DD2424 Deep Learning in Data Science - Assignment 1

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Optimize the performance of the network

Now we make some changes to see if we can increase the performance of the network. There are many possible options to consider but I will mainly focus on

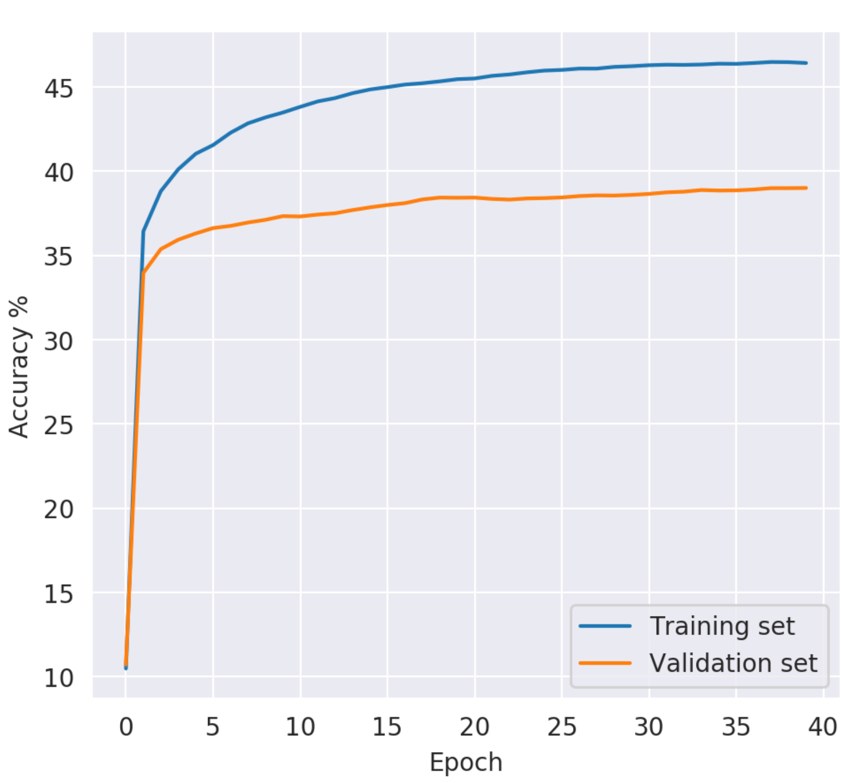
- Add some decay to the learning rate parameter after each epoch
- Train for a longer time
- Shuffle the order of the training data batch in the beginning of each epoch
- Add geometric and photometric jitter to the training samples

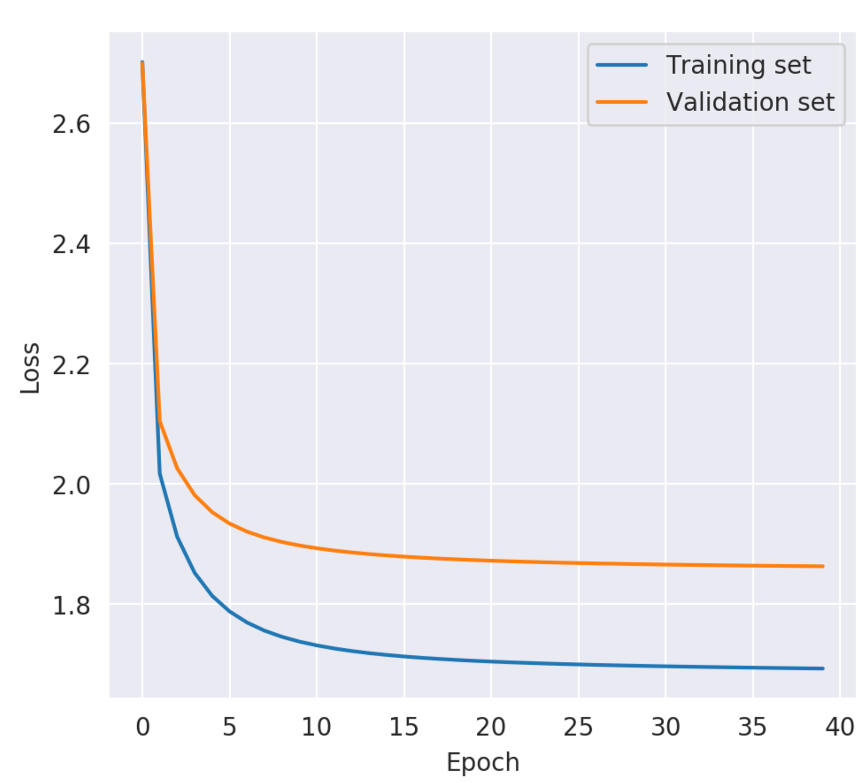
The results from these attempts are then compared to the currently best performing configuration (Model 3), which has a 39.01% prediction accuracy on the test data.

Adding decay to the learning rate

The parameters used to train this model are kept constant and identical to model 3 while introducing a decay rate to the learning rate. The rate of decay is set to 0.95, meaning that the learning rate decays by 5% in each epoch.

```
Model parameters:
   loss:         cross
   lambda:       0.1
   eta:          0.01
   n_epochs:     40
   n_batches:    100
   decay:        0.95

Training data:
   accuracy (untrained):       10.48%
   accuracy (trained):         46.43%
   cost (final):               1.69
Validation data:
   accuracy (untrained):       10.71%
   accuracy (trained):         39.01%
   cost (final):               1.86
Test data:
   accuracy (untrained):       10.85%
   accuracy (trained):         39.33%
   cost (final):               1.84
```



