

Team Indiscriminant Analysis Final Project: Cats vs Dogs

Featuring:

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Overview

- Safwat - Principal Component Analysis & Kohonen's Novelty
- Matt - Linear Discriminant Analysis
- Ángel - Deep Neural Network
- Aaron - Convolutional Neural Network, Support Vector Machine



Principal Component Analysis

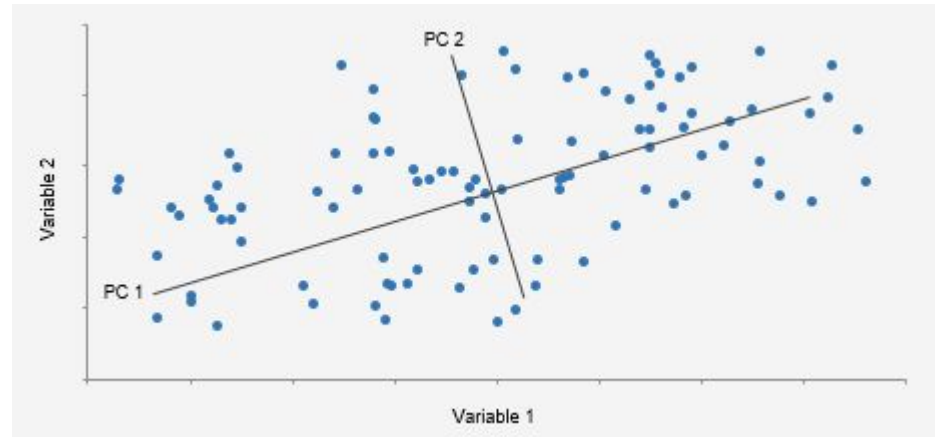
Goal: Reduce Dimensionality

Steps:

Center Data (mean subtract)

