# Automatic Detection of Whale Lunges: A Deep Learning Approach

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# Roadmap

- Background
- Formal Problem Definition
- Dataset
- Results
- Algorithm Details
- Neural Networks Overview

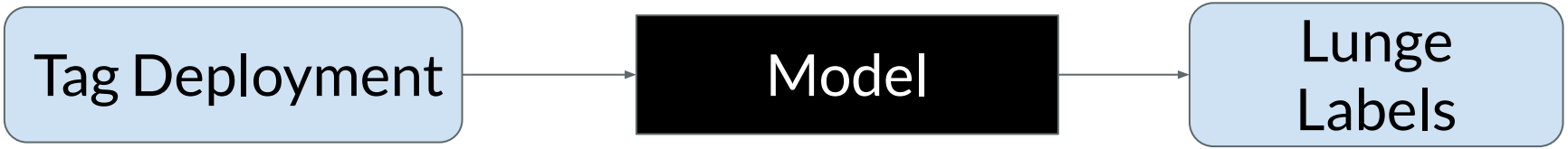
# Background

- Variety of whale species engage in lunge-feeding behavior
- Analysis of such behavior is important for understanding these species
- Hand-labeling of lunge feeding times is inefficient use of time

We want to improve this process.

# Objective

## Automate the labeling process!



# Formal Problem Definition

**Data:**

$\{x^{(t)} : t \in \{1, 2, ..., T\}\}$ Deployment time series from accelerometer measurements

$y^{(t)} \in \{0, 1\}$ Hand-labeled lunge times

**Problem:**

Given an unlabeled deployment, predict the lunge times.

# Dataset

| **Species** | Blue Whale | Minke Whale |
|---|---|---|
| **Number of Deployments** | 29 | 6 |
| **Number of Lunges** | 4768 | 6151 |
| **Hours of Data** | 319.7 | 127.3 |
| **Sampling Rate** | 10 Hz | 10 Hz |

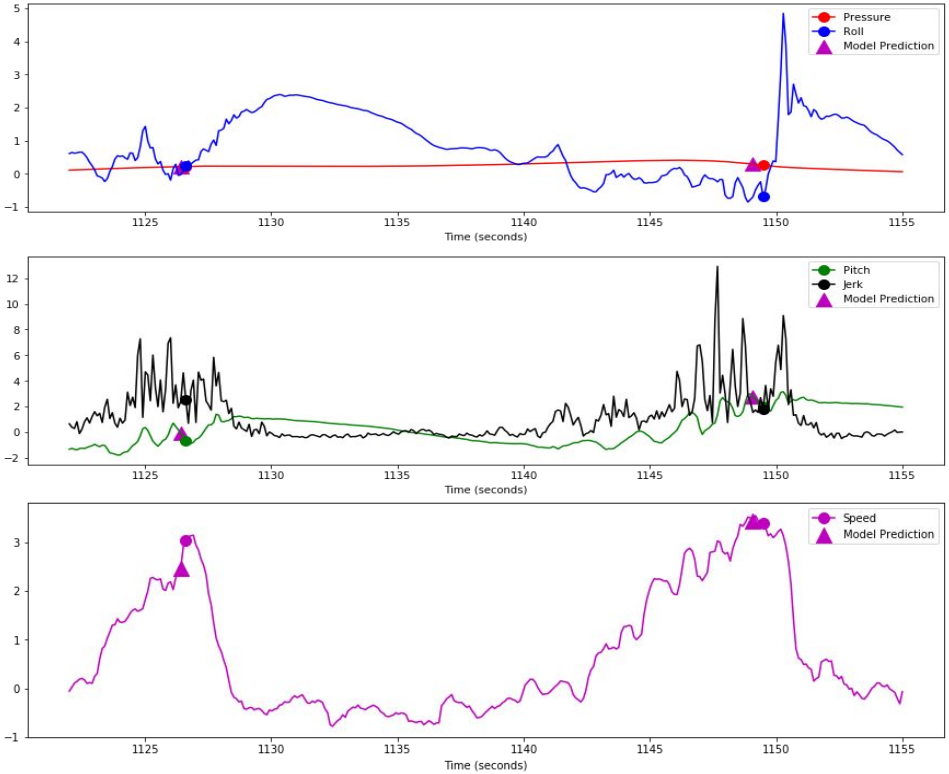
# Feature Selection And Preprocessing

- Features Used
  - Speed
  - Pitch
  - Jerk
  - Roll
  - Pressure (proxy for depth)
- Preprocessing
  - Time series are standardized (mean=0, standard deviation=1) per deployment