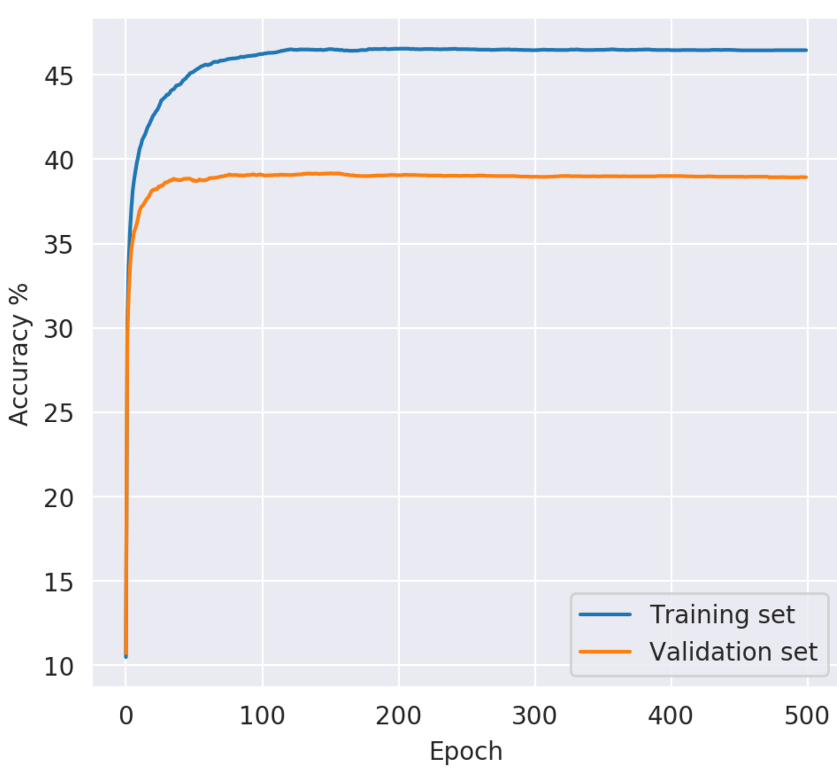


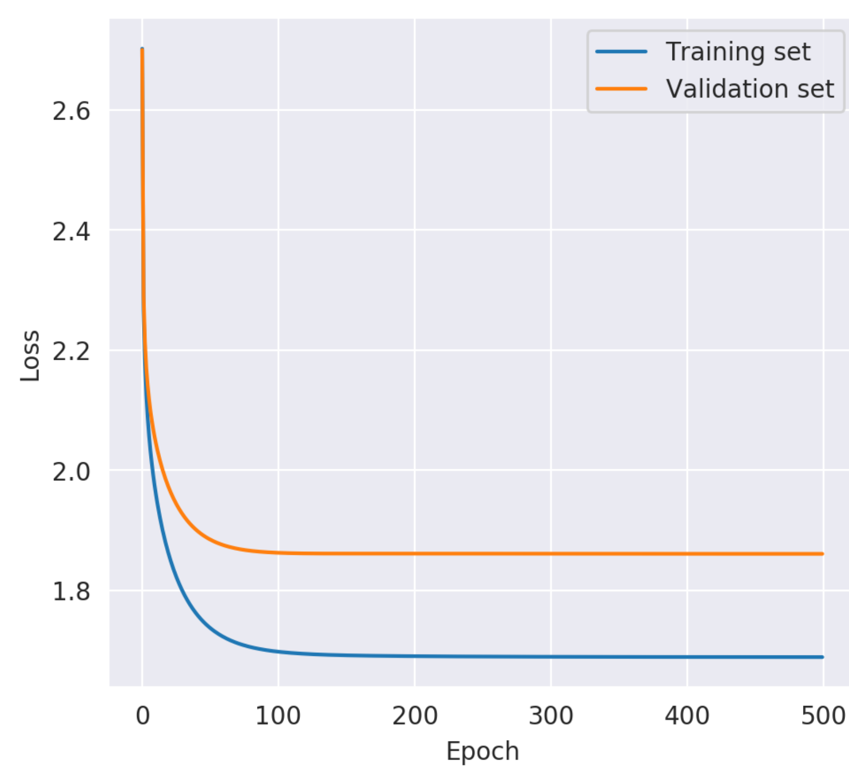
This gave a small performance boost, an increase with 0.32 percentage points of the accuracy on the test data, relative to model 3.

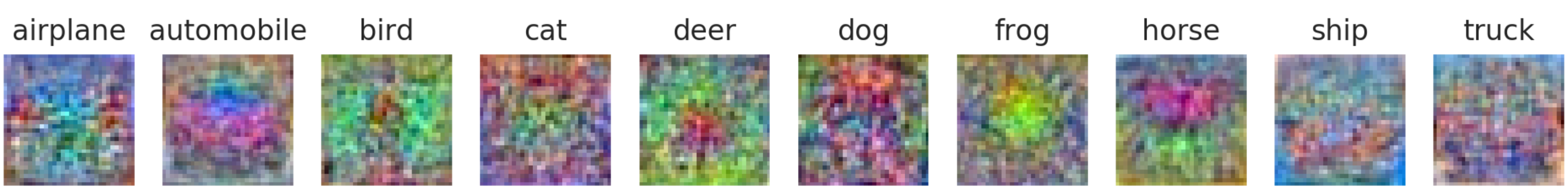
Train for a longer time

Take the best performing model (3) and increase the number of training epochs from 40 to 500.

```
Model parameters:
   loss:         cross
   lambda:       0.1
   eta:          0.001
   n_epochs:     500
   n_batches:    100

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          46.46%
   cost (final):                1.69
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          38.93%
   cost (final):                1.86
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          39.55%
   cost (final):                1.84
```