Project to new coordinates/dimensions

Select Dimensions to maximize variance



Overview



Mean subtract raw training data

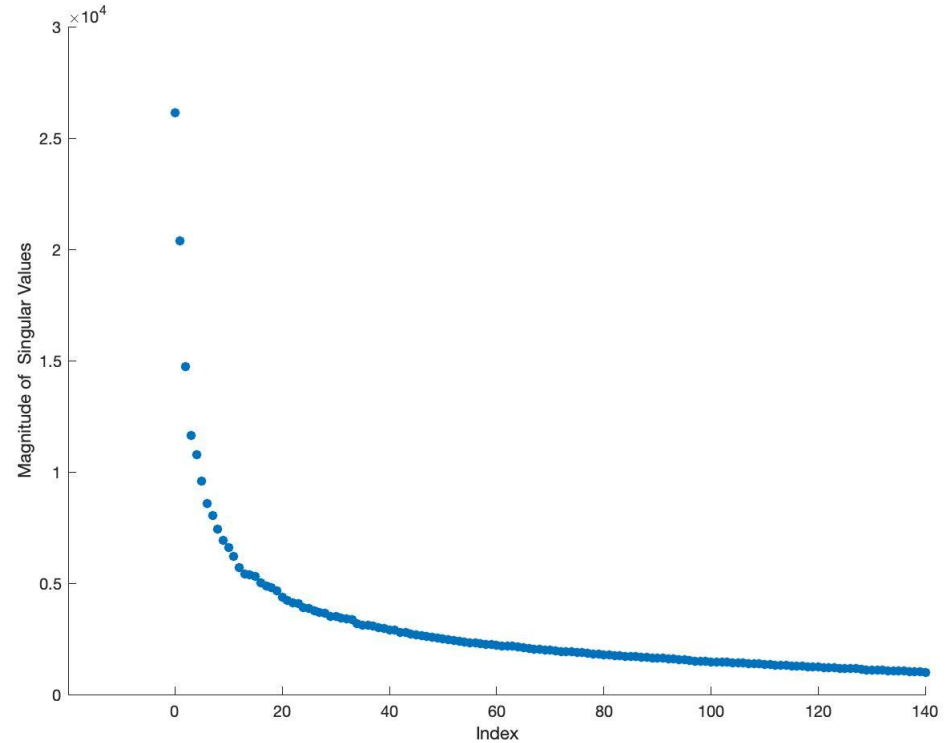
Run SVD

Select value for Dimension reduction

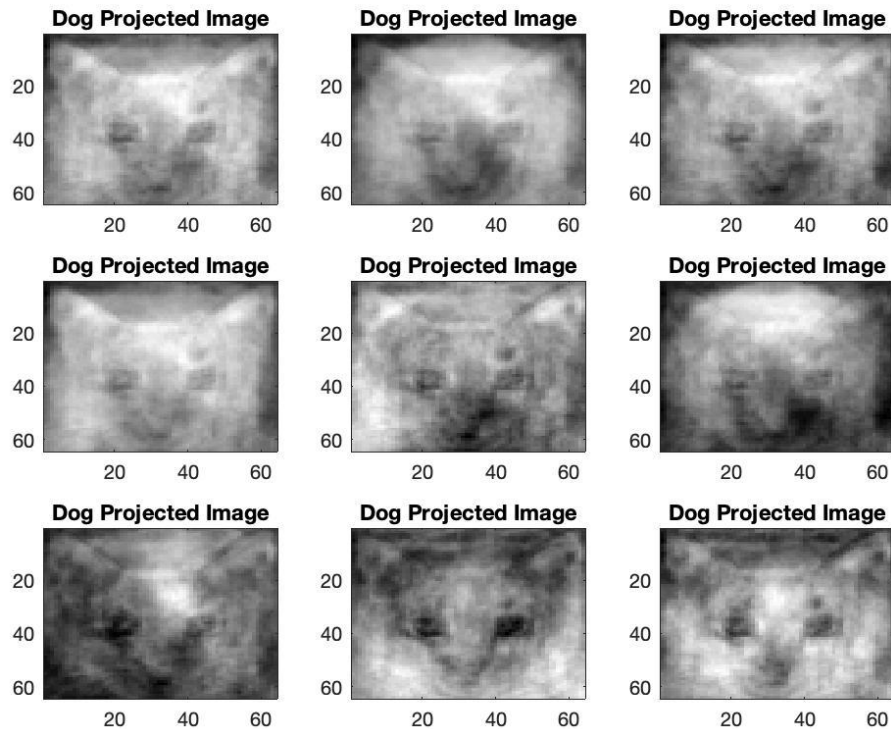
Test Data

Dog & Cat Coefficients and Principal Components

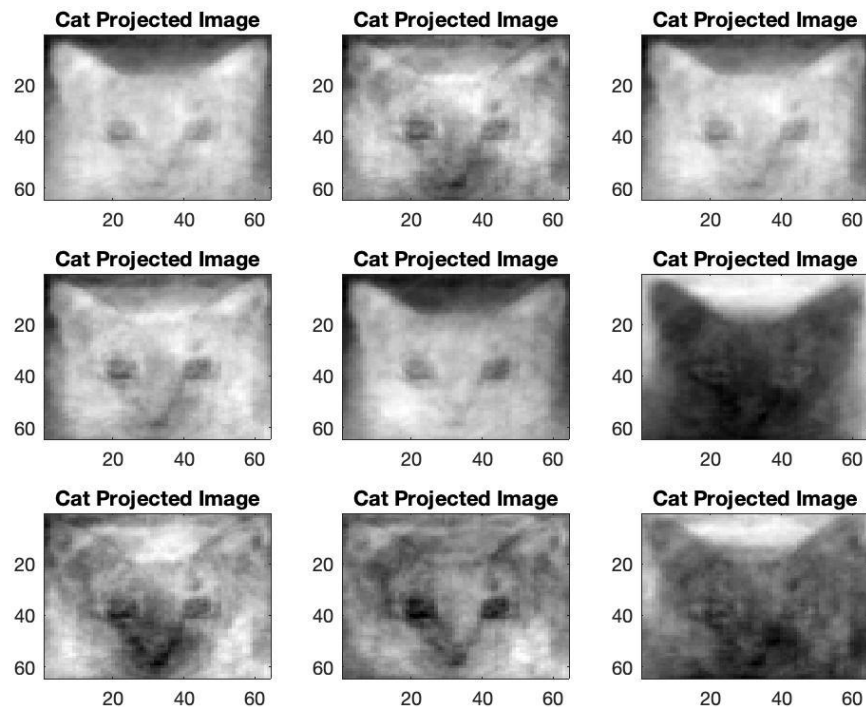
Reconstruct Images



Dog Reconstruction



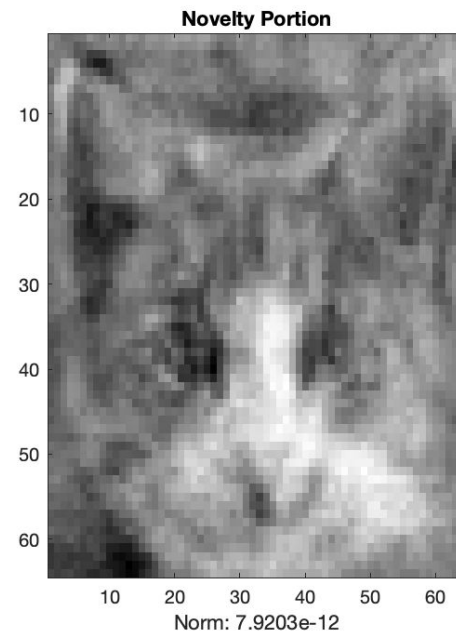
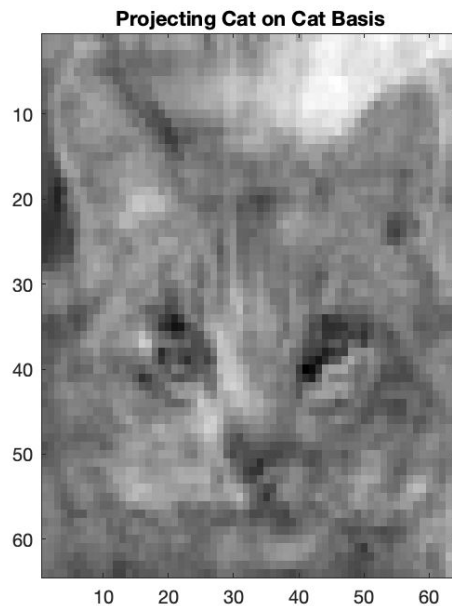
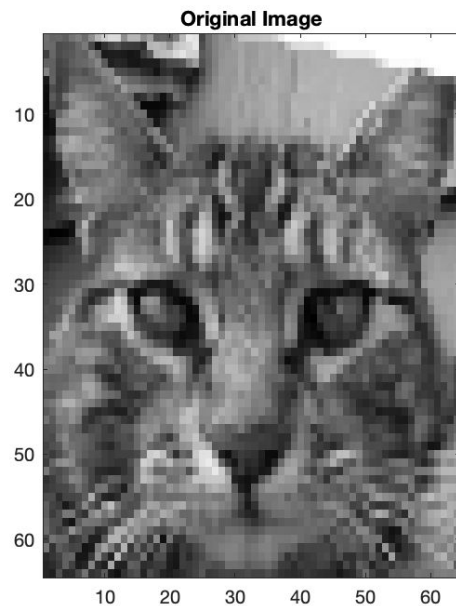
Cat Reconstruction



