources as the cloud and storage industry is not advancing as exponentially as the Deep Learning industry is.
- Increasing complexity of models to adapt to future use cases where autonomous systems have been integrated into society.
- Need to deploy models on edge/mobile devices to remove the barrier of Deep Learning as just a cloud/remote deployable system.

**How does SqueezeNet solve this problem**

- The need for squeezenet is justified by the model size which has just about 1.2M parameters.
- Comes handy when use cases demand of real time edge computing without significant performance drop and onboard memory is limited.



| Model | No. of Layer | Parameters (Million) | Size |
|---|---|---|---|
| AlexNet | 8 | 60 | - |
| VGGNet-16 | 23 | 138 | 528 MB |
| VGGNet-19 | 26 | 143 | 549 MB |
| Inception-V1 | 27 | 7 | - |
| Inception-V3 | 42 | 27 | 93 MB |
| ResNet-152 | 152 | 50 | 132 MB |
| ResNet-101 | 101 | 44 | 171 MB |
| InceptionResNetV2 | 572 | 55 | 215 MB |
| MobileNet-V1 | 28 | 4.2 | 16 MB |
| MobileNet-V2 | 28 | 3.37 | 14 MB |
| EfficientNet B0 | - | 5 | - |

Some models with their footprint size and number of parameters

## Principal Theorems

1. **Wiener-Khinchin theorem (cross-correlation):**
   Wiener-Khinchin theorem is applied to understand the frequency-domain representation of signals.

$$(I * K)(i,j) = \sum_{m=0}^{F-1} \sum_{n=0}^{F-1} I(i+m, j+n) \cdot K(m,n)$$

2. **Universal Approximation theorem:**
   Universal Approximation Theorem assures that any neural network with at least one single hidden layer can approximate any continuous function within a certain error margin.

$$|f(x) - F(x)| < \epsilon$$

3. **Lipschitz Continuity of Neural Networks:**
   Lipschitz continuity ensures stability and smoothness of neural network outputs with respect to small changes in inputs.

$$\|f(x) - f(y)\| \leq L\|x - y\|$$

4. **Gradient Descent algorithm:**
   Gradient descent efficiently updates neural network parameters by iteratively minimizing a loss function.

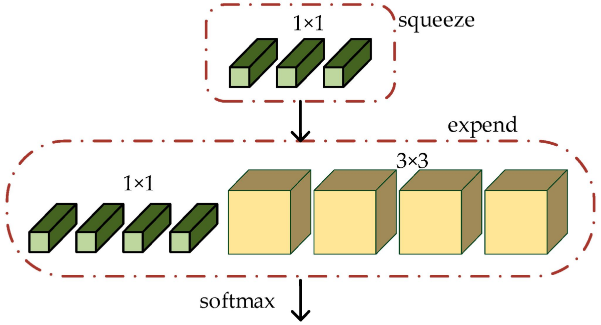
$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

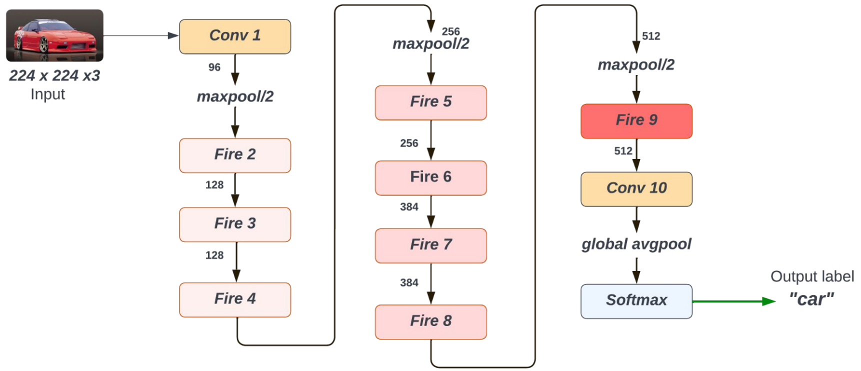
# SqueezeNet Architecture

***Stages of the Fire module:***

1. **Compression**
   - Replacing 3x3 filters with 1x1 filters (squeeze layers).
   - Downsampling feature maps.
2. **Expansion**
   - Applying 1x1 and 3x3 convolution on the input parallelly.
   - 1x1 keeps input dimension intact and the 3x3 filter captures spatial features.
3. **Concatenation**
   - Channel-wise addition of 1x1 and 3x3 convolutions.
4. **Activation**
   - Introduces non-linearity in the module.