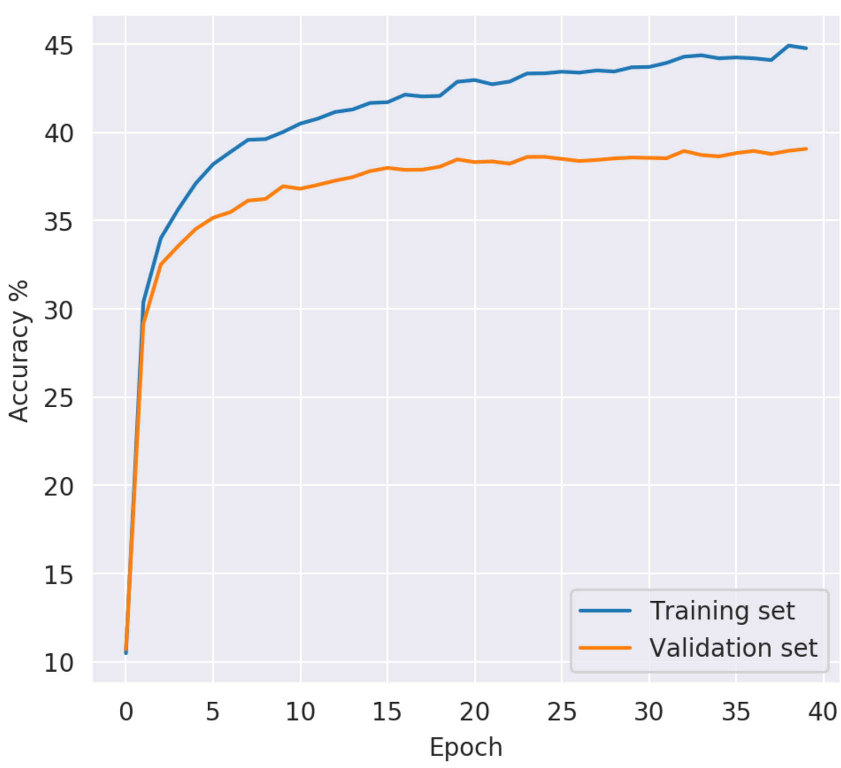


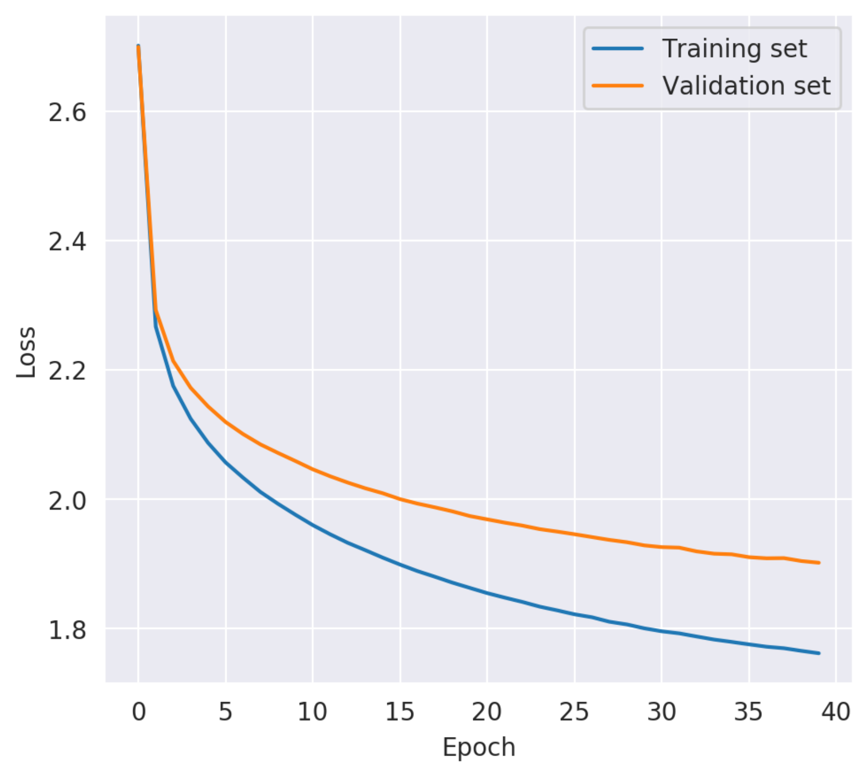
This also gave a slightly larger performance boost, about 0.54 percentage point increase of the accuracy on the test data, relative to model 3.

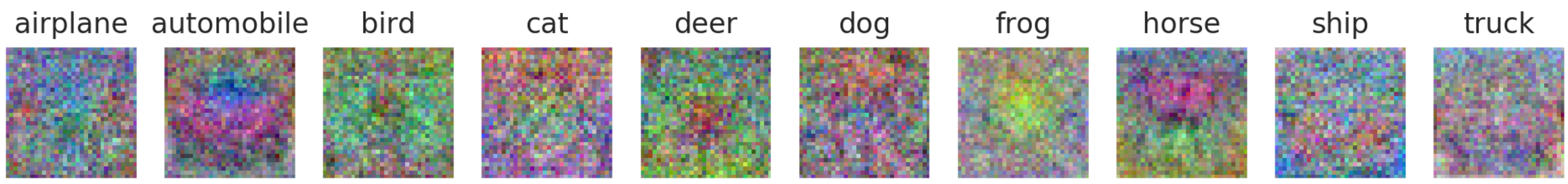
Shuffle the training data

The parameters used to train this model are kept constant and identical to model 3 while introducing shuffling of the training data at each epoch.

```
Model parameters:
   loss:         cross
   lambda:       0.1
   eta:          0.001
   n_epochs:     40
   n_batches:    100
   shuffle:      True

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          44.76%
   cost (final):                1.76
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          39.06%
   cost (final):                1.90
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          39.23%
   cost (final):                1.88
```







Shuffling the training data at each epoch gave a slight performance boost, 0.22 percentage point increase in accuracy on test data relative to model 3.

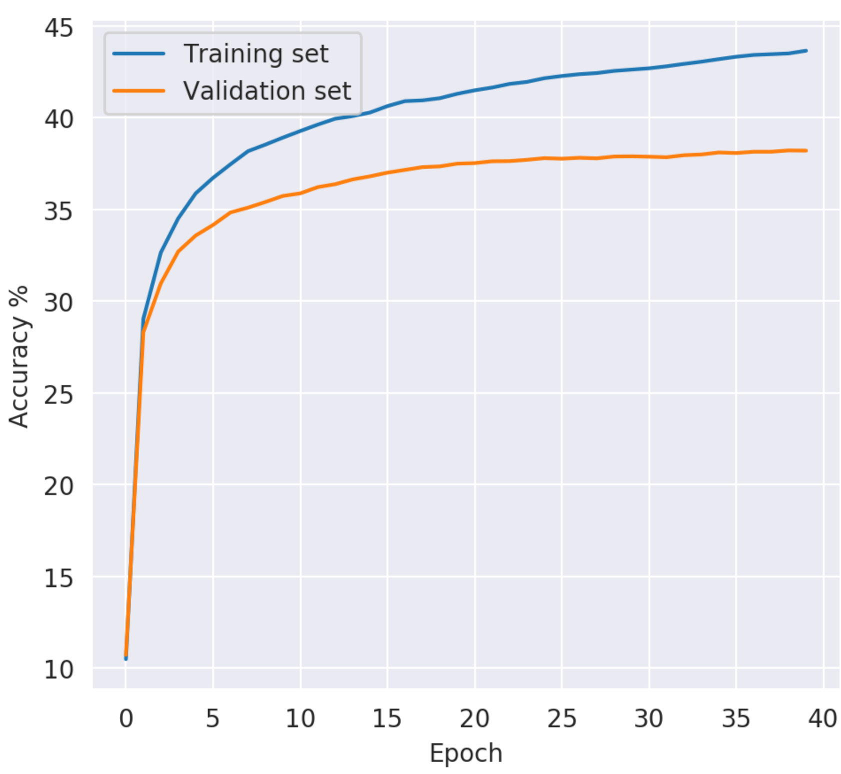
Add noise to training data

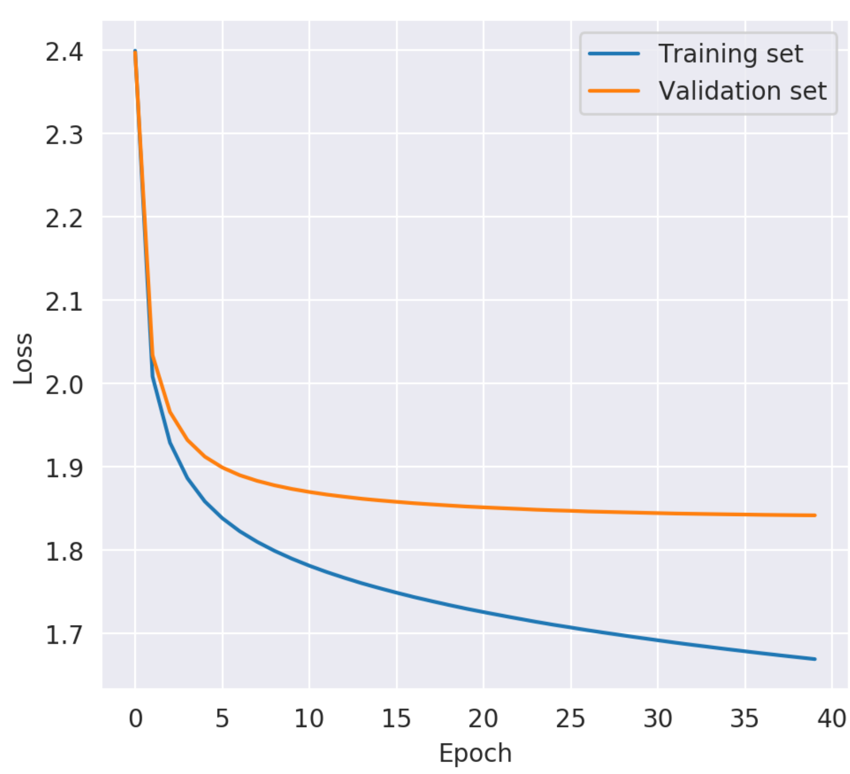
By adding noise to the data will make it more difficult for the network to make a precise fit to the training data and will therefore reduce the risk of overfitting the model. As such, we should see similar results between a model that is trained with L2 regularization and a model that has no L2 regularization but has noise added to the training data.

