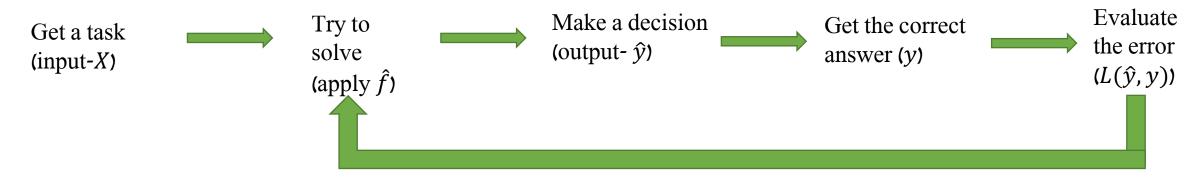


#### What is learning?

Learning is a process that leads to *change*, which occurs as a result of running through *data* and increases the potential of improved *performance* 

#### How do we learn?

At the end of the training period, we will apply what we have learned and hope for the best ©



Fix  $\hat{f}$  accordingly

$$f(X) = y$$

$$f = ?$$

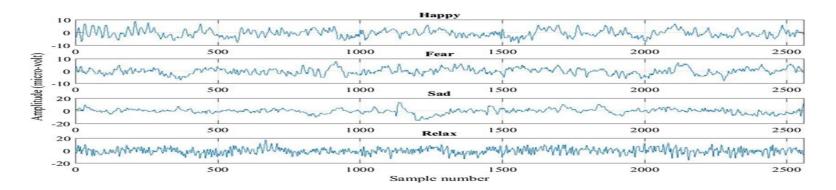
$$\hat{y} = \hat{f}(X)$$

$$\hat{y} \approx y \rightarrow L(\hat{y}, y) \approx \min(L) \rightarrow \hat{f} \approx f$$
Actually we are looking for  $P(y|X)$ 

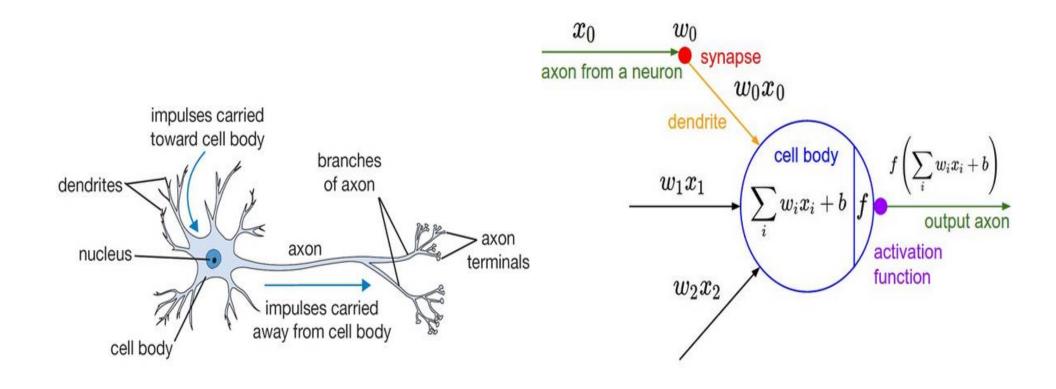
$$P\left(y = 1[shekel]|X = \binom{4.5[g]}{19[mm]}\right) = 0.1$$

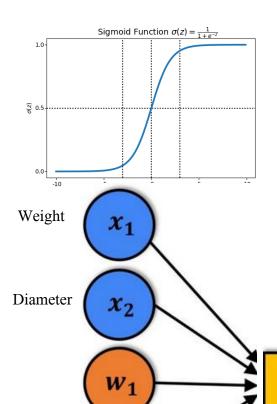
#### Estimating current feeling with EEG

- Get an EEG signal as an input.
- Estimate the probability of every feeling (apply  $\hat{f}$ ).
- Show the computer the correct answer (feeling).
- Fix the probability function through the weights using our loss function.
- Get a new signal with its' label (adequate feeling) and repeat.