***Fire module representation***





***Vanilla squeezenet architecture***

# Experiments

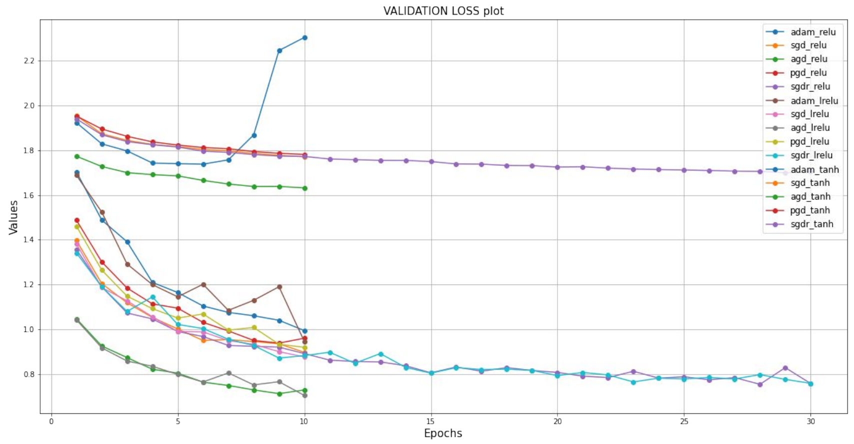
**Optimizers used:**

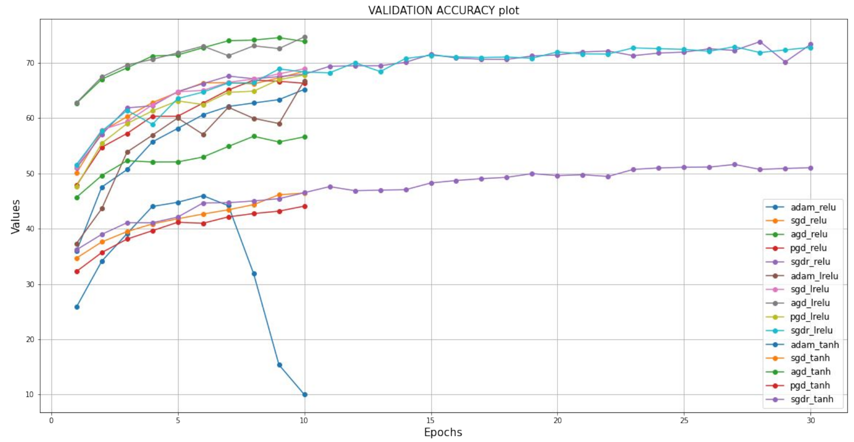
- Adaptive Moment (Adam)
- Stochastic Gradient Descent (SGD)
- Perturbed Gradient Descent (PGD)
- Accelerated Gradient Descent AGD (SGD with momentum)
- SGD with restart