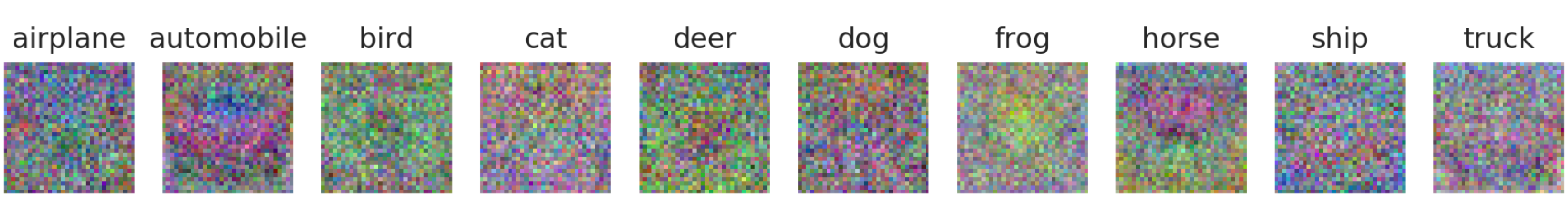
Now adding gaussian noise with mean 0 and standard deviation 0.01 to the training batches. Here's an example of what this does to the images.

The result when adding gaussian noise to the training data.

```
Model parameters:
   loss:         cross
   lambda:       0.0
   eta:          0.001
   n_epochs:     40
   n_batches:    100
   noise:        gaussian

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          43.66%
   cost (final):                1.67
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          38.21%
   cost (final):                1.84
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          38.46%
   cost (final):                1.81
```



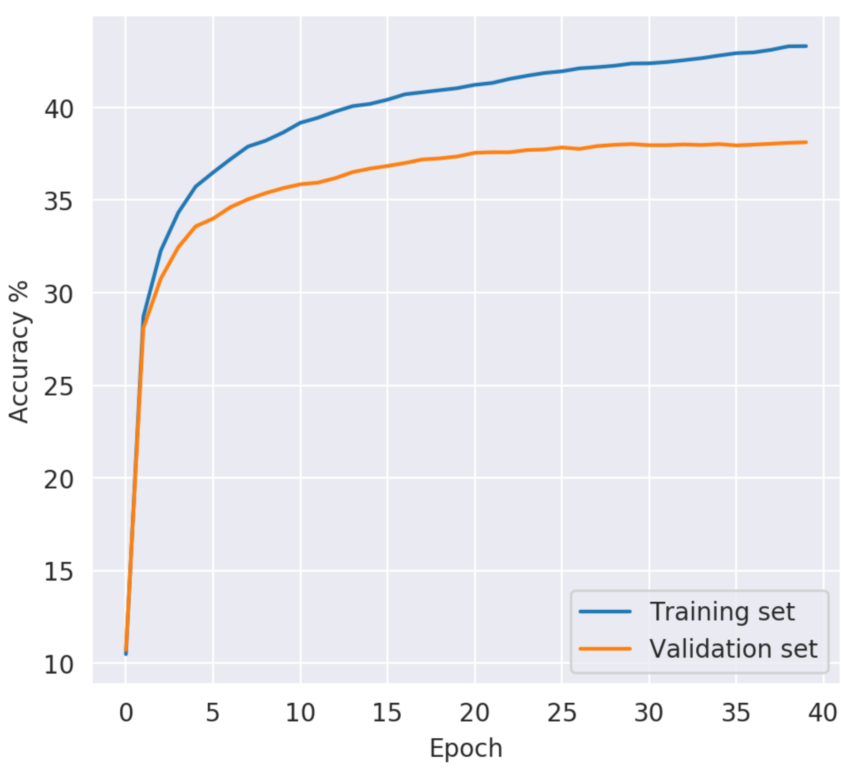


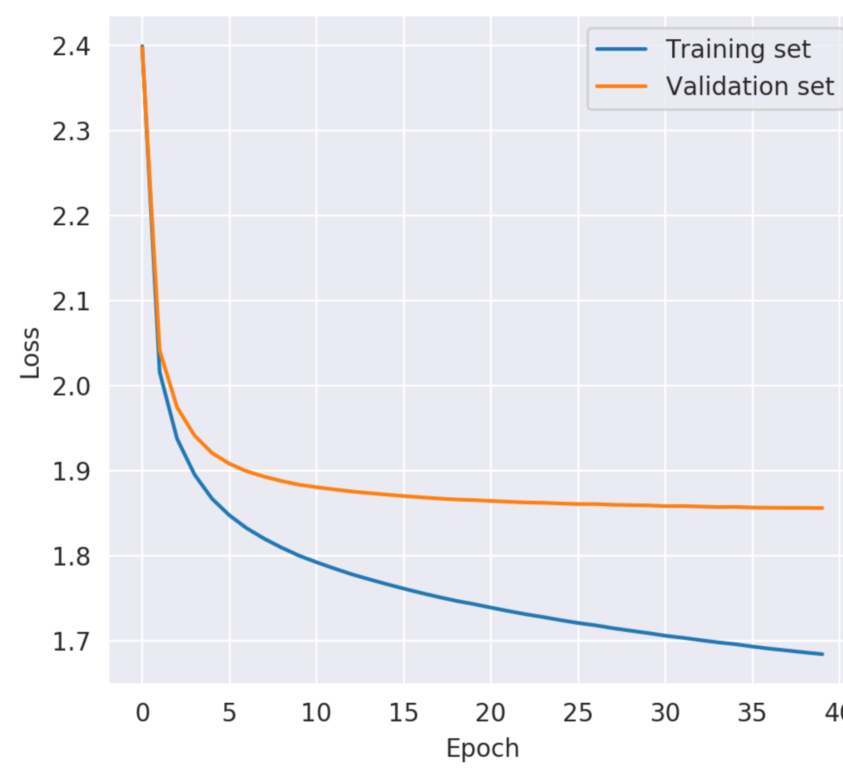


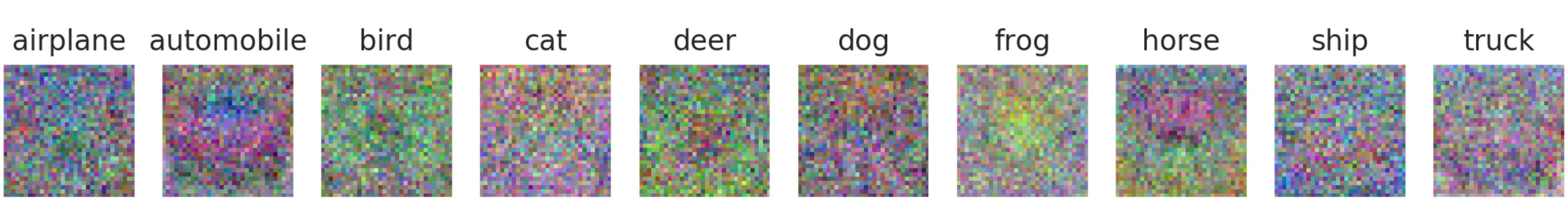
Now we also try to add some salt&pepper noise to the training batches. This will randomly set some pixels to either 0 or 1. Here's an example of what this does to the images.