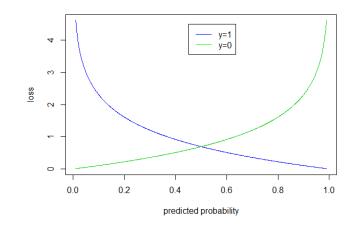
#### How do we decide?





$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\mathcal{L}(\widehat{y}, y) = -(y \log \widehat{y} + (1 - y) \log(1 - \widehat{y}))$$



The idea of loss is saying "bad computer" when it is wrong. The loss is lower for "more correct" prediction and higher for "less correct".

$$z = x_1 w_1 + x_2 w_2 + b$$
 
$$\widehat{y} = \sigma(z)$$
 
$$\mathcal{L}(\widehat{y}, y)$$

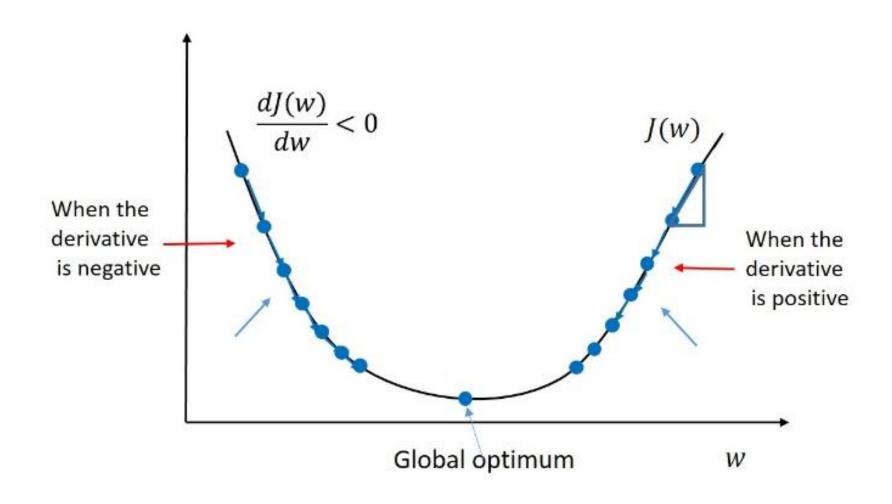
$$P\left(y = 1[shekel]|X = {4.5[g] \choose 19[mm]}\right) = \sigma(4.5w_1 + 19w_2 + b) = 0.9$$

$$P\left(y = 5[shekel]|X = {4.5[g] \choose 19[mm]}\right) = 1 - \sigma(z) = 0.1$$

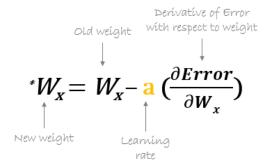
$$P(y = 1|X) > P(y = 5|X) \to \hat{y} = 1$$

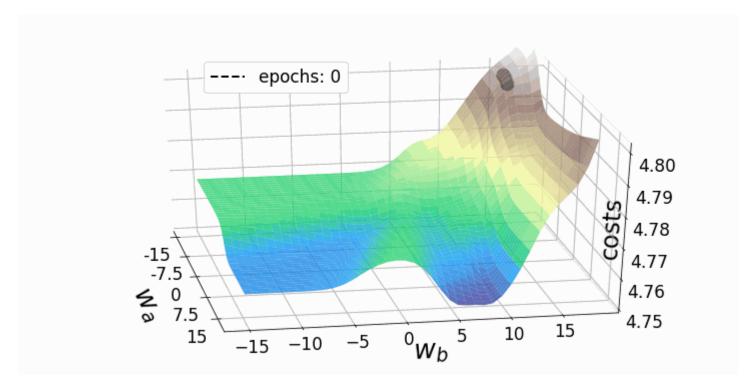
Our aim is to LEARN correctly  $(w_1, w_2, b)$  i.e. the set of parameters that minimizes the loss