**Activations used:**

- ReLU
- Leaky ReLU
- TanH

**No. of parameters:** 740554
**Model Size after training:** 11.3 Mb



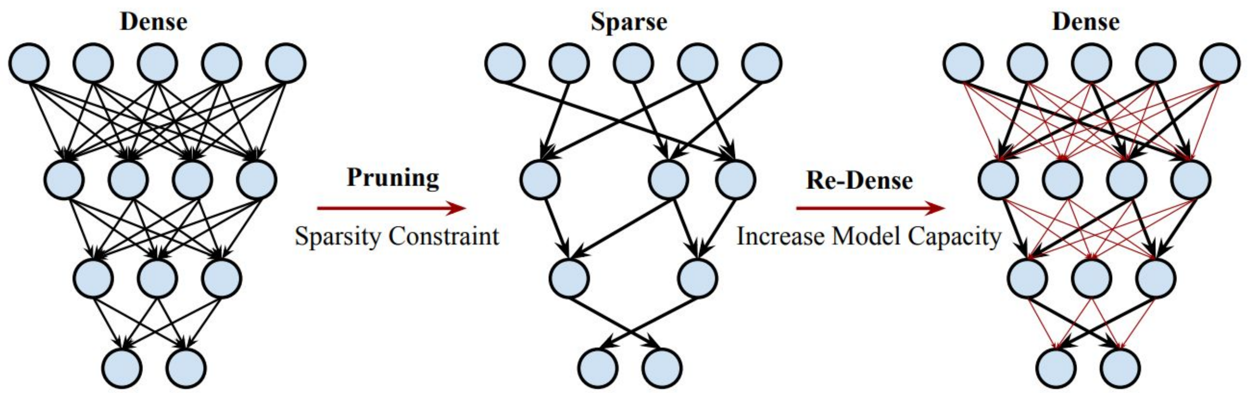


## *Our Implementations*

1. **Dense Sparse Dense Training**

2. **Squeezenet with Residual Connections**

# Dense-Sparse-Dense Training



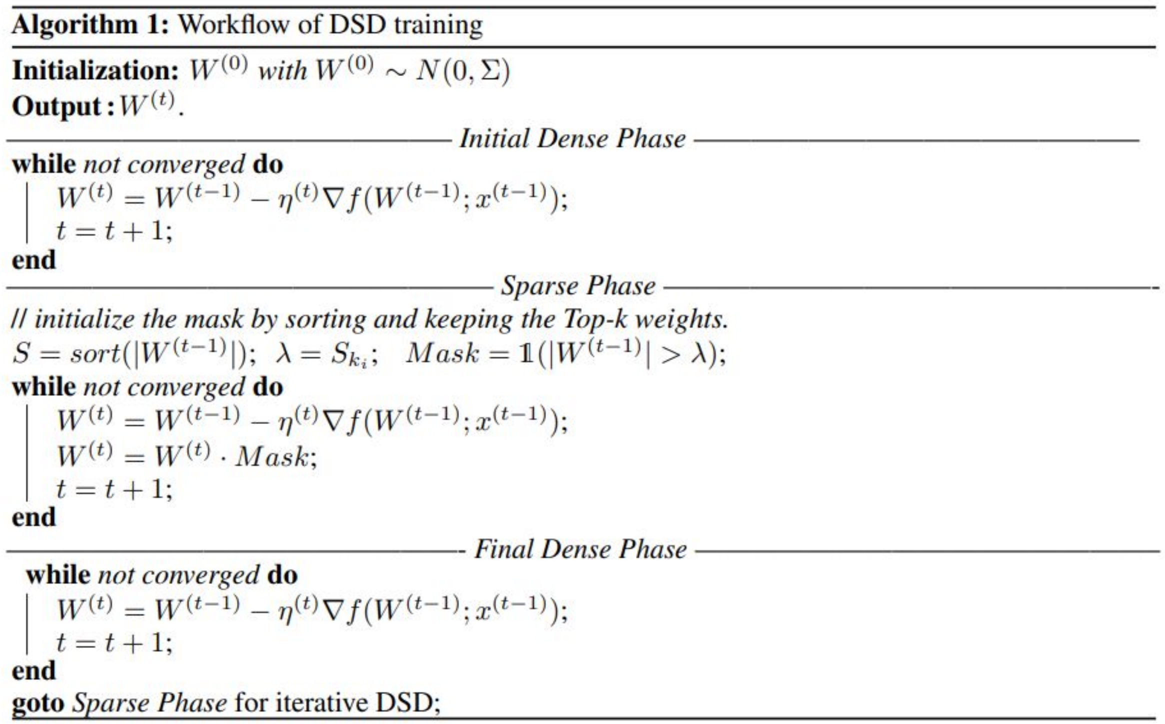
- **Motivation**: Large complicated models are prone to capturing background noise, instead of finding patterns in the dataset, which leads to **overfitting** and high variance. Only decreasing the model capacity leads to **underfitting** and high bias.

- **Approach:** The authors of the parent paper propose a new solution - “**Dense Sparse Dense**” approach - a novel training strategy that starts with conventional training methodology, then uses with optimization with sparsity constraints, and then increases the model capacity by recovering, reinitializing and re-training the weights.

# DSD Algorithm Overview

Three step process -

- Initial Dense Training
- Regularization with sparse training
- Final Dense Training by restoring and re-training the pruned weights