# Generalization: Key Goal of Machine Learning

- Want model to perform well on unseen data
- To achieve this, split deployments into 3 sets: training, validation, test
  - Model will see the training set but not the others.
- Training set (~80% of lunges)
  - Learning algorithm needs data to learn how to predict
- Validation set (~10% of lunges)
  - Fake test set to prevent overfitting to training set and tune accordingly
- Test set (~10% of lunges)
  - Real world performance test to assess model at the very end

# Example Output (Minke Val Deployment)



# Metrics

- A predicted lunge is considered correct it is within 5 seconds of a true lunge
  - True lunge = expert-labeled lunge
- True positive rate:
  - Rate at which true lunges are detected
- False positive rate:
  - Rate at which false predictions are made
- Number of correct predictions
- Number of predictions
- Number of overcounted correct predictions
- Average prediction error (in seconds)
- F_1 and F_2 scores

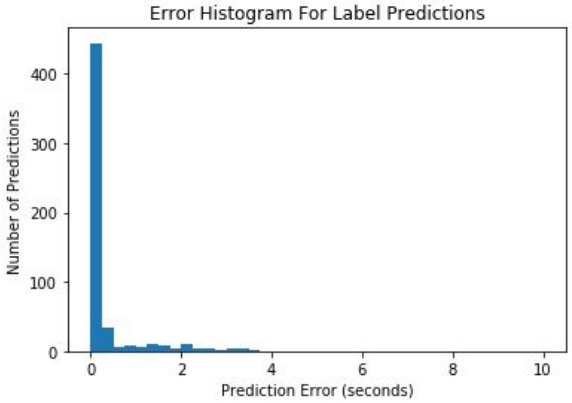
$$\frac{\#\text{true lunges detected}}{\#\text{true lunges}}$$

$$\frac{\#\text{incorrect predictions}}{\#\text{total number of predictions}}$$

# Test Set Results (Blue Whales)

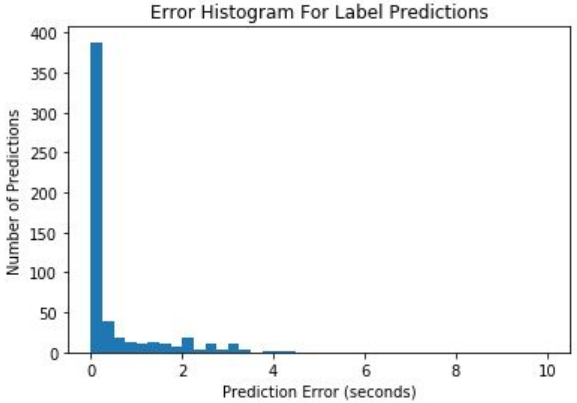
## Feed Forward Model

```
The true positive rate for tolerance  5  seconds is  0.97
The false positive rate for tolerance  5  seconds is  0.037
Total lunges in files:  568
Num correct lunges:  551
Num predicted lunges:  572
We overcount by  0
We are off by an average of this many seconds:  0.31724137931034496
The f_1 score is  0.967
The f_2 score is  0.969
```




## ResNet Model

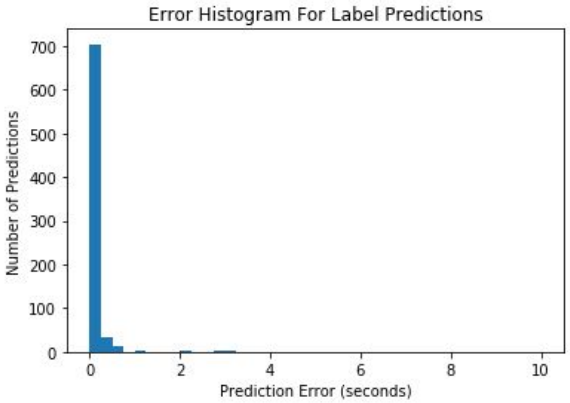
```
The true positive rate for tolerance  5  seconds is  0.972
The false positive rate for tolerance  5  seconds is  0.03
Total lunges in files:  568
Num correct lunges:  552
Num predicted lunges:  569
We overcount by  0
We are off by an average of this many seconds:  0.48550724637681136
The f_1 score is  0.971
The f_2 score is  0.971
```