Kohonen Novelty Filter



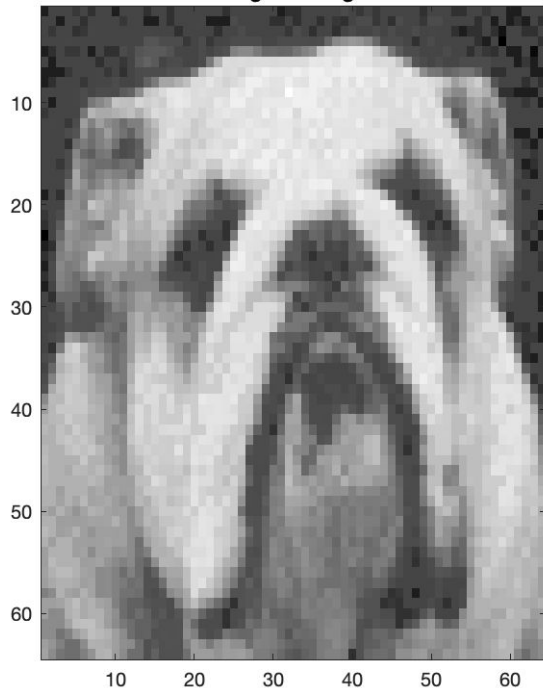
Cats Projected on Cats Basis



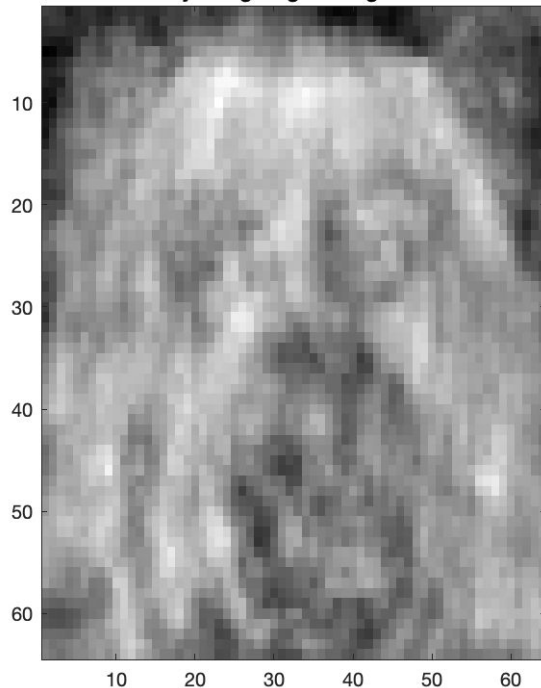


Dog Projected on Dog Basis

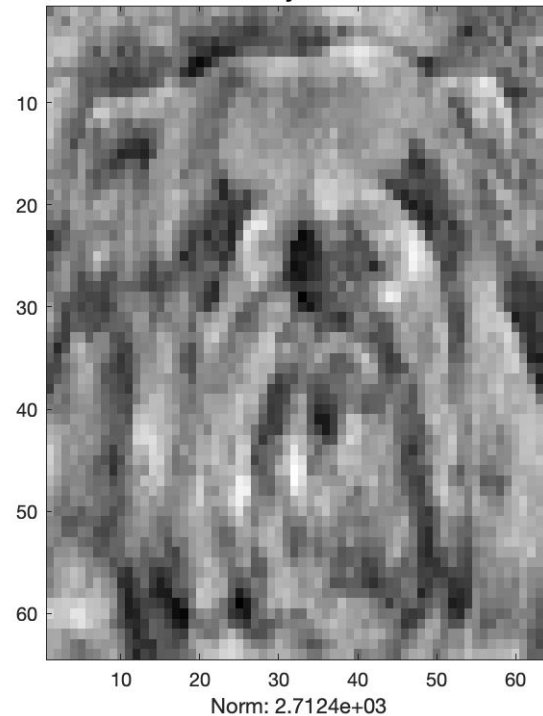
Original Image



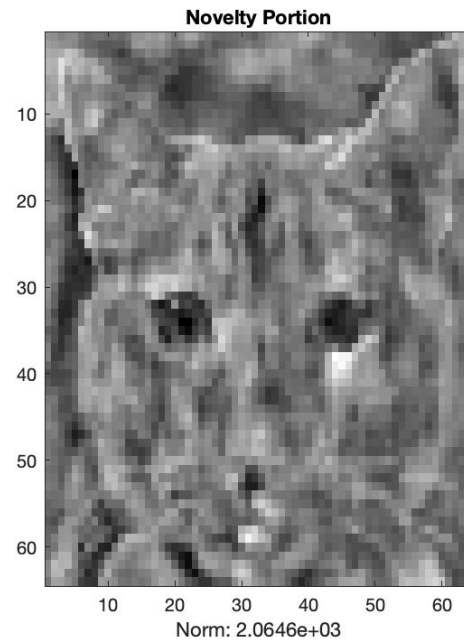
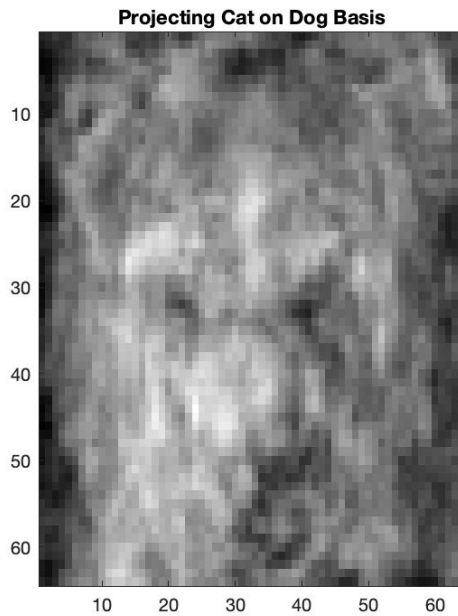
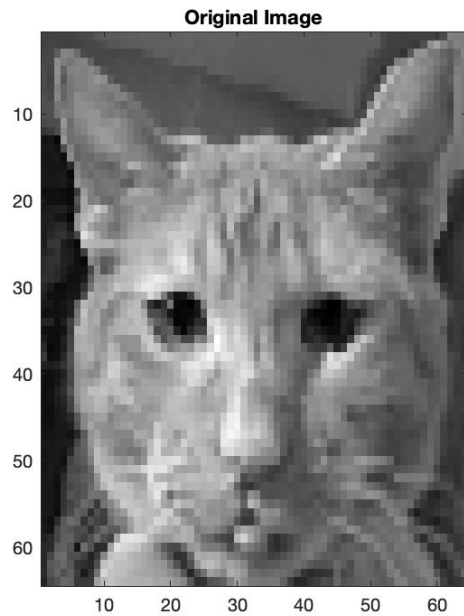
Projecting Dog on Dog Basis



Novelty Portion



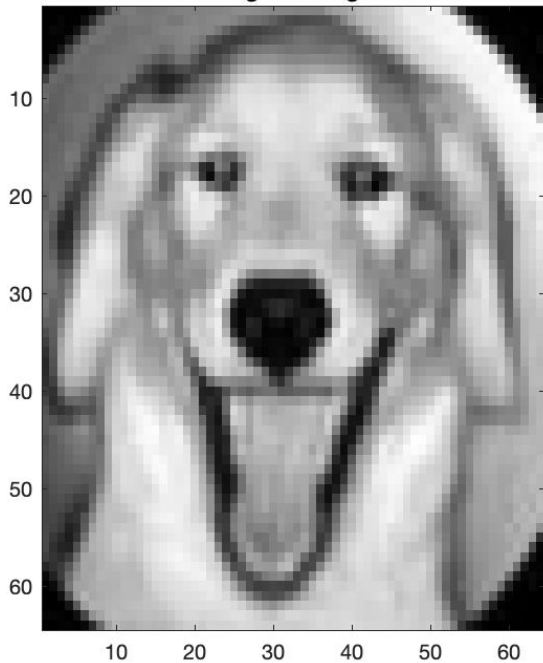
Projecting Cat on Dog Basis



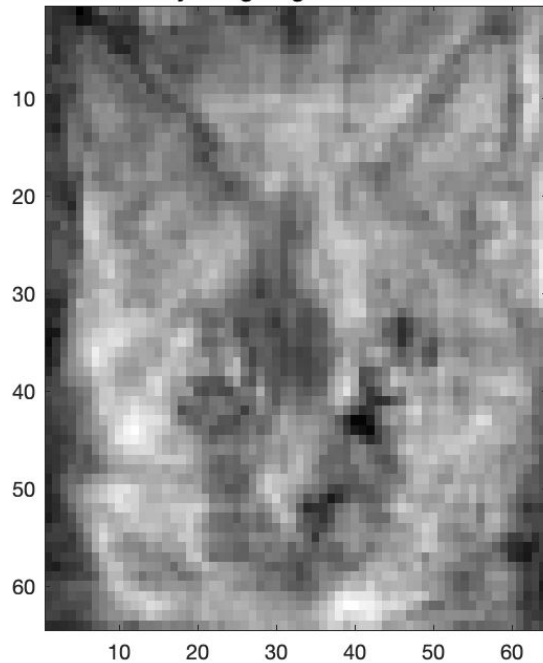


Dogs Projected on Cat Basis

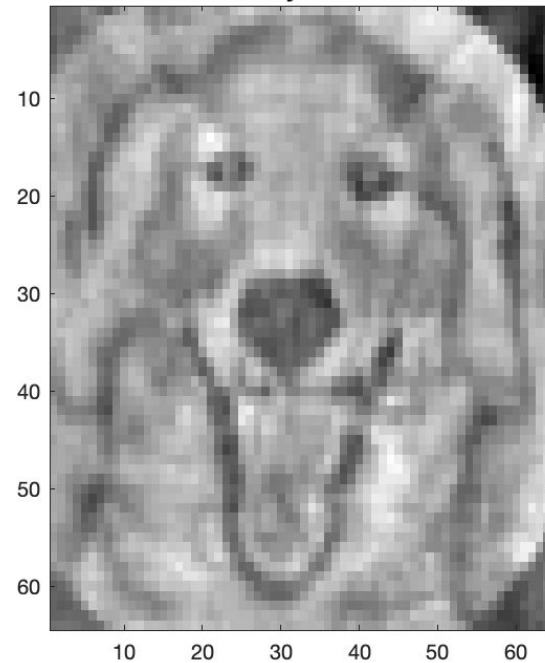
Original Image



Projecting Dog on Cat Basis



Novelty Portion



Norm: 3.2464e+03



Confusion Matrix & Accuracy

C =

15	4
2	17

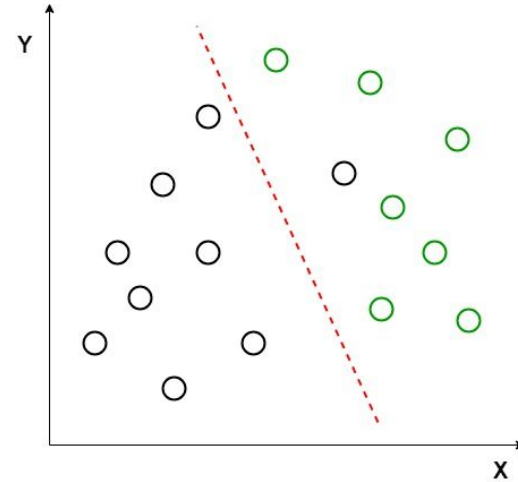
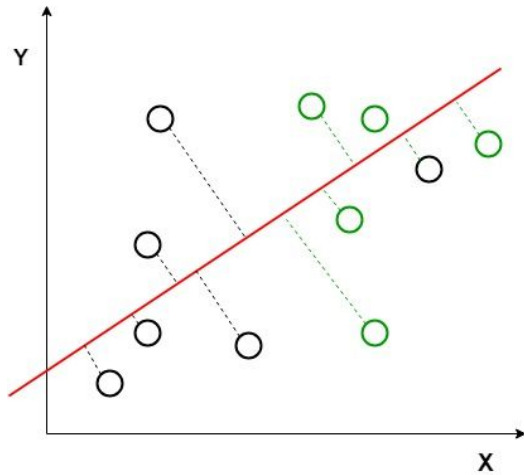
```
>> Accuracy=(15+17)/(15+17+2+4)
```