**Algorithm 1:** Workflow of DSD training

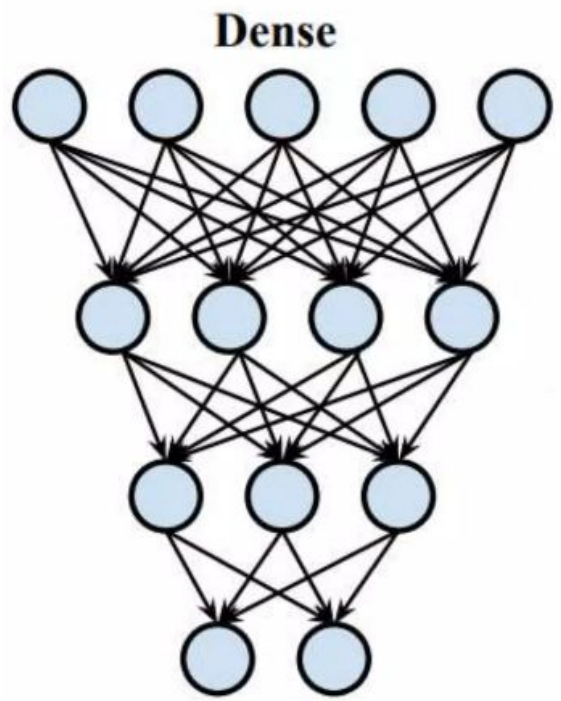
```
Initialization: $W^{(0)}$ with $W^{(0)} \sim N(0, \Sigma)$
Output : $W^{(t)}$.
―――――――― Initial Dense Phase ――――――――
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
    $t = t + 1$;
end
―――――――― Sparse Phase ――――――――
// initialize the mask by sorting and keeping the Top-k weights.
$S = sort(|W^{(t-1)}|); \quad \lambda = S_{k_i}; \quad Mask = \mathbb{1}(|W^{(t-1)}| > \lambda)$;
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
    $W^{(t)} = W^{(t)} \cdot Mask$;
    $t = t + 1$;
end
―――――――― Final Dense Phase ――――――――
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
    $t = t + 1$;
end
goto Sparse Phase for iterative DSD;
```

# Phase-1 Dense Training

**Dual Objective**

- The first step focuses on training the network using all connections.
- The network learns both the values of the weights and identifies the important connections.
- The importance of connections is quantified by simply taking the absolute value of the weights - weights with higher absolute values are considered important.

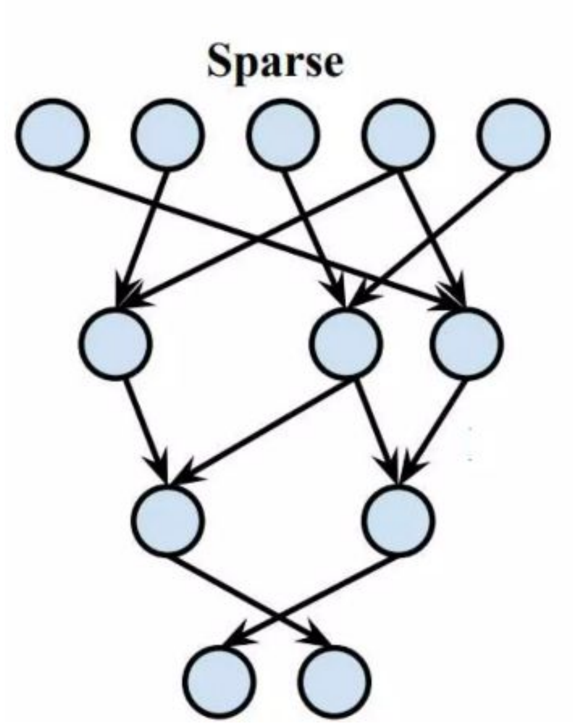
```
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
    $t = t + 1$;
end
```



# *Phase-2 Sparse Training*

- Connecting with low weights are pruned to induce sparsity. The degree of sparseness is controlled by a hyperparameter “sparsity”.
- Threshold = kth largest weight, where k=N(1 - sparsity).
- Binary Mask is generated for each layer to prune weights.
- Network is trained while enforcing the binary mask

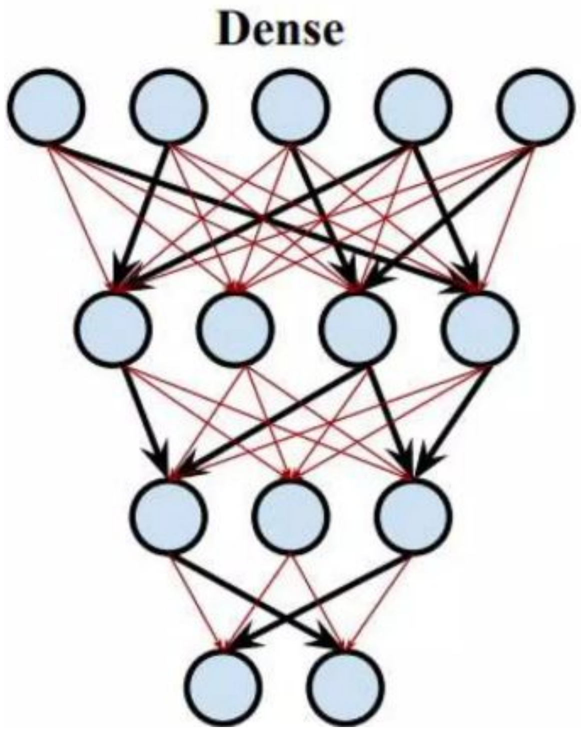
```
// initialize the mask by sorting and keeping the Top-k weights.
$S = sort(|W^{(t-1)}|);\quad \lambda = S_{k_i};\quad Mask = \mathbb{1}(|W^{(t-1)}| > \lambda);$
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)});$
    $W^{(t)} = W^{(t)} \cdot Mask;$
    $t = t + 1;$
end
```