# Test Set Results (Minke Whales)

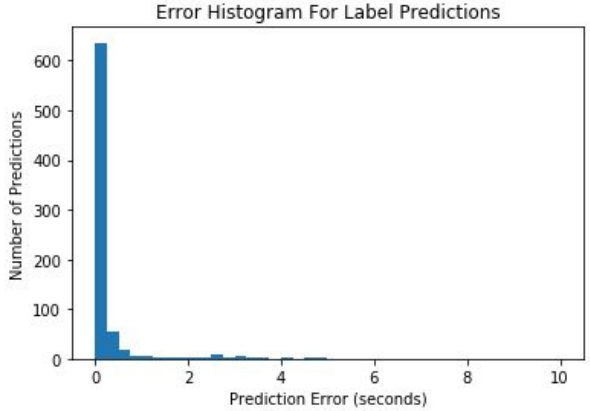
## Feed Forward Model

```
The true positive rate for tolerance  5  seconds is  0.962
The false positive rate for tolerance  5  seconds is  0.088
Total lunges in files:  799
Num correct lunges:  769
Num predicted lunges:  843
We overcount by  0
We are off by an average of this many seconds:  0.14395318595578616
The f_1 score is  0.937
The f_2 score is  0.952
```




## ResNet Model

```
The true positive rate for tolerance  5  seconds is  0.935
The false positive rate for tolerance  5  seconds is  0.141
Total lunges in files:  799
Num correct lunges:  747
Num predicted lunges:  870
We overcount by  3
We are off by an average of this many seconds:  0.21311914323962408
The f_1 score is  0.895
The f_2 score is  0.919
```



# Clicks Saved (Test Set)

$$\#\text{clicks still needed} = \#\text{incorrect predictions} + \#\text{missed true lunges}$$

$$\#\text{clicks saved} = \#\text{true lunges - } \#\text{clicks still needed}$$

$$\text{clicks saved rate} = \frac{\#\text{clicks saved}}{\#\text{true lunges}}$$

## Blue Whales (568 True Lunges)

| **Model** | Feed Forward | ResNet |
|---|---|---|
| **Clicks Saved** | 531 | 535 |
| **Clicks Saved Rate** | 93.4% | 94.1% |

# Clicks Saved (Test Set)

$$\#\text{clicks still needed} = \#\text{incorrect predictions} + \#\text{missed true lunges}$$

$$\#\text{clicks saved} = \#\text{true lunges - } \#\text{clicks still needed}$$

$$\text{clicks saved rate} = \frac{\#\text{clicks saved}}{\#\text{true lunges}}$$

## Minke Whales (799 True Lunges)

| **Model** | Feed Forward | ResNet |
|---|---|---|
| **Clicks Saved** | 695 | 624 |
| **Clicks Saved Rate** | 87.5% | 78.1% |