This is the result when training with salt&pepper noise.

```
Model parameters:
   loss:         cross
   lambda:       0.0
   eta:          0.001
   n_epochs:     40
   n_batches:    100
   noise:        s&p

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          43.31%
   cost (final):                1.68
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          38.12%
   cost (final):                1.86
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          38.51%
   cost (final):                1.82
```



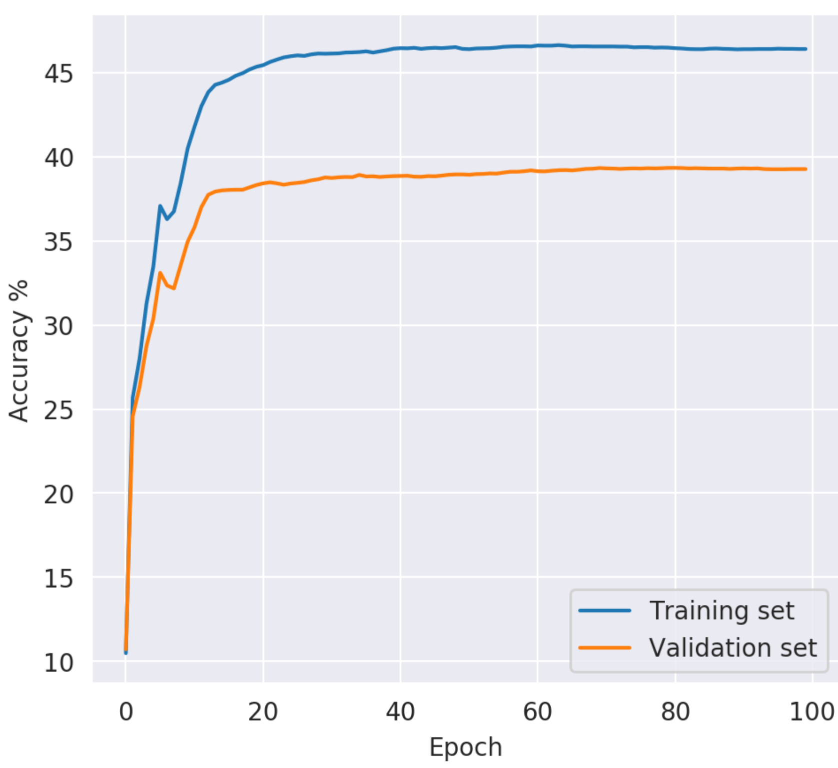


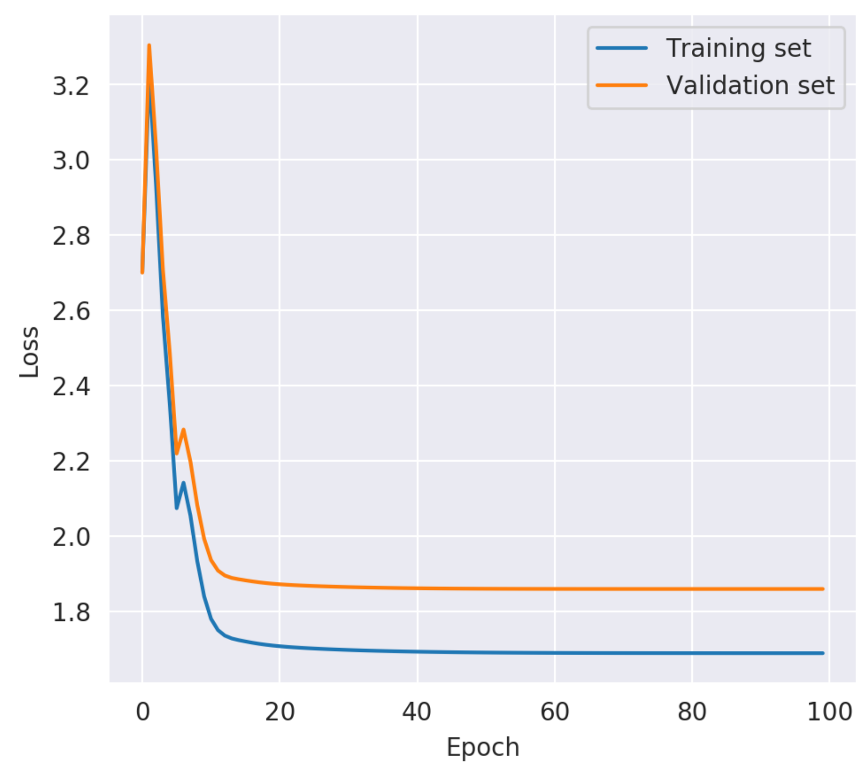


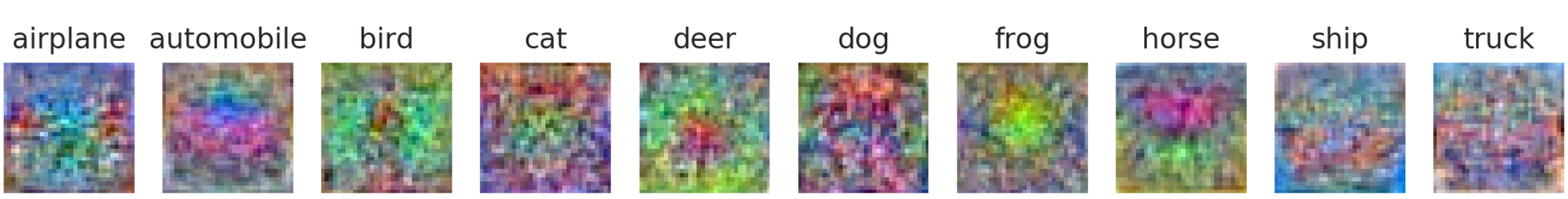
The models trained with noise added and no regularization showed similar results in terms of the accuracies on the test and training data as models that has some regularization introduced.

Now using what we've learned, we'll combine some of the tricks from above and tune our hyperparameters to see if we can get even better performance. We'll train the model for a longer time and add a decay to the learning rate. After some trial and error with the parameter values, the best performing model was chosen as

```
Model parameters:
   loss:         cross
   lambda:       0.1
   eta:          0.04
   n_epochs:     100
   n_batches:    500
   decay:        0.95

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          46.41%
   cost (final):                1.69
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          39.27%
   cost (final):                1.86
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          39.89%
   cost (final):                1.83
```







Where the best accuracy obtained on the test data is 39.89%.