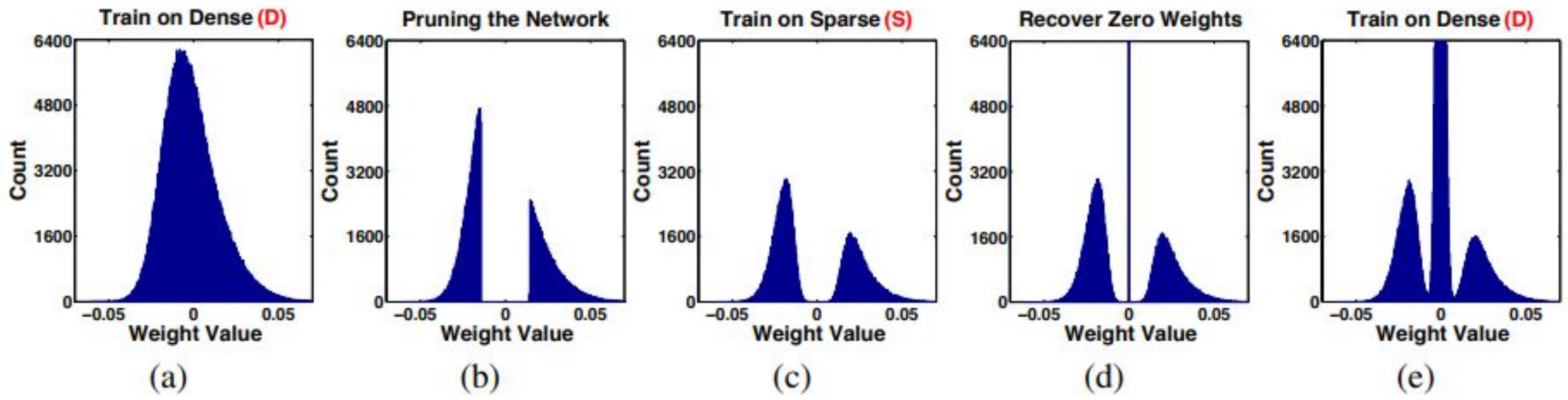
## *Phase-3 Dense Training*

- Initially the pruned connections are recovered from the network and initialized anew
- The entire network is trained on a reduced learning rate (1/10th) of the initialized rate - since the sparse network is already close to an optimal local minimum.
- Other hyperparameters remain unchanged to maintain consistency and stability in the training process.
- Final dense training enhances capacity of the model - allowing the model to reach to a better local minimum.

```
while not converged do
    $W^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)});$
    $t = t + 1;$
end
goto Sparse Phase for iterative DSD;
```



# DSD Weights Visualization



Weight distribution is initially concentrated around zero with rapid tail decay.

Pruning based on absolute value truncates the central region, leading to a bimodal distribution during retraining.

Weights post pruning are then re-assigned around zero at the start of re-dense training and eventually retrained alongside un-pruned weights.

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## *DSD Experiments*

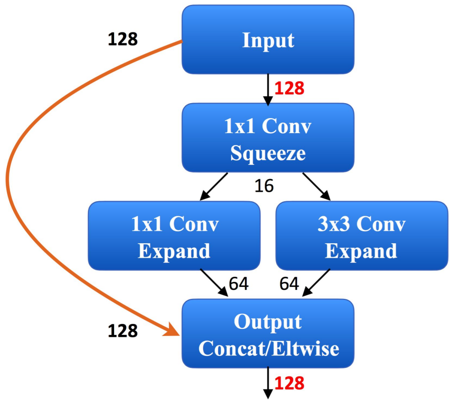
- **Varying Sparsity Levels**
  - Sparsity Level is systematically varied to observe it’s effects on performance.
  - Optimal sparsity level between 25-50%
  - For our set-up, optimal sparsity turned out to be 40%
  - Trade-off between sparsity and accuracy
- **Different Epochs Distribution**
  - Distribution of dense and sparse epochs
  - Instead of allocating equal number of epochs to each phase, tested out different combinations.
  - Differences observed in accuracy and training time
  - 5 - 3 - 5 resulted in best performance

# Residual connections

***SqueezeNet with residual connections***

- **Motivation:** Helps reformulate the underlying mapping as a residual mapping, rather than anticipating the stacked layers to directly model a underlying mapping.