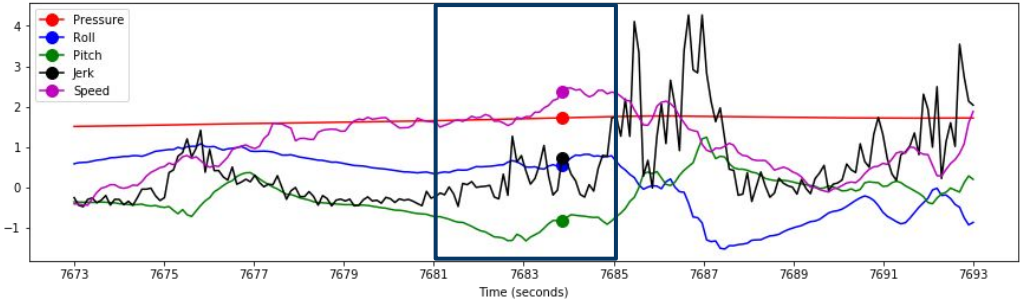
# Algorithm Details

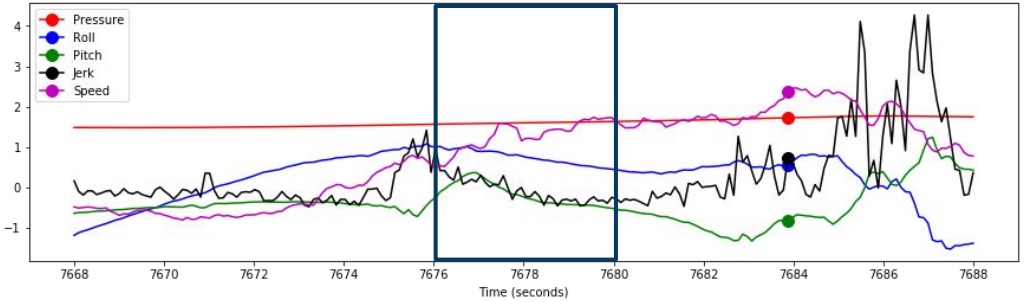
Prediction On Windows

- Take a window of length *T* from the data
  - Assign the window a 1 if there is a lunge within *x* seconds of the center
  - Assign the window a 0 otherwise

# Algorithm Details

## Minke Whale Example (20 second windows, 2 second tolerance)




1

0

# Algorithm Details

Model Prediction

- Model attempts to predict the assigned value (1 or 0)
- Model predicts probability that output is 1

Sliding Windows

- To predict at time *t*, feed the model the window centered at time *t*.
- To predict on whole deployment, make predictions every second.

# Algorithm Details

Consolidating Predictions

- Output predictions can be noisy
  - Use a moving average filter to reduce false positives
- Now many predictions with probability > 0.5 correspond to a given true lunge
- To consolidate:
  - Cluster output predictions if they are within *C* seconds of each other
  - Output the max probability prediction (probability *P*) if *P*>*T* where T is a threshold value
  - Values *C* and *T* are chosen using performance on deployments in the validation set

# Algorithm Details

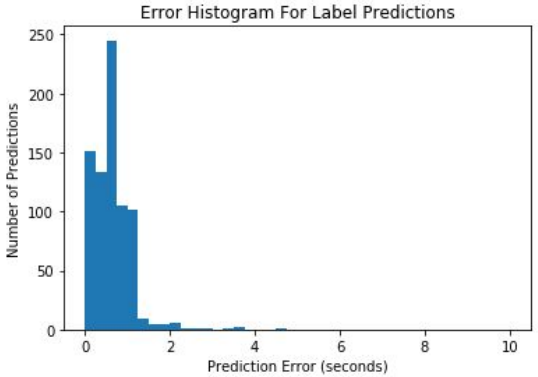
## Correcting Predictions

- First (detection) model detects whether there is a lunge in the middle x seconds
  - No guarantee that predictions tightly align with true labels
- Second (correction) model
  - Takes a predicted time and predicts offset to true label
  - Trained using synthetically-generated incorrect labels
    - Offsets sampled from the distribution of errors that first model created

# Correction Model Results (Minke)

## Uncorrected Predictions

```
The true positive rate for tolerance  5  seconds is  0.962
The false positive rate for tolerance  5  seconds is  0.088
Total lunges in files:  799
Num correct lunges:  769
Num predicted lunges:  843
We overcount by  0
We are off by an average of this many seconds:  0.6243172951885562
The f_1 score is  0.937
The f_2 score is  0.952
```