Train the network by minimizing the SVM multi-class loss

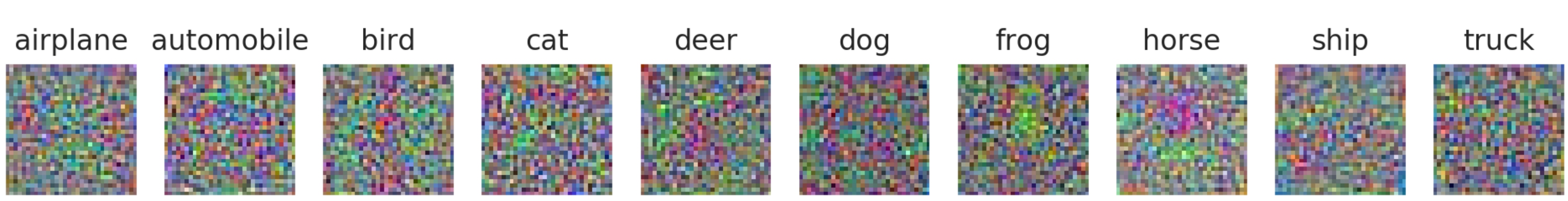
The SVM multi-class loss function with L2 regularization is given by

$$L_{svm}(D, W, b) = \frac{1}{|D|} \sum_{(\mathbf{x},y)} \sum_{j=1, j\neq y} max(0, s_j(\mathbf{x}, W, b) - s_y(\mathbf{x}, W, b) + 1) + \lambda \sum_{i,j} W_{ij}^2$$

Where $s_j(\mathbf{x}, W_j, b_j) = W_j^T \mathbf{x} + b_j$ is the score function. Once the methods for calculating the loss function and the corresponding gradients have been implemented we're ready to test the model. The same parameters are used as when the minimization was done with respect to the cross-entropy loss function in order to make a comparison between the two approaches. The figures below show the results obtained.

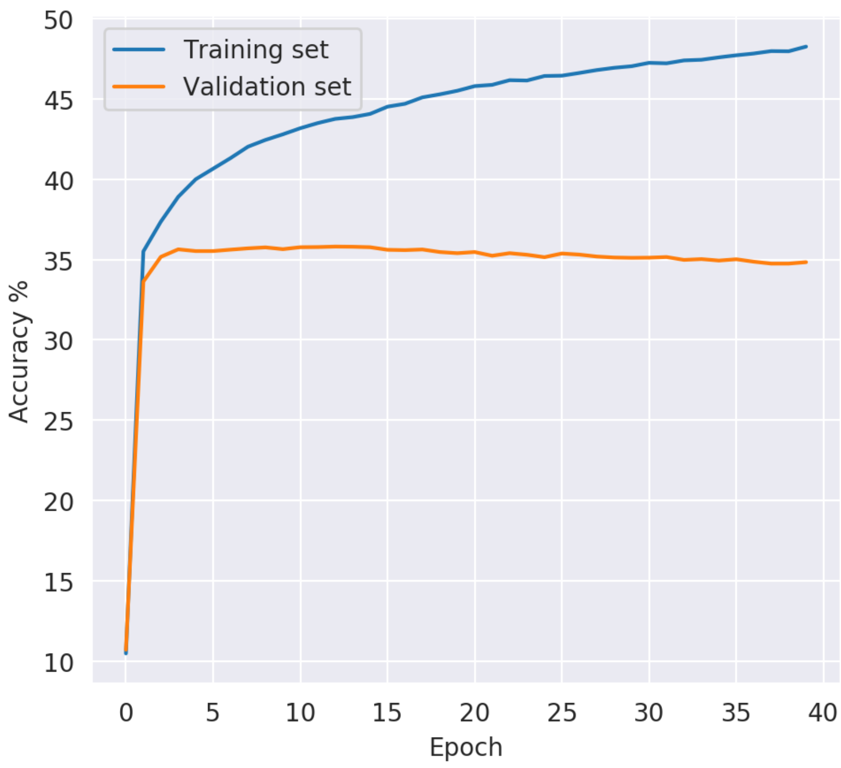
Model 1

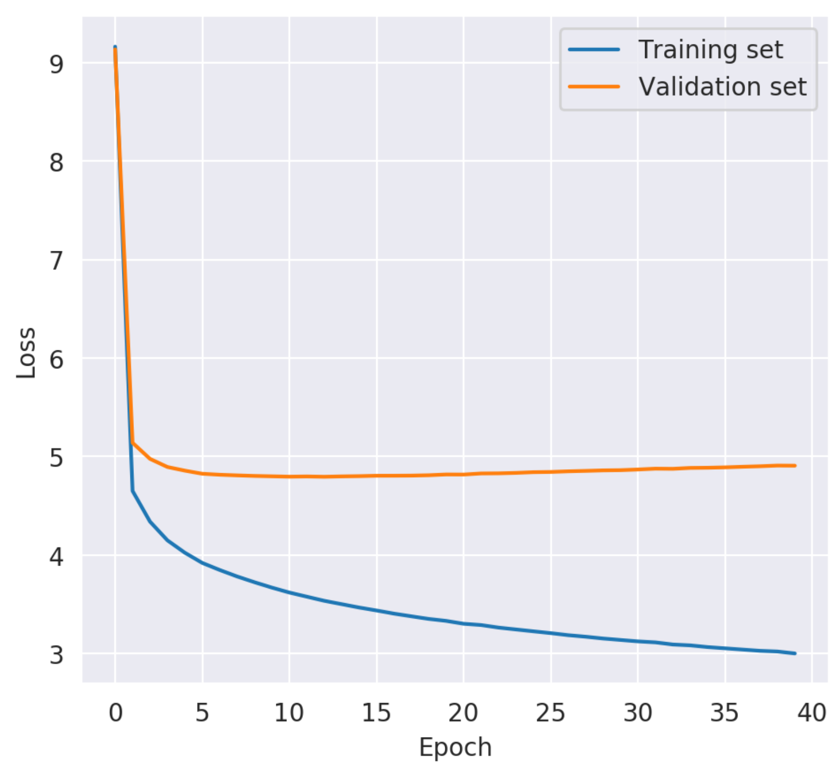
```
Model parameters:
   loss:         svm
   lambda:       0
   eta:          0.1
   n_epochs:     40
   n_batches:    100

Training data:
   accuracy (untrained):       10.48%
   accuracy (trained):         42.80%
   cost (final):               15.97
Validation data:
   accuracy (untrained):       10.71%
   accuracy (trained):         29.14%
   cost (final):               41.90
Test data:
   accuracy (untrained):       10.85%
   accuracy (trained):         30.04%
   cost (final):               41.43
```