- If the underlying mapping is *H(x)*, the residual learning framework lets the model fit another mapping *F(x) = H(x) + x*. Here *x* is the input to the layer.

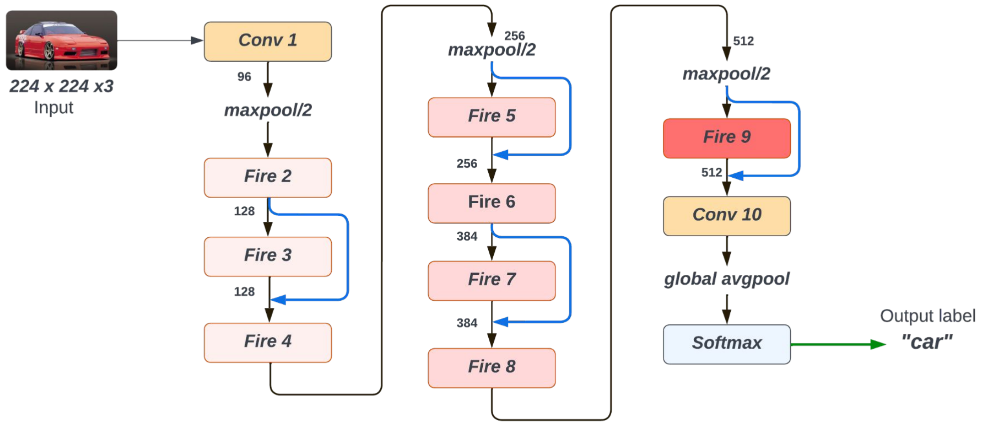


$$y_i^{res} = y_i + x_{i+1}$$

***Fire module with residual connections between layers to improve backpropagation of error.***

# Residual connections

***SqueezeNet architecture with residual connections***



***Cross-Entropy loss function***

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{i,j}\log(p_{i,j})$$

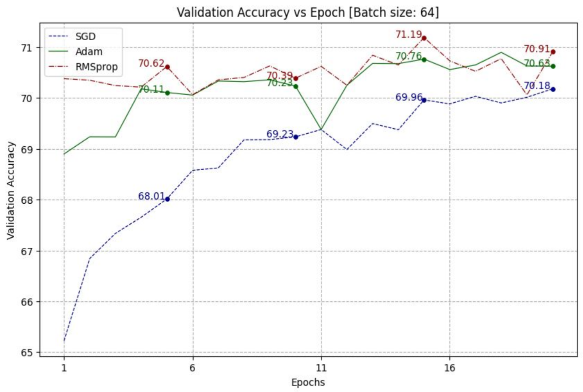
***Error computation for backpropagation***

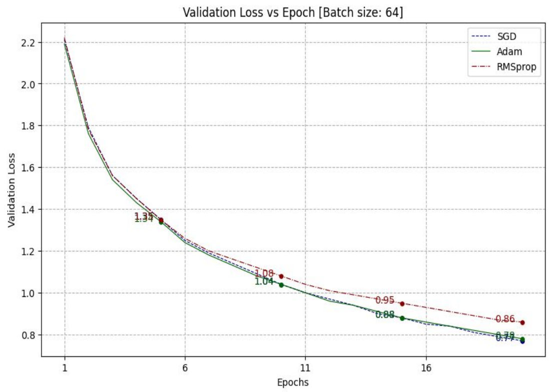
$$\frac{\partial \mathcal{L}}{\partial x_l} = \frac{\partial \mathcal{L}}{\partial y_L}\frac{\partial y_L}{\partial y_{L-1}}\cdots\frac{\partial y_{l+1}}{\partial y_l}\frac{\partial y_l}{\partial F_l(x_l)}\frac{\partial F_l(x_l)}{\partial x_l} + \frac{\partial \mathcal{L}}{\partial y_{l+1}}\frac{\partial y_{l+1}}{\partial x_l}$$