### Calculus as learning factor

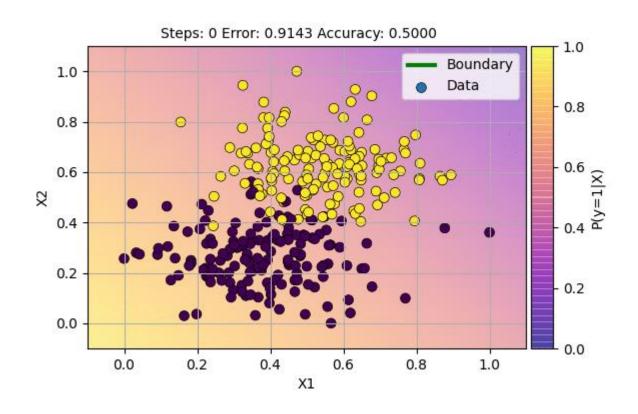


#### Gradient descent

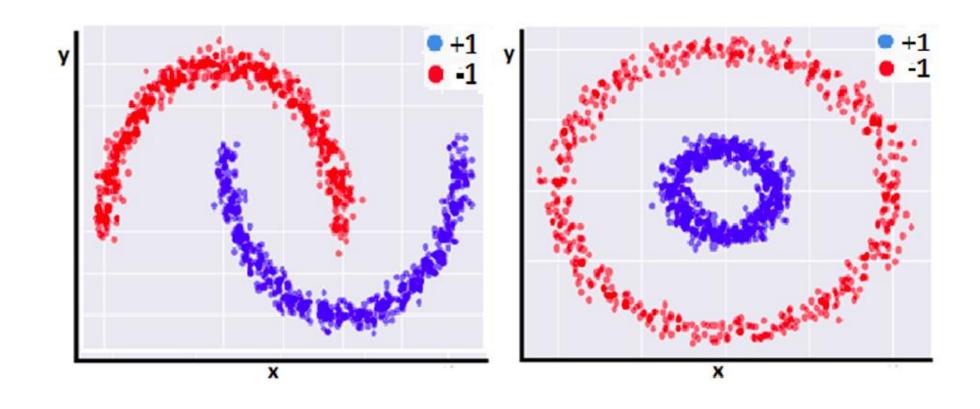