## Corrected Predictions

```
The true positive rate for tolerance  5  seconds is  0.962
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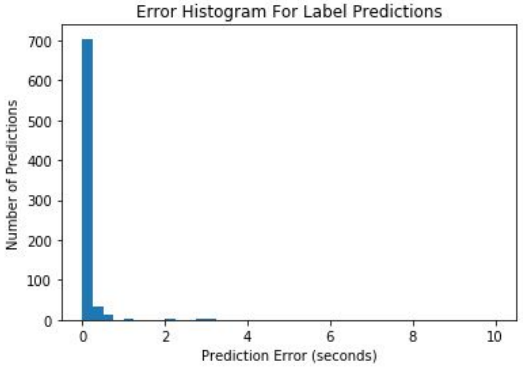
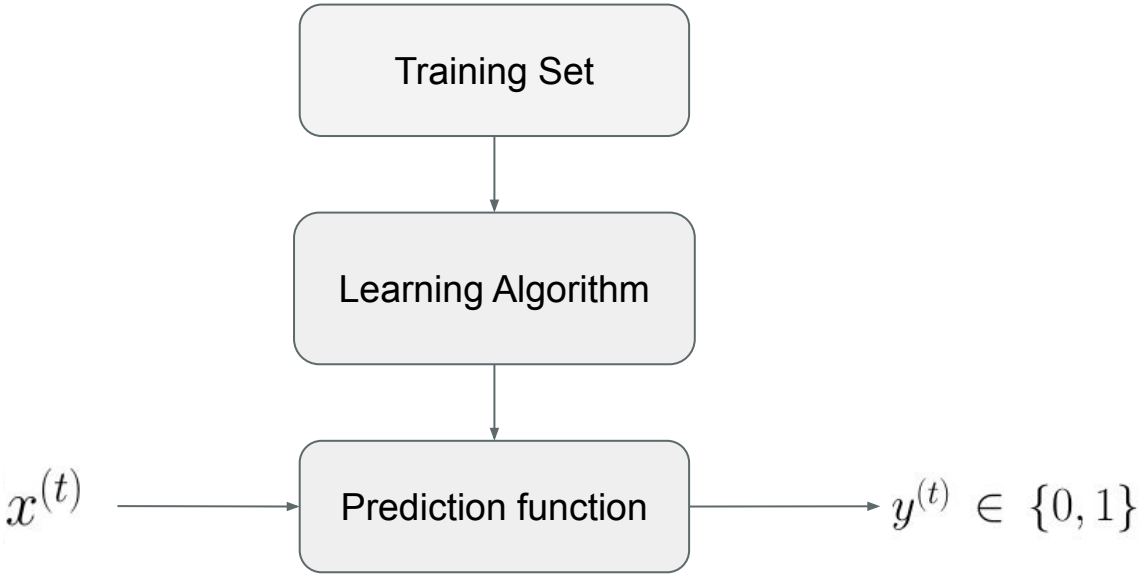
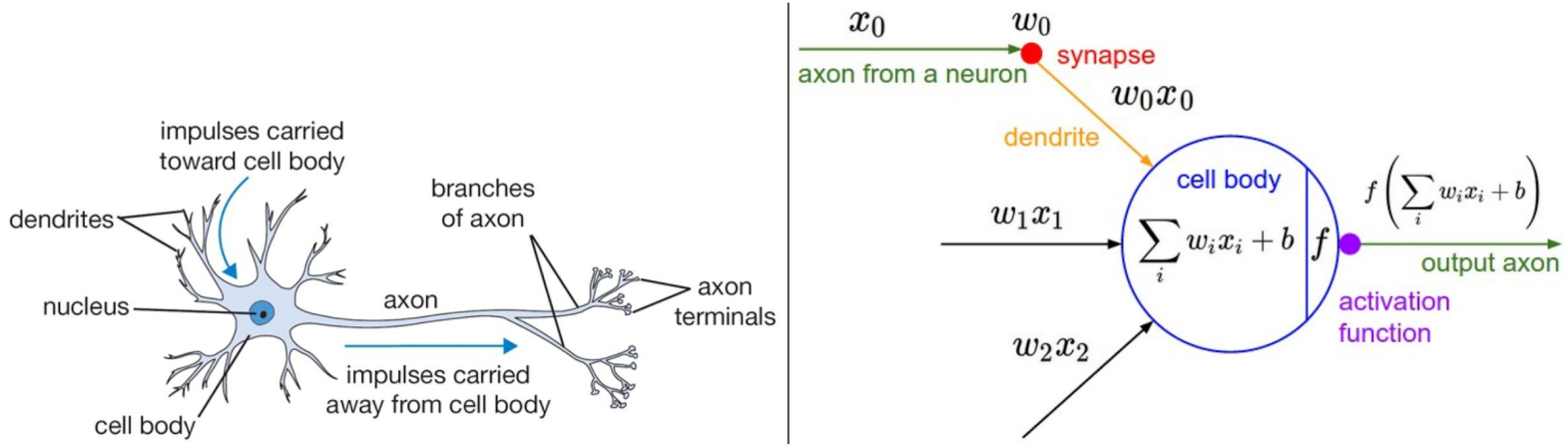


# Supervised Learning: Binary Classification




Source: CS229 Lecture Notes (http://cs229.stanford.edu/main_notes.pdf)

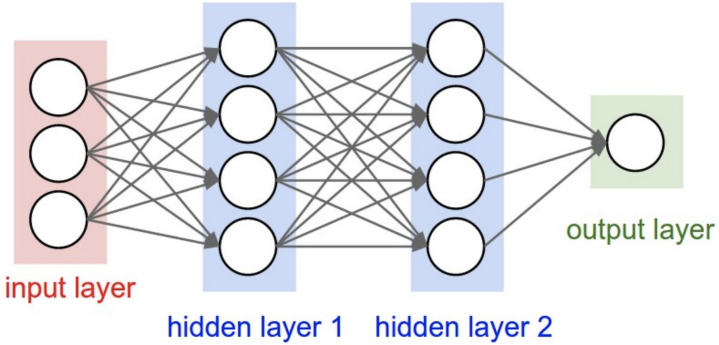
# Neural Networks




A cartoon drawing of a biological neuron (left) and its mathematical model (right).

**Source: CS231N Lecture Notes** (http://cs231n.github.io/neural-networks-1/)

# Neural Networks

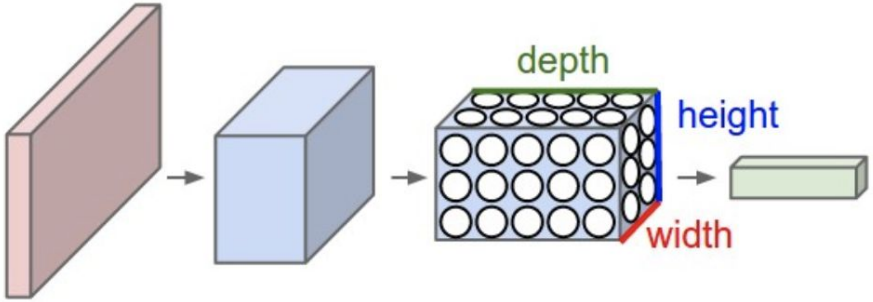


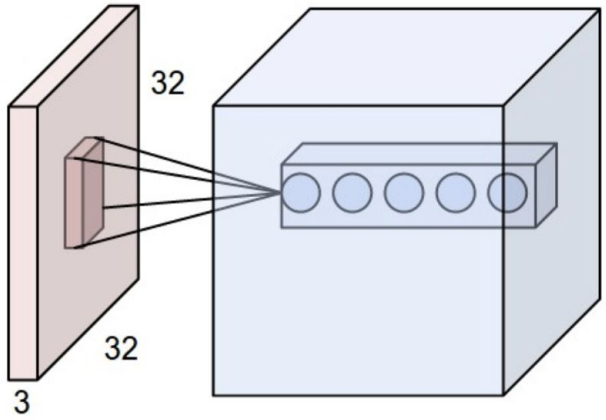

- Connected, acyclic graph of neurons
- Single neuron linear classifiers
  - Can be equivalent to logistic regression and SVM
- General feed-forward neural networks
  - A series of matrix multiplications linked with non-linearities