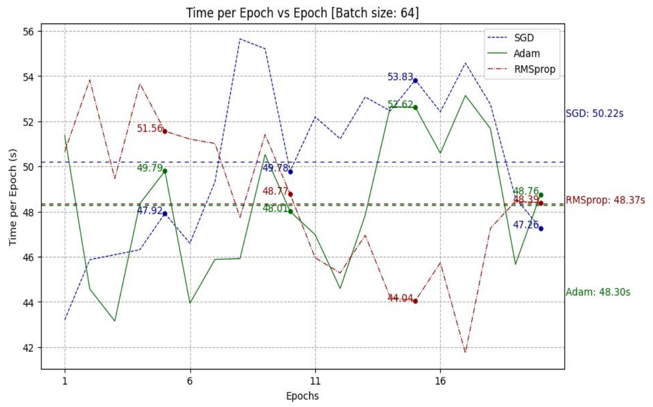
- The key difference is the addition of the second term which represents the gradient flowing through the residual connection, and the residual connection ensures that the gradients can be expressed as a sum of two terms, where one term is not subject to the exponential decay caused by the product of derivatives.
- This residual connection provides an alternative path for the gradients to flow, bypassing the potentially vanishing gradients through the layers. As a result, the gradients can be maintained and effectively propagated to the earlier layers, mitigating the vanishing gradient problem

# Results & Discussions

***Batch Size:*** *64*
***Learning rate:*** *0.001*







***for RMSProp:***

Exponentially decaying average: $v_t = \beta \cdot v_{t-1} + (1-\beta) \cdot (g_t)^2$

Update rule: $\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{v_t} + \epsilon} \cdot g_t$

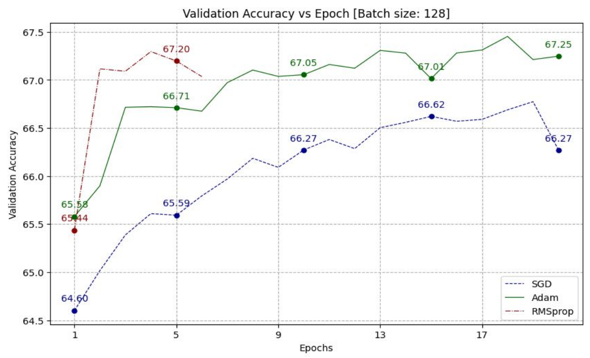
- RMSprop changes the learning rates for every parameter based on the root mean square (RMS) of recent gradients. This adaptiveness allows it to converge faster and more robustly, especially in scenarios where the gradients exhibit large variations or are sparse.
- Average time(s) per epoch is highest for SGD as the no of updations required in that during the update rule is slightly higher than that ADAM and RMSProp where update takes place without momentum instead utilizing adaptive gradient.

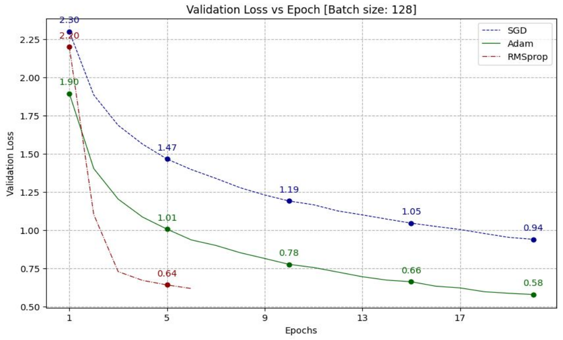
***Note**: Time per epoch is a very lucrative measure as it is highly dependant on instruction pipeline and so we consider average time per epoch*

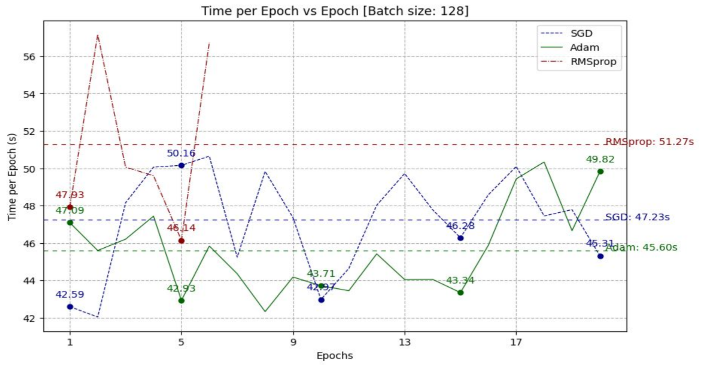
## Results & Discussions

***Batch Size:** 128*

***Learning rate:** 0.001*







***for ADAM:***

Moment estimates:

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$$

Bias correction:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Update rule:

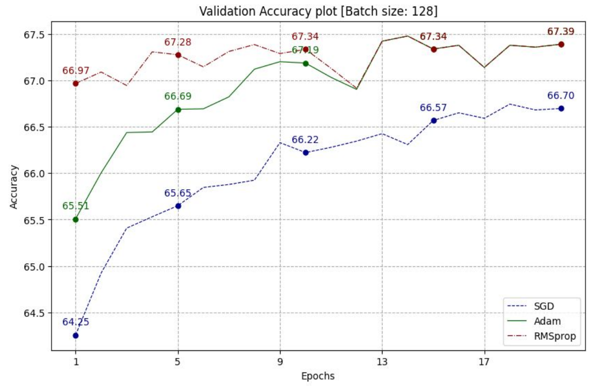
$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