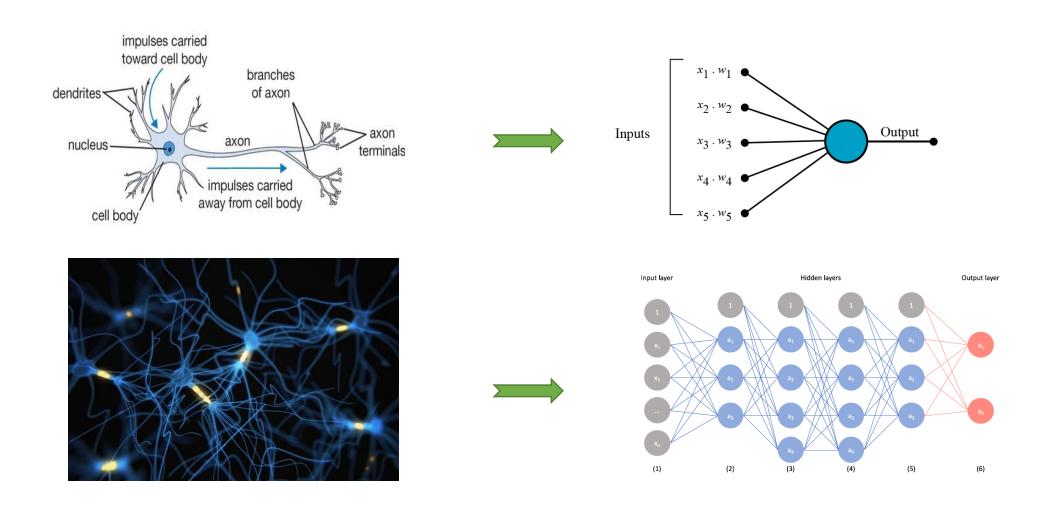
## Visualize learning



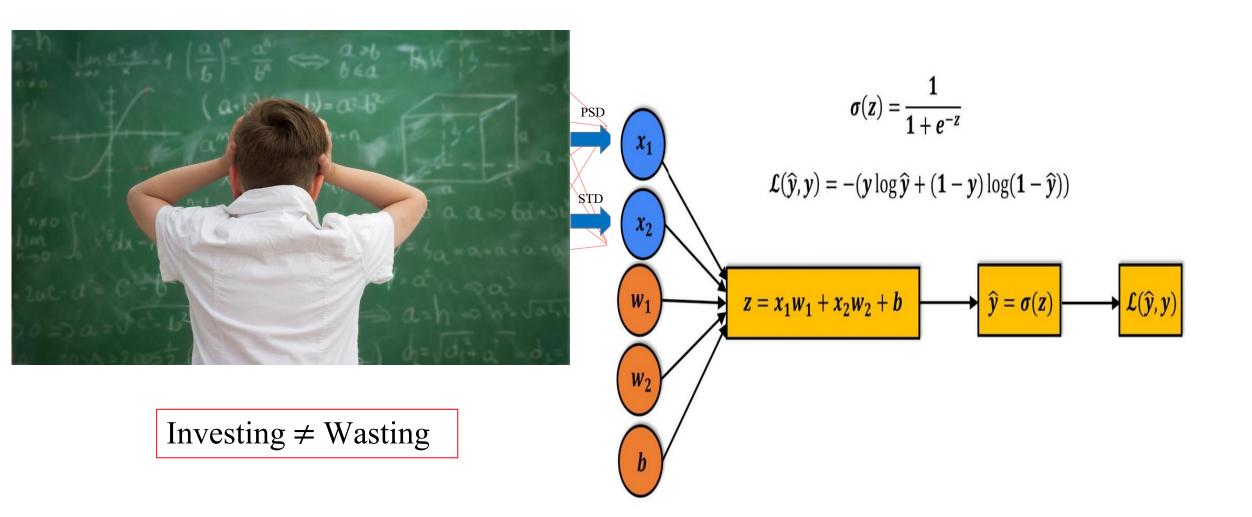
## Why not stop here?

