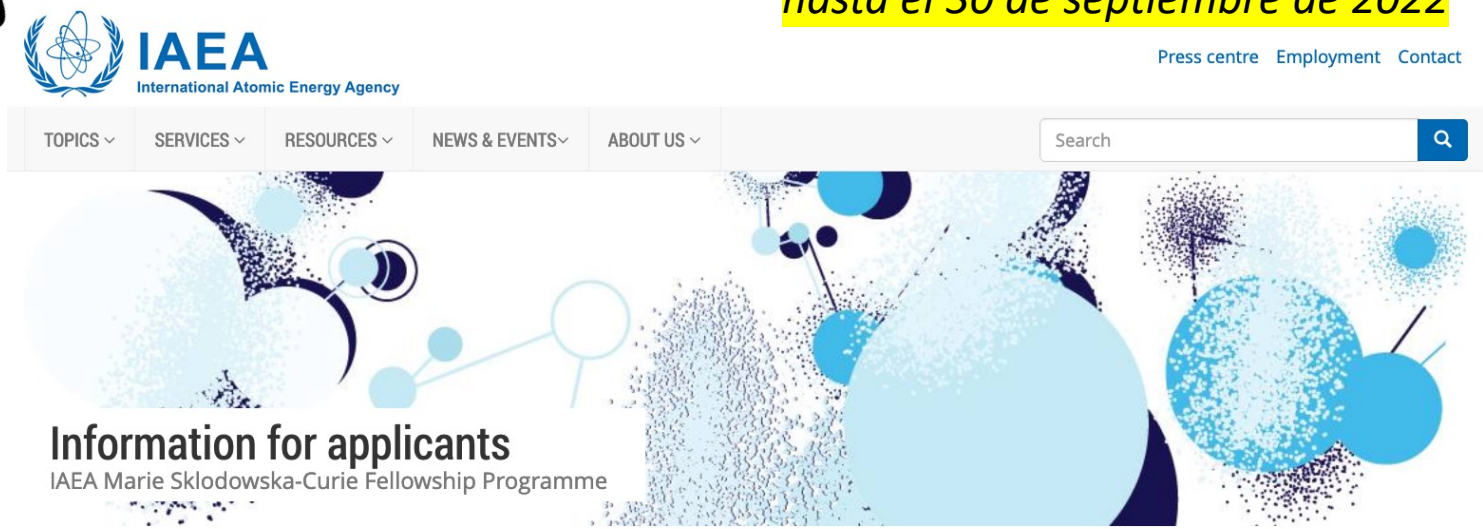
ML Fundamentals

Instituto Balseiro

Instituto Balseiro
19/09/2022

Programa de Becas Marie Skłodowska-Curie

hasta el 30 de septiembre de 2022



Information for applicants

Introduction

The IAEA Marie Sklodowska-Curie Fellowship Programme (MSCFP) seeks to inspire and support young women to pursue a career in the nuclear field. To that end, the MSCFP provides scholarships to selected students studying towards a Master's degree in nuclear related subjects as well as internship opportunities facilitated by IAEA.

Who should apply? Eligibility criteria

The IAEA MSCFP is open to students from IAEA Member States who meet the following entry requirements:

- Female candidates;
- Accepted by or enrolled in an accredited university in Master's programme in a nuclear related field.

Preference will be given to applicants with above average academic credentials (75% or above or GPA > 3.0 out of 4.0).

Related resources

- Applicant Reference Form
- Meet the Marie Sklodowska-Curie Fellowship Programme students
- IAEA Marie Sklodowska-Curie Fellowship Programme

Frequently asked questions

- Frequently asked questions

Contact

- Send an email

https://www.iaea.org/es/about/overview/gender-at-the-iaea/iaea-marie-sklodowska-curie-fellowship-programme/Information-for-applicants

Lecture 8
Deep learning I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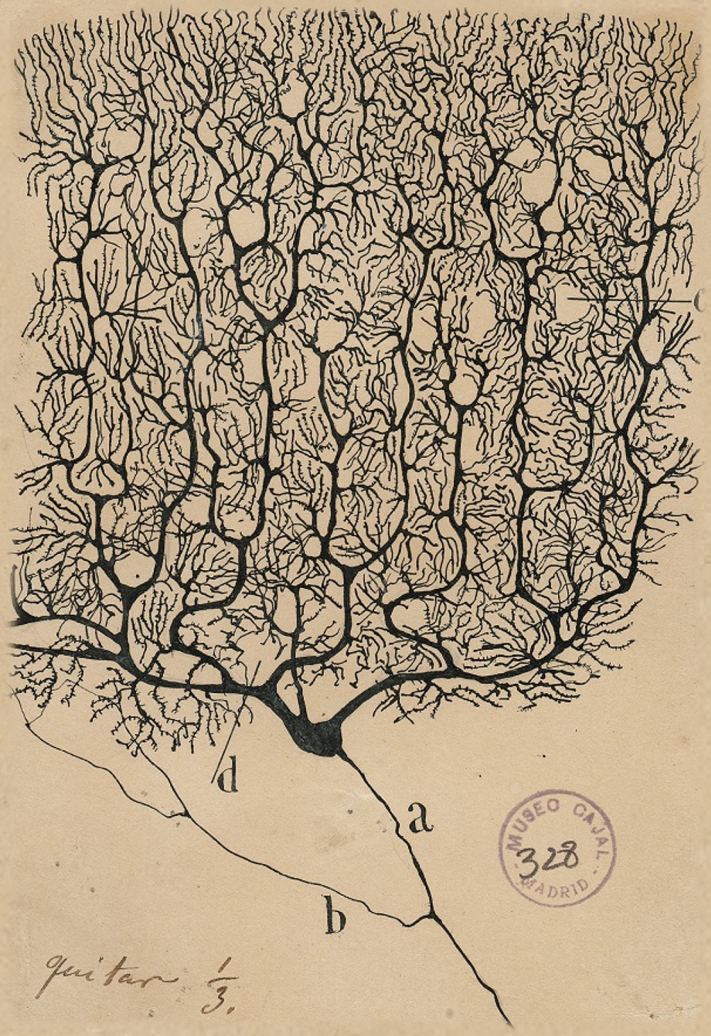