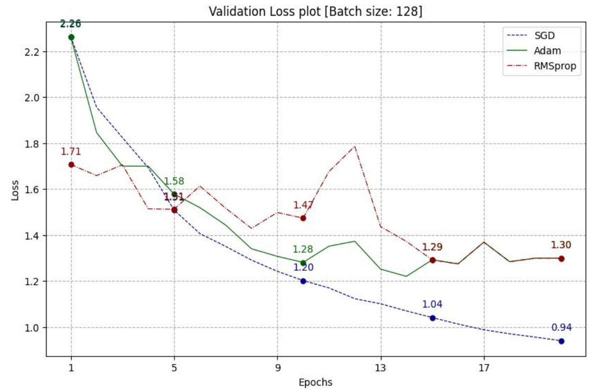
***Note**: With a large batch size of 128 RMSProp crashes as the computations are large and calculation of moments becomes complex with a complexity of $O(2n^2)$*

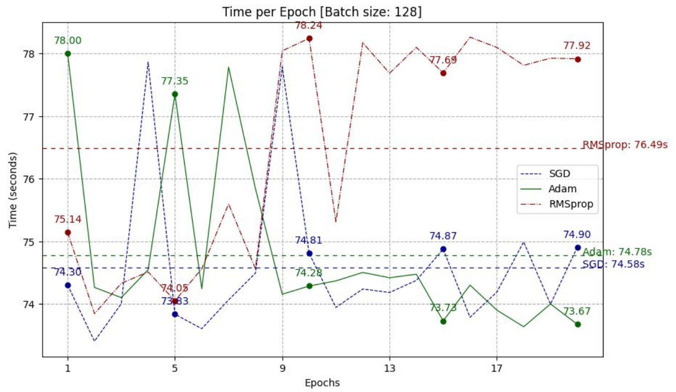
- The adaptive moment estimation formulae dynamically adjust the learning rates, first moment estimates, and second moment estimates using exponential decay rates.
- This adaptiveness allows Adam to efficiently navigate varying gradients and converge to more optimal parameter values, resulting in improved training accuracy and lower validation loss over epochs compared to traditional optimizers like SGD and RMSprop.

# Results & Discussions

**_Batch Size: 128 with LR scheduler_**







***for SGD with Nesterov momentum:***

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t) + \alpha \cdot \Delta\theta_{t-1}$$

- In complex landscapes like CIFAR10, the momentum term will exacerbate oscillations or hinder convergence in narrow valleys, leading to suboptimal solutions compared to adaptive methods like Adam and RMSprop, which adjust learning rates based on gradient magnitudes.
- It is noteworthy to note that despite this the validation loss is lowest, which can be explained by the momentum being taken into consideration and making the “distance” closest to global minima.
- Also varying learning rate doesn’t help in RMSProp in our case because moment updation will be costly

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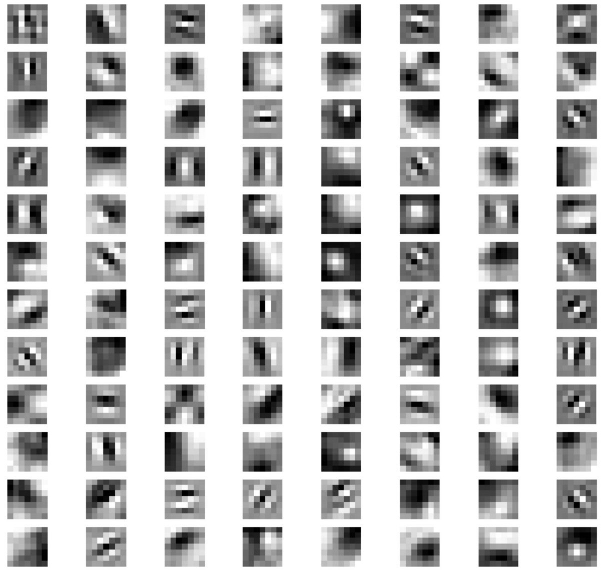
## *Results & Discussions*

- Weights clearly are much more distributed than the vanilla squeezenet implementation.
- Residual connections helped backpropagate the error and not vanish the gradients with lower values.
- Propagation of error signals through the network more effectively, residual connections have enabled the model to learn richer and more nuanced representations of the input data.



***Sample weights in conv1 layer***

# Thank You :)