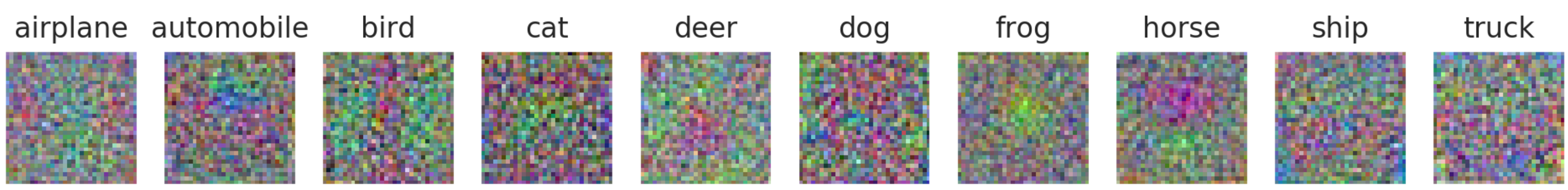


Model 2 - Decrease the learning rate

```
Model parameters:
   loss:         svm
   lambda:       0
   eta:          0.001
   n_epochs:     40
   n_batches:    100

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          48.26%
   cost (final):                3.00
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          34.84%
   cost (final):                4.91
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          35.35%
   cost (final):                4.86
```

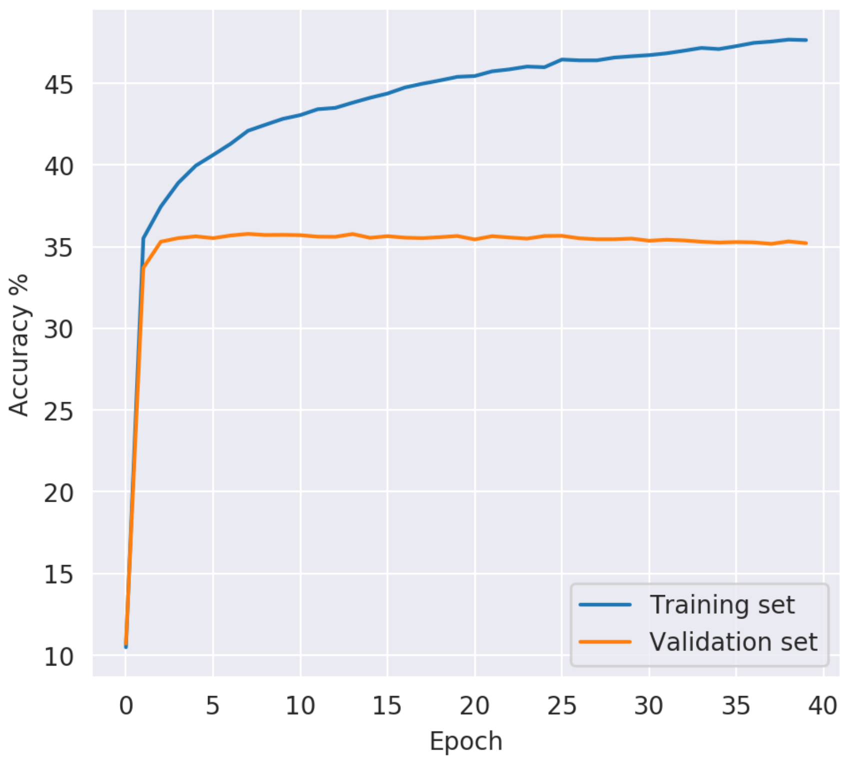


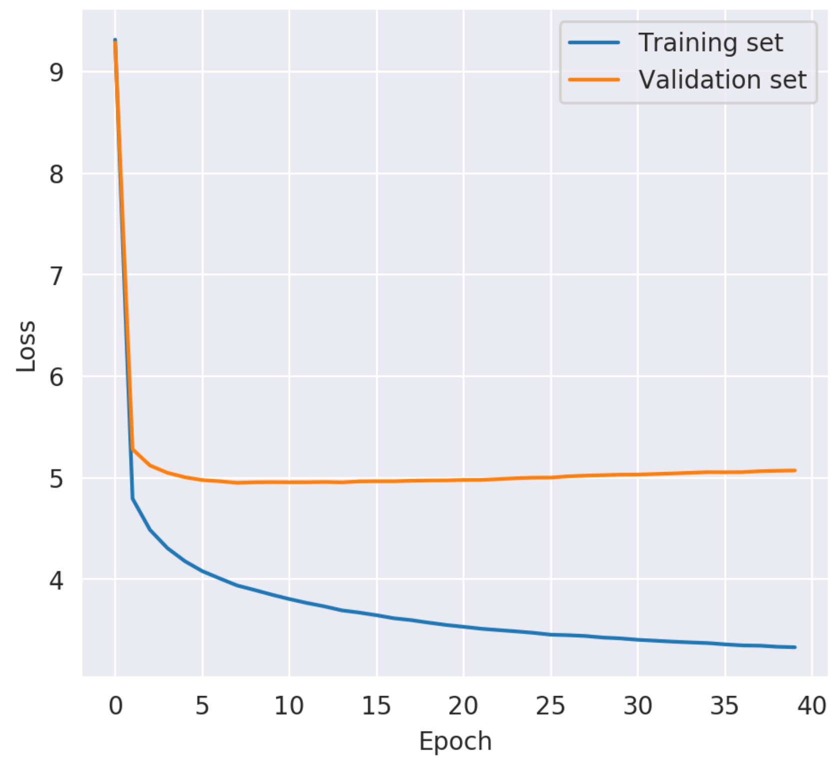


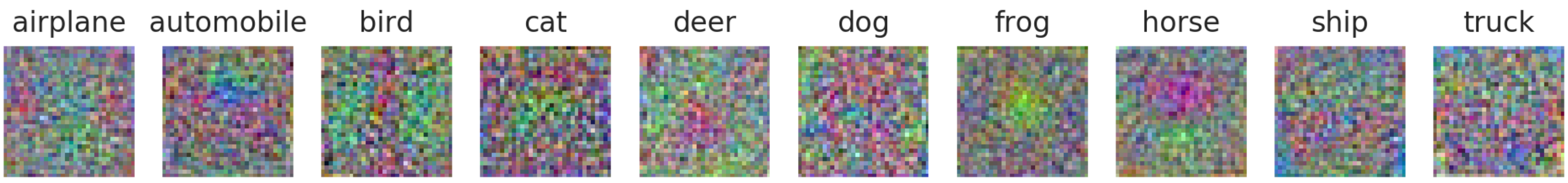


Model 3 - Add regularization to the loss function

```
Model parameters:
   loss:         svm
   lambda:       0.1
   eta:          0.001
   n_epochs:     40
   n_batches:    100

Training data:
   accuracy (untrained):        10.48%
   accuracy (trained):          47.64%
   cost (final):                3.33
Validation data:
   accuracy (untrained):        10.71%
   accuracy (trained):          35.21%
   cost (final):                5.07
Test data:
   accuracy (untrained):        10.85%
   accuracy (trained):          35.78%
   cost (final):                5.01
```