Accuracy =

0.8421

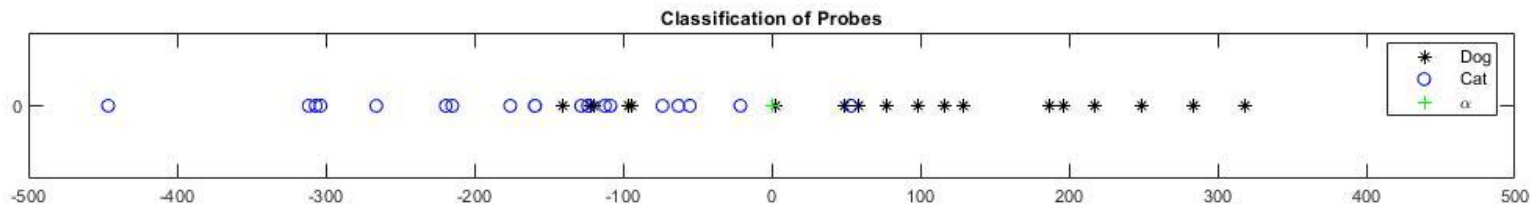


Linear Discriminant Analysis





Initial Results



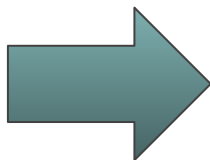
Confusion Matrix		Projected	
		Dog	Cat
Actual	Dog	14	5
	Cat	1	18

- Accuracy: 84.2%
- Better at classifying cats as cats



Filters

Original



3x3 Blur and Laplacian



Increased Contrast



5x5 Blur

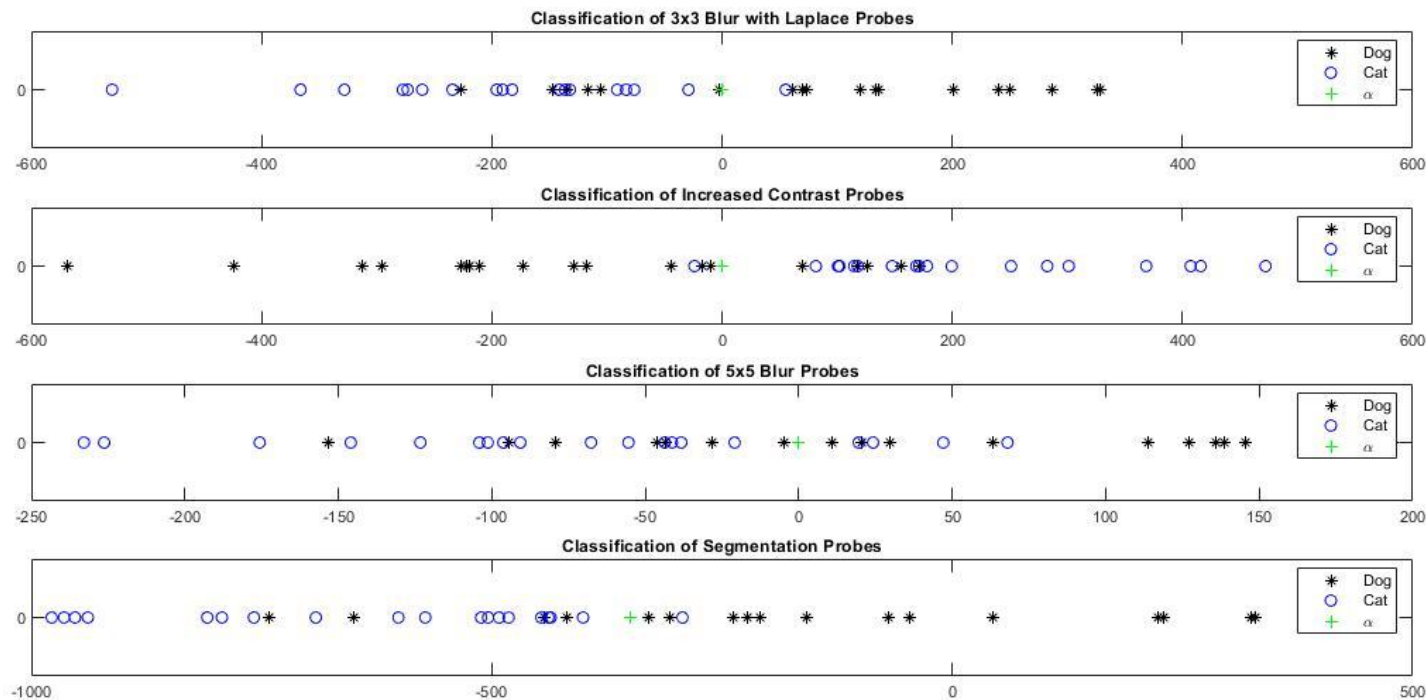


Image Segmentation





Filtered Results





Filtered Results - Cont.

3x3 Blur + Laplacian Acc: 81.6%		Projected	
		Dog	Cat
Actual	Dog	13	6
	Cat	1	18

5x5 Blur Acc: 71.1%		Projected	
		Dog	Cat
Actual	Dog	12	7
	Cat	4	15

Increased Contrast Acc: 84.2%		Projected	
		Dog	Cat
Actual	Dog	14	5
	Cat	1	18

Segmentation Acc: 86.8%		Projected	
		Dog	Cat
Actual	Dog	15	4
	Cat	1	18





Data Preparation:

```
```\r }\ntrain <- readMat("Desktop/MATH521/Final Project/tiffstudentdata_raw_vectorized.mat")$X\n test  <- readMat("Desktop/MATH521/Final Project/PatternRecAns.mat")$TestSet\n\ny_test  <- readMat("Desktop/MATH521/Final Project/PatternRecAns.mat")$hiddenlabels\n\nn <- 80 # sample size\nx = sample(1, replace=TRUE, size=n)\ny = sample(0, replace=TRUE, size=n)\ny_train = c(x,y)\n\ntraining = data.matrix(train, rownames.force = NA)\ntest      = data.matrix(test, rownames.force = NA)\n\nx_training = t(training)\nx_test     = t(test)\n\n```\n
```



# R & Python: Keras Package