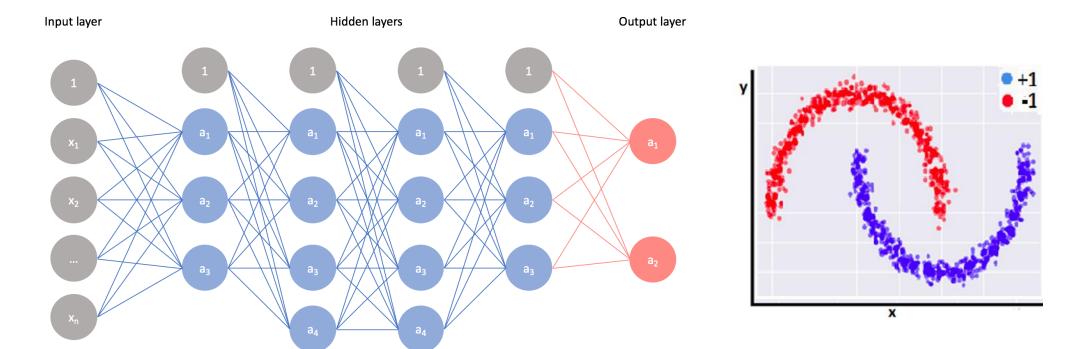


### Mimicking our brain

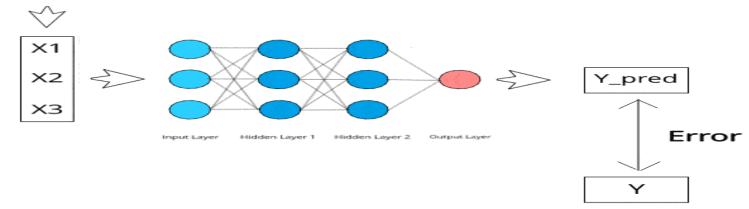


# From feature engineering to representation learning





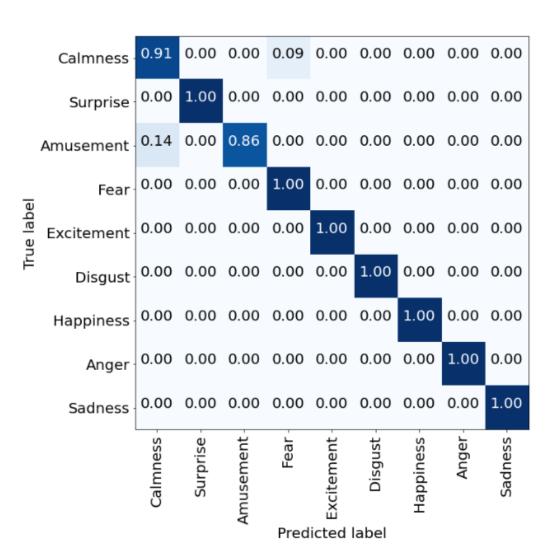




## Hands on with Python

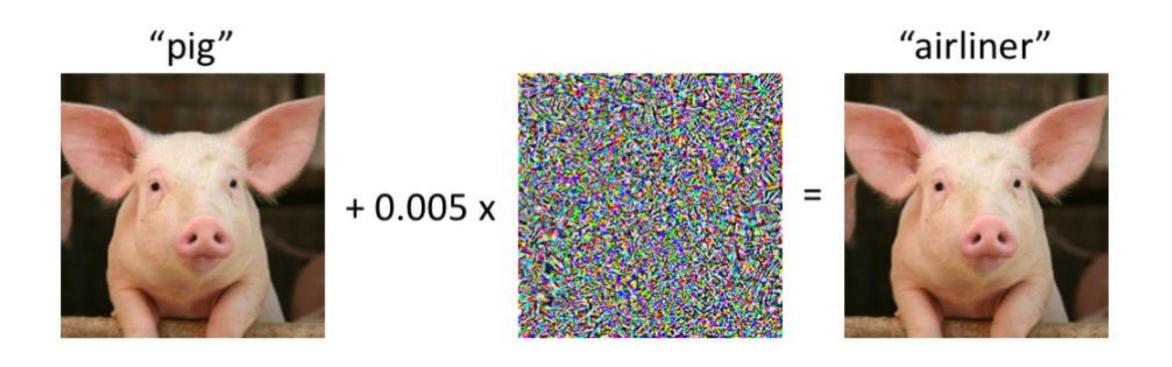
```
from sklearn.model_selection import train test_split
from sklearn.linear model import LogisticRegression
X # nX2
y # 1Xn
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred_test = log_reg.predict(X_test)
y_pred_proba_test = log_reg.predict_proba(X_test)
EEG # nXt
X_train, X_test, y_train, y_test = train_test_split(EEG, y, test_size=0.2)
window_size=60
n filters start=64
n hidden start=512
len_sub_window=10
dropout=0.5
model = Sequential()
model.add(Conv1D(n_filters_start, len_sub_window, activation='relu', input_shape=(60, 1)))
#------ #----- Implement your code here:-----
model.add(Conv1D(2 * n filters start, len sub window, activation='relu'))
model.add(MaxPool1D())
model.add(Conv1D(4 * n filters start, len sub window, activation='relu'))
model.add(Dropout(dropout))
model.add(Flatten())
model.add(Dense(n hidden start, activation='relu'))
model.add(Dense(int(n hidden start / 2), activation='relu'))
model.add(Dense(int(n_hidden_start / 4), activation='relu'))
model.add(Dropout(dropout))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='adam', metrics=['accuracy'], loss='binary_crossentropy')
model.fit(rr train, y train, batch size=1024, epochs=20)
model.predict(X_test)
```

#### Results for NN





### Why we should **not** throw away engineering









(A) Cow: 0.99, Pasture:

(B) No Person: 0.99, Water:

(C) No Person: 0.97,



# Beyond Classification



## Beyond Classification