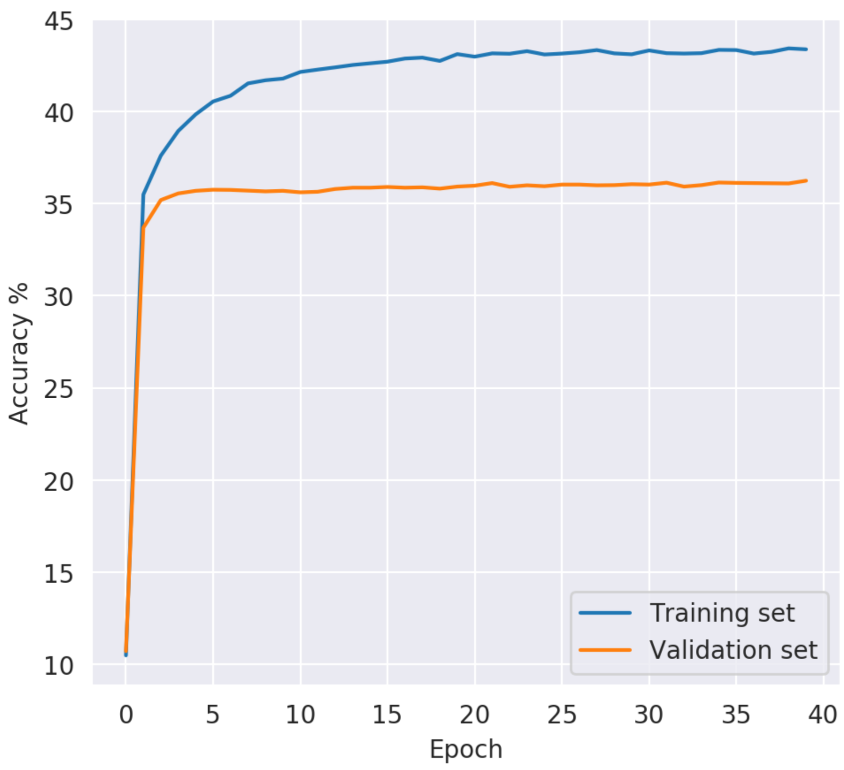


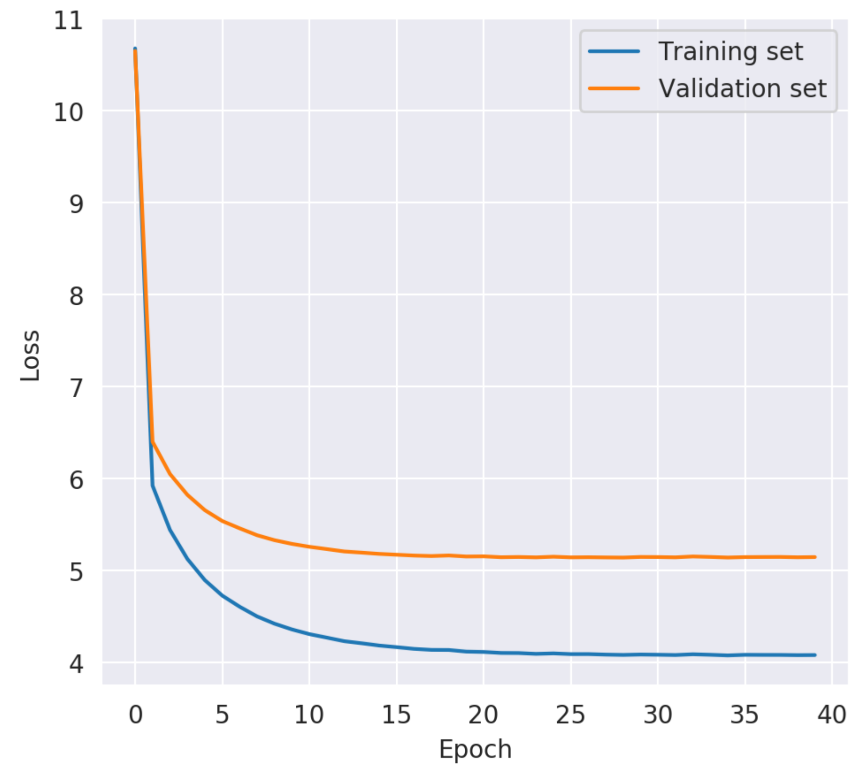


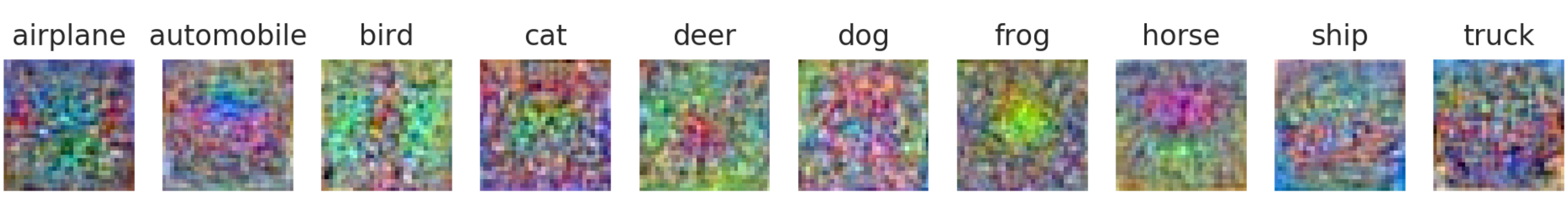


Model 4 - Further increase of the regularization

```
Model parameters:
   loss:        svm
   lambda:      1
   eta:         0.001
   n_epochs:    40
   n_batches:   100

Training data:
   accuracy (untrained):       10.48%
   accuracy (trained):         43.37%
   cost (final):               4.08
Validation data:
   accuracy (untrained):       10.71%
   accuracy (trained):         36.24%
   cost (final):               5.14
Test data:
   accuracy (untrained):       10.85%
   accuracy (trained):         36.62%
   cost (final):               5.06
```







The final accuracy on the test data for the chosen parameters and the two different loss-functions are shown in the tables below.

loss	λ	η	**Epochs**	**Batches**	**Accuracy on test data**
cross	0.0	0.1	40	100	28.70%
cross	**0.0**	**0.001**	**40**	**100**	**38.86%**
cross	**0.1**	**0.001**	**40**	**100**	**39.01%**
cross	**1.0**	**0.001**	**40**	**100**	**37.50%**

loss	λ	η	**Epochs**	**Batches**	**Accuracy on test data**
svm	**0.0**	**0.1**	**40**	**100**	**30.04%**
svm	0.0	0.001	40	100	35.35%
svm	0.1	0.001	40	100	35.78%
svm	1.0	0.001	40	100	36.62%

Conclusions

Comparing the performance of the model when minimizing the SVM multi-class loss vs the cross-entropy loss we can draw some conclusions. The svm-models 1,2 and 3 seem to suffer from overfitting as the accuracy on the training set continues to increase while it has leveled out for the validation set. As such they seem to require more aggressive regularization than the cross-entropy loss models in order to avoid overfitting. It is also clear from the table above that the prediction accuracies on the test data are slightly lower for the svm-models, by about 1-2 percentage points, relative to the cross-entropy counterparts. This can likely be addressed by fine-tuning the parameters for the svm loss, which should allow those models to perform approximately the same as the models that minimize the cross-entropy loss. All things considered I think the cross-entropy loss is the better alternative due to the slight performance advantage and because the gradient is easy to implement and efficient to compute.