```
```{r }
model <- keras_model_sequential()
model %>%
  # Directly outputs positive values. Zeros negatives values.
  # 32 nodes.
  layer_dense(units = 32, activation = 'relu') %>%

  layer_dense(units = 1, activation = 'sigmoid') #
```
```

- Layer\_Dense
  - Nodes = 32
  - Relu = Rectified Linear Activation Function
- Layer\_Dense
  - Level = 1
  - Output: Sigmoid (Logistic/Binary)

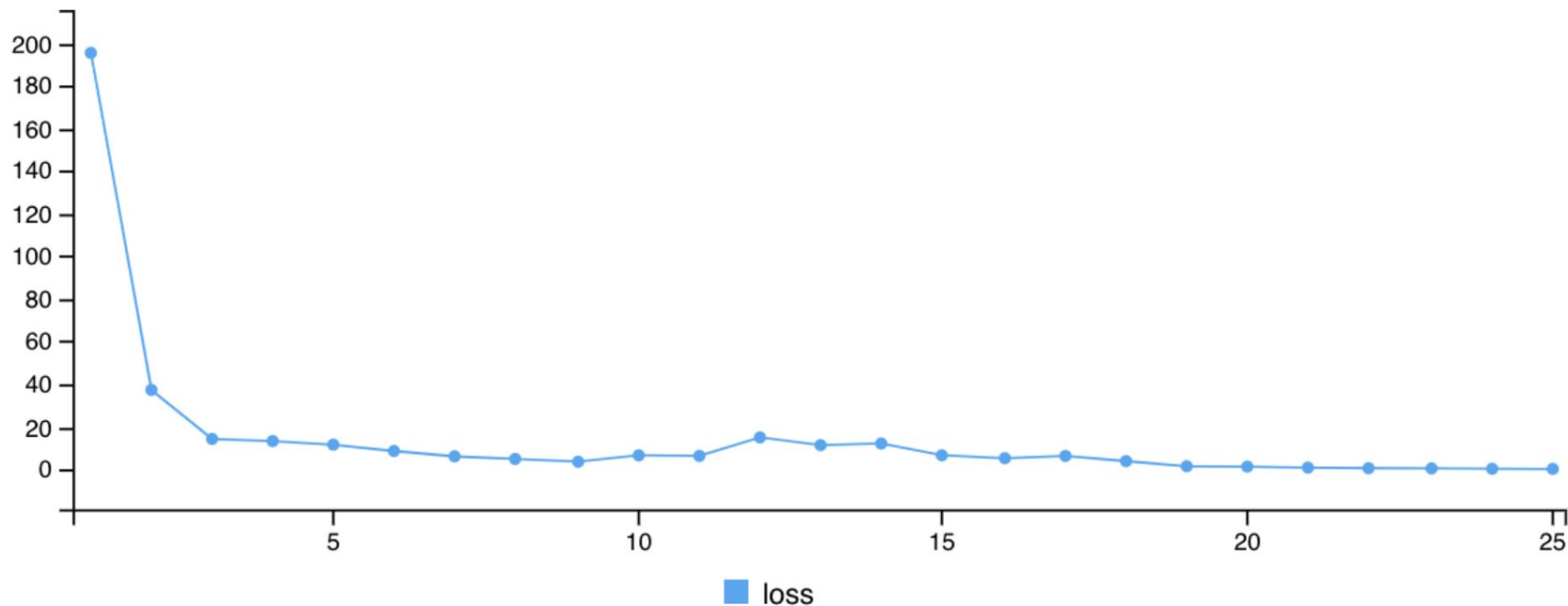


# Compile: Learning Rate, Probabilistic Losses, and Accuracy

- Stochastic Optimizer (Learning Rate):
  - Adam Algorithm: Stochastic Gradient Descent Method that estimates 1st and 2nd moments.
- Loss:
  - Cross Entropy =  $E_p[q]$ ,  $q = 1 - p$ ,  $p \sim \beta(\alpha, \beta)$
  - Loss between predicted and actual
- Metrics (Accuracy)
  - Outputs a variable that counts true and false frequency

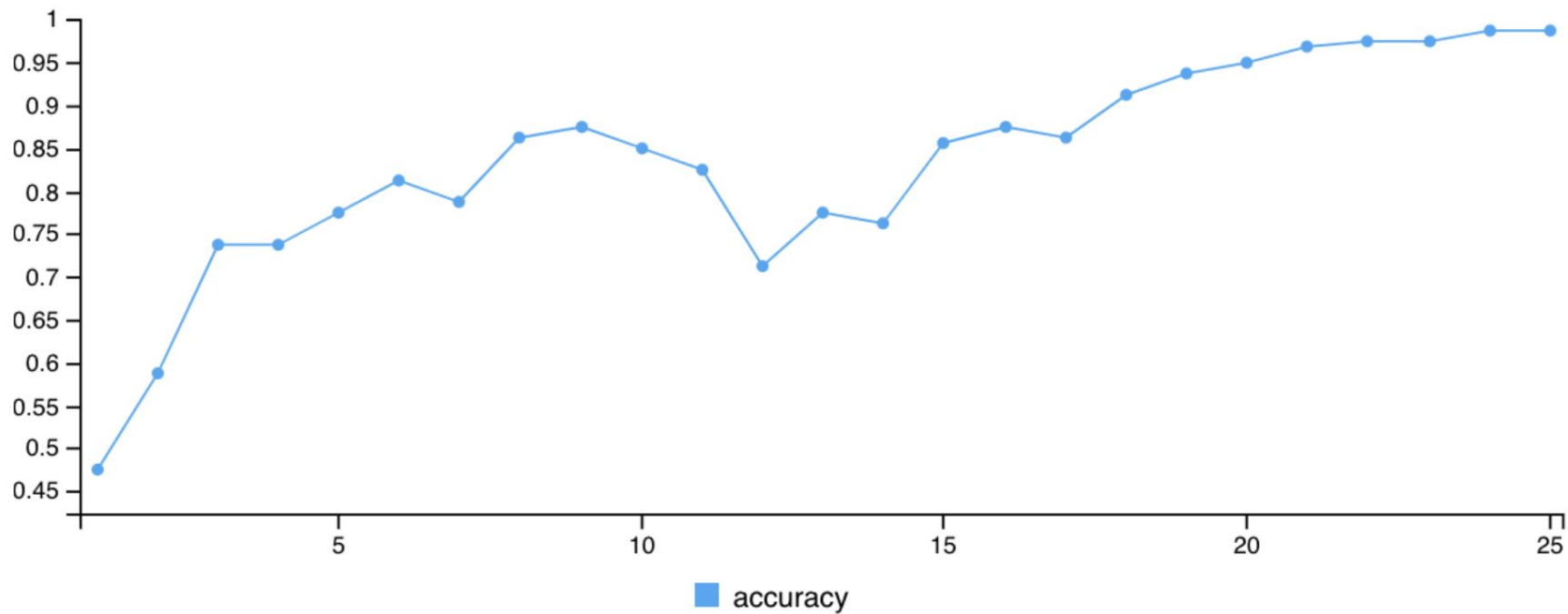
```
```{r }  
model %>% compile(  
  optimizer = 'adam', loss = 'binary_crossentropy', metrics = c('accuracy')  
)  
```
```

# Cross Entropy: Error between True Labels & Predicted Labels



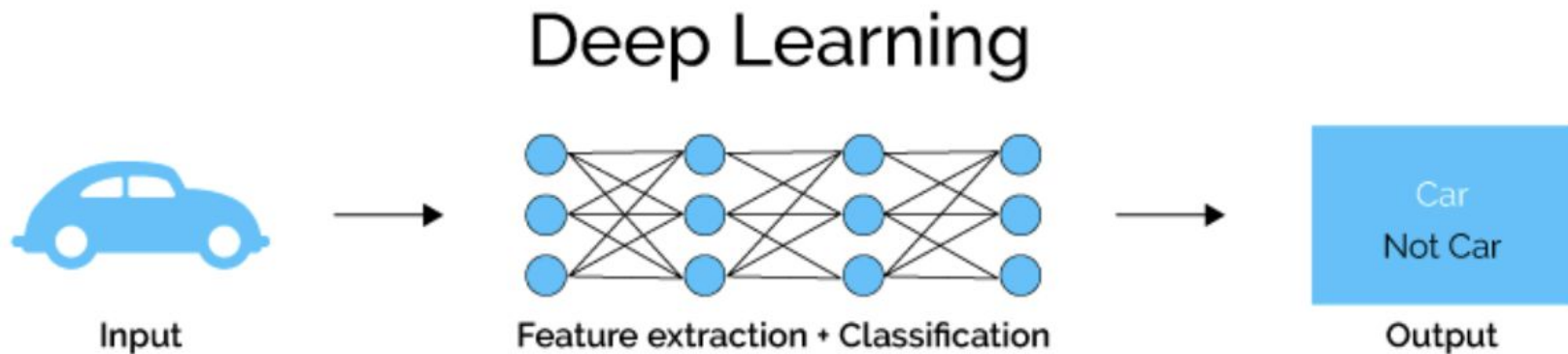


# Accuracy



# Fit the Model

Epochs: Defined by an arbitrary cutoff. An interaction through the entire dataset.  
Verbose: “How do you want to see the process?”



```
model %>% fit(x_training ,y_train , epochs = 25, verbose = 2)
```





## Prediction:

---

### Confusion Matrix and Statistics

| Prediction | Reference |    |
|------------|-----------|----|
|            | 0         | 1  |
| 0          | 10        | 9  |
| 1          | 0         | 19 |

Accuracy : 0.7632

95% CI : (0.5976, 0.8856)

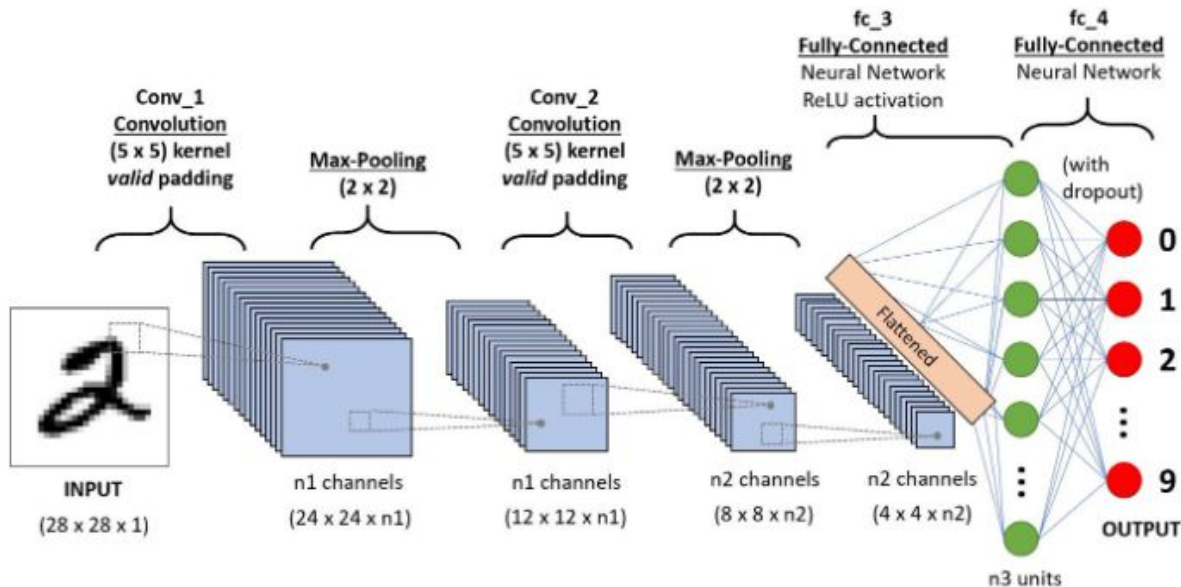
# Convolutional Neural Network

|                 |                 |                 |   |   |
|-----------------|-----------------|-----------------|---|---|
| 1 <sub>x1</sub> | 1 <sub>x0</sub> | 1 <sub>x1</sub> | 0 | 0 |
| 0 <sub>x0</sub> | 1 <sub>x1</sub> | 1 <sub>x0</sub> | 1 | 0 |
| 0 <sub>x1</sub> | 0 <sub>x0</sub> | 1 <sub>x1</sub> | 1 | 1 |
| 0               | 0               | 1               | 1 | 0 |
| 0               | 1               | 1               | 0 | 0 |

Image

|   |  |  |
|---|--|--|
| 4 |  |  |
|   |  |  |
|   |  |  |

Convolved  
Feature

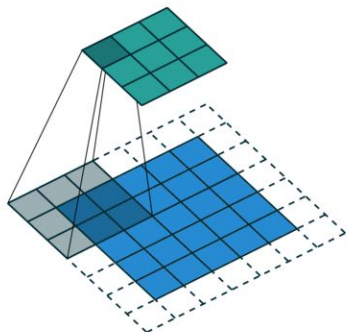


A CNN sequence to classify handwritten digits



# Convolutional Neural Network

Padding (Same)

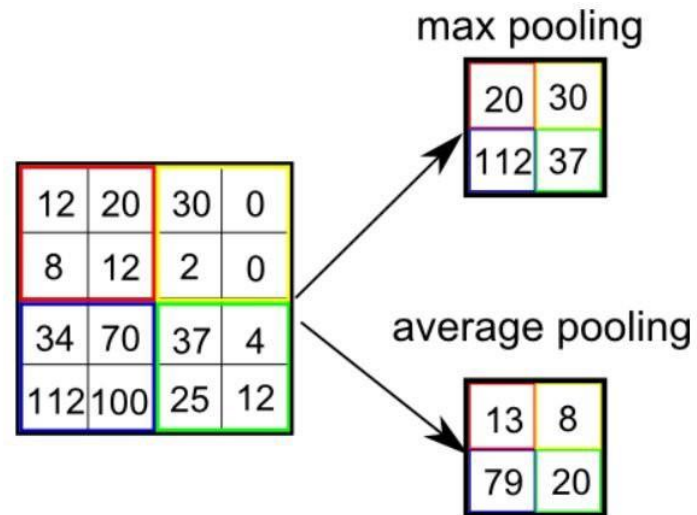


Pooling Layer

|     |     |     |
|-----|-----|-----|
| 3.0 | 3.0 | 3.0 |
| 3.0 | 3.0 | 3.0 |
| 3.0 | 2.0 | 3.0 |

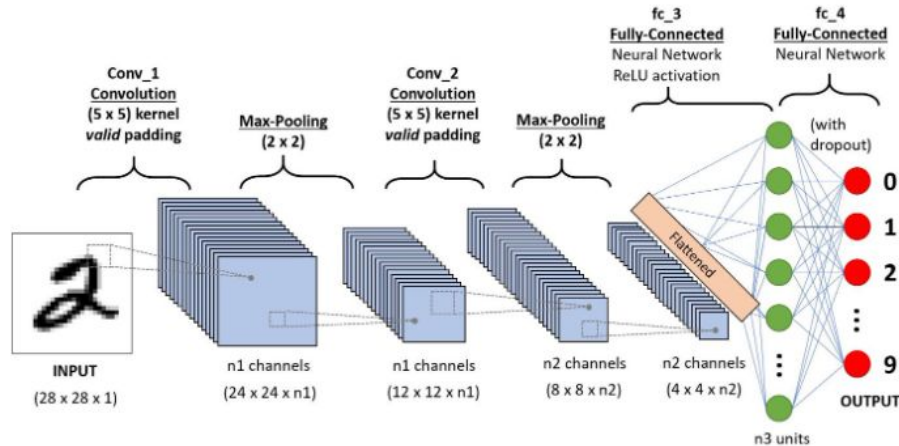
|   |   |   |   |   |
|---|---|---|---|---|
| 3 | 3 | 2 | 1 | 0 |
| 0 | 0 | 1 | 3 | 1 |
| 3 | 1 | 2 | 2 | 3 |
| 2 | 0 | 0 | 2 | 2 |
| 2 | 0 | 0 | 0 | 1 |

Max vs Average Pooling



# Convolutional Neural Network

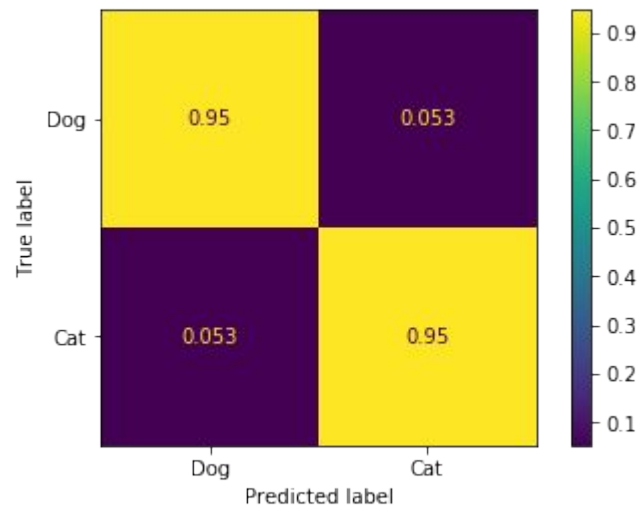
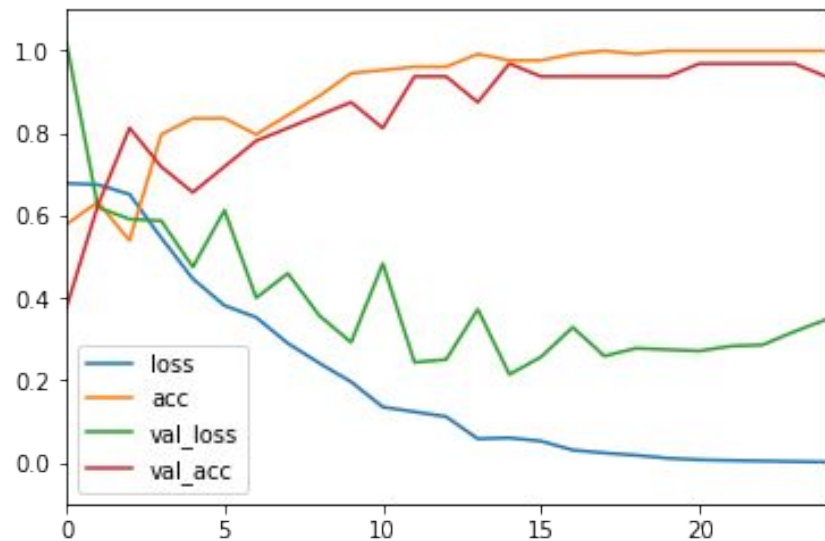
```
model = keras.Sequential()
model.add(keras.layers.Conv2D(32, (3,3), input_shape = (64,64,1), activation='relu', padding='same'))
model.add(keras.layers.MaxPooling2D(2,2))
model.add(keras.layers.Conv2D(64, 3, activation='relu', padding='same'))
model.add(keras.layers.MaxPooling2D(2))
model.add(keras.layers.Conv2D(128, 3, activation='relu', padding='same'))
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(32, activation='relu'))
model.add(keras.layers.Dense(1, activation='sigmoid'))
```



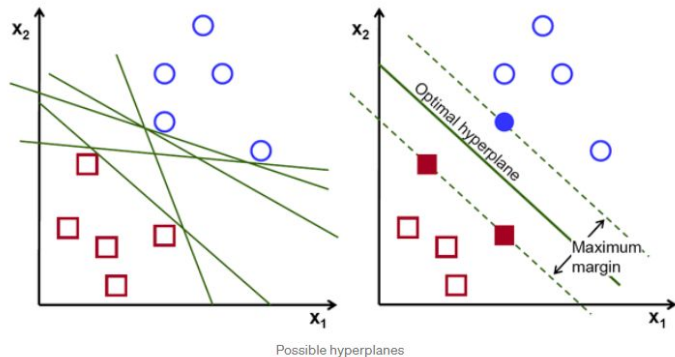
A CNN sequence to classify handwritten digits



# Convolutional Neural Network



# Support Vector Machine

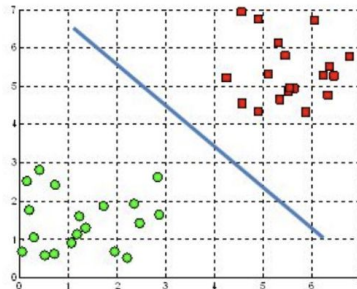


Possible hyperplanes

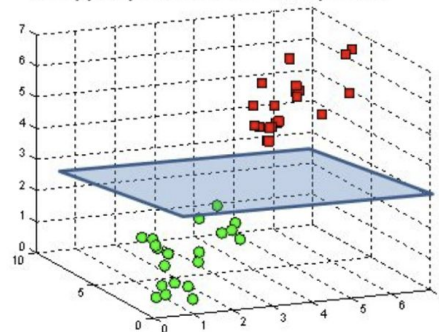
The objective of the support vector machine algorithm is to find a **hyperplane** in an N-dimensional space (N — the number of features) **that distinctly classifies the data points.**

Our objective is to **find a plane that has the maximum margin**, i.e. the maximum distance between data points of both classes.

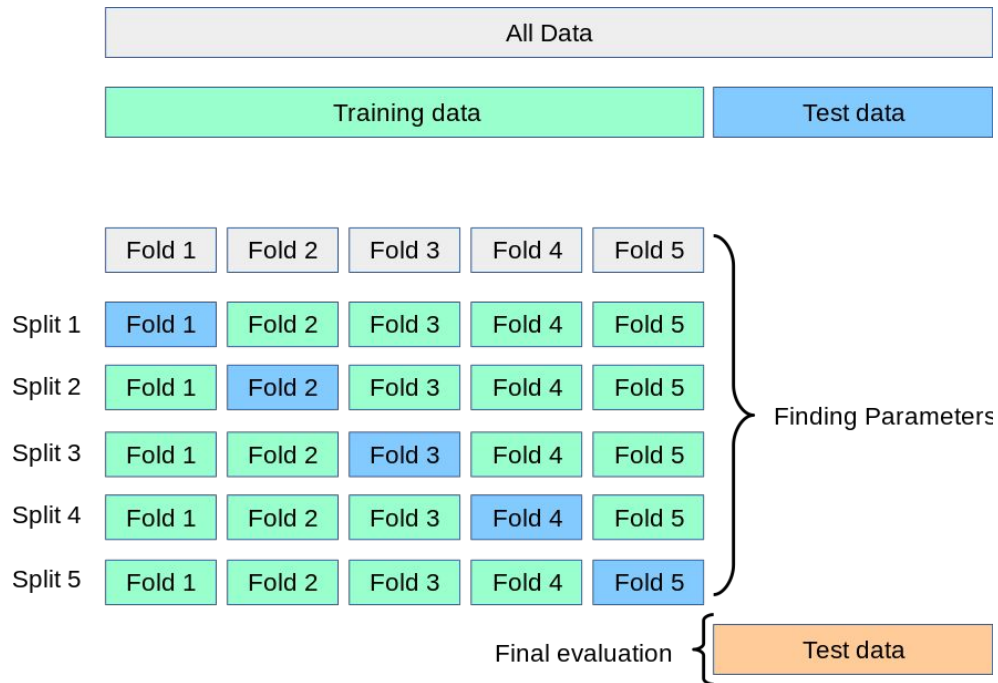
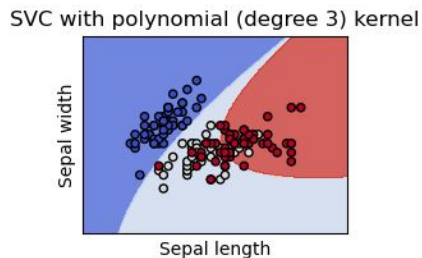
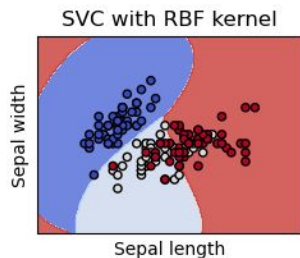
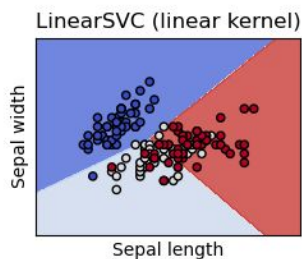
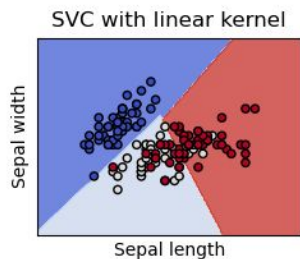
A hyperplane in  $\mathbb{R}^2$  is a line



A hyperplane in  $\mathbb{R}^3$  is a plane

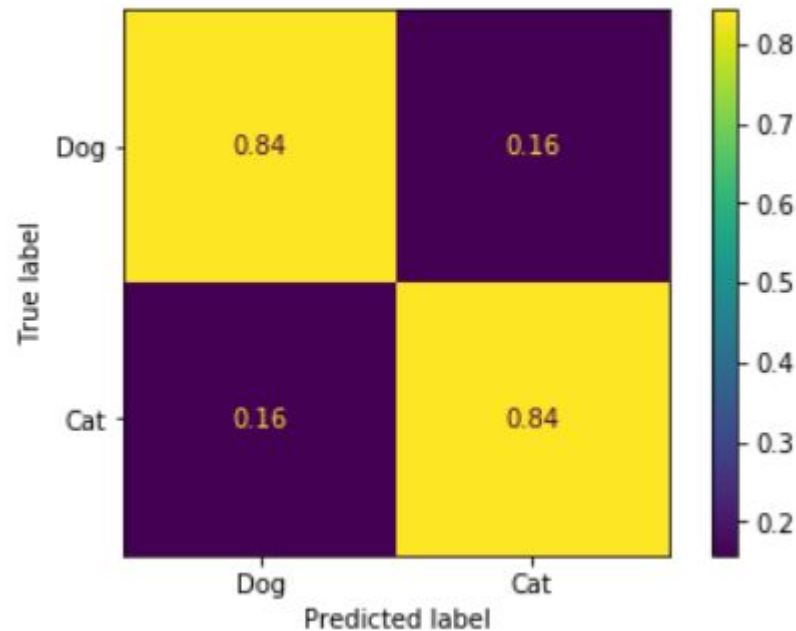
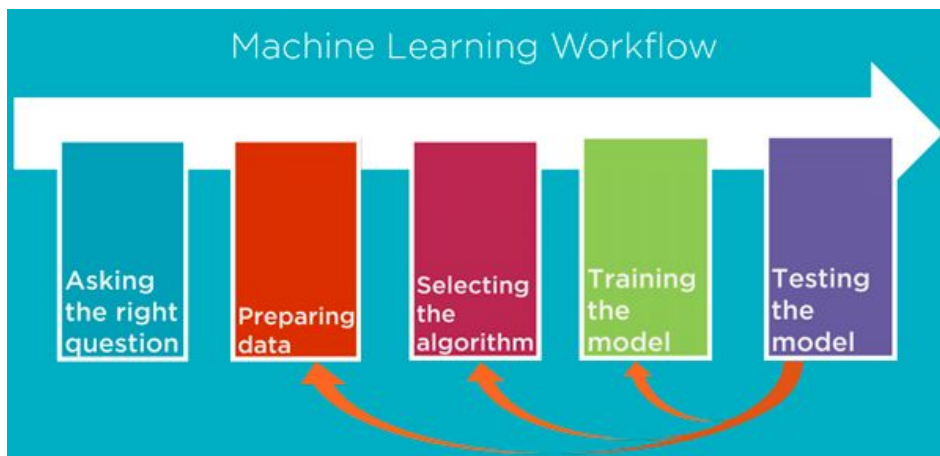


# Support Vector Machine



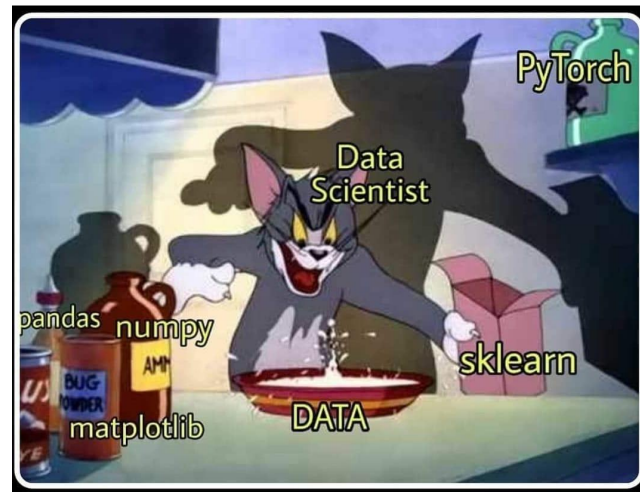
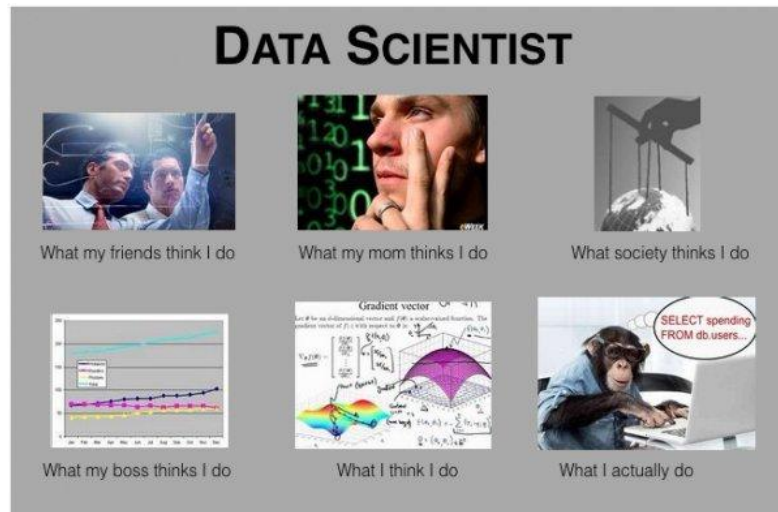


# Support Vector Machine





# Q&A and Feedback



Thanks!