- Representational Power
  - Single hidden layer is enough to approximate any continuous function
  - However, just because a function can be learned doesn't mean it will be learned
    - Empirically, deeper networks will work much better in practice but must be tuned appropriately
  - Key takeaway: neural networks are able to learn well-behaving functions that fit real-world data tremendously well.

**Source: CS231N Lecture Notes** (http://cs231n.github.io/neural-networks-1/)

# Convolutional Networks

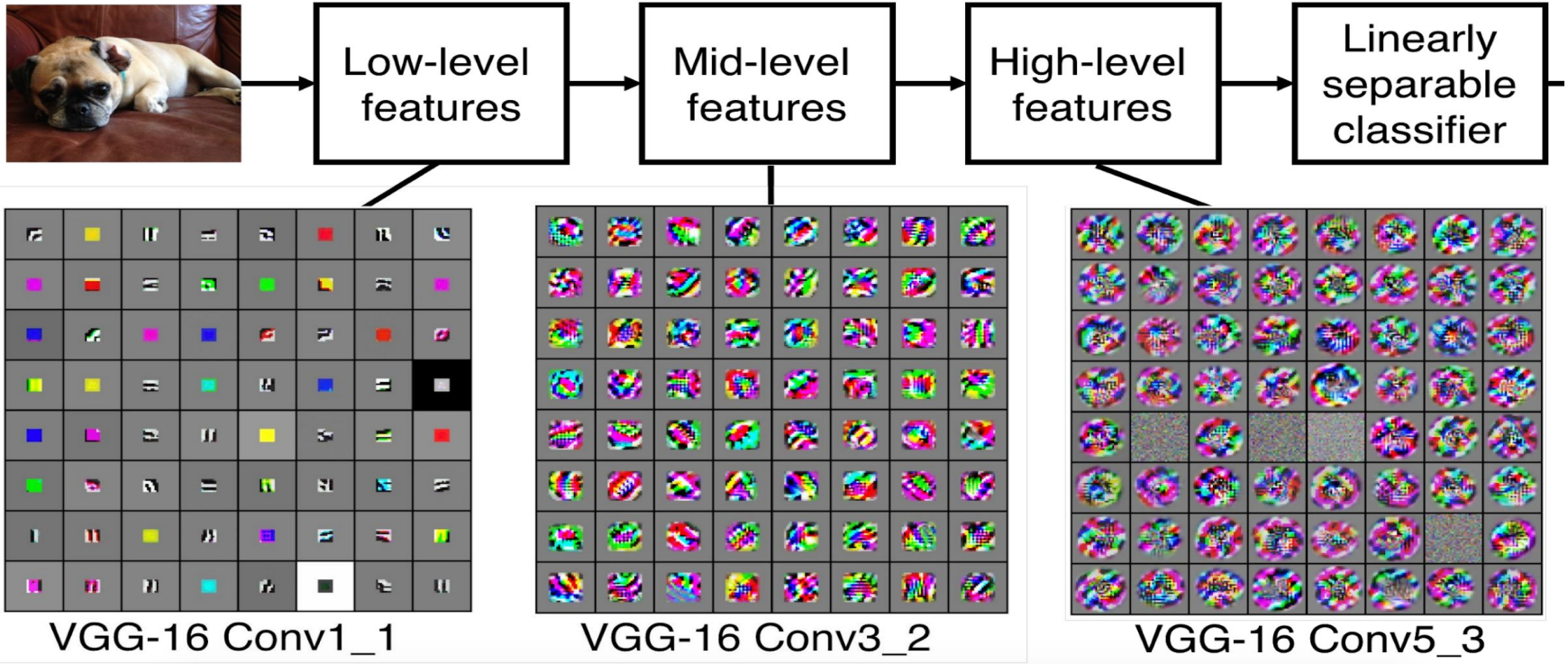
- Optimized architecture for images
  - Parameter sharing to decrease number of parameters
- Typical architecture consists of CONV, POOL, and FC layers
- Most important is CONV
  - Small filters slide across image to output a new image that holds the filter's response to each spatial section
  - Filters will activate when they detect a certain feature




**Source: CS231N Lecture Notes (**http://cs231n.github.io/convolutional-networks/**)**

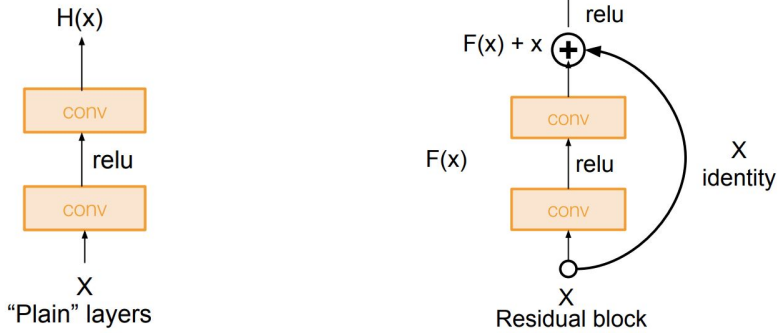
# Convolutional Networks: Visualized




Source: CS231N Lecture Notes (http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture05.pdf)

# Residual Networks (ResNets)

- Trend towards deeper networks
  - Makes sense to learn more low/mid/high-level features
  - But much harder to train
- ResNets allow for much deeper networks (~1000-layer networks)
- Have been found to work quite well on time series data




**Source:** He, Kaiming et al. "Deep Residual Learning for Image Recognition." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): n. pag. Crossref. Web.

# External Resources

- Code base can be found at:
  - https://github.com/valdivia4/Deep-Learning-Lunge-Detection
- Implemented in Python
- Detailed documentation provided
  - No prior Python experience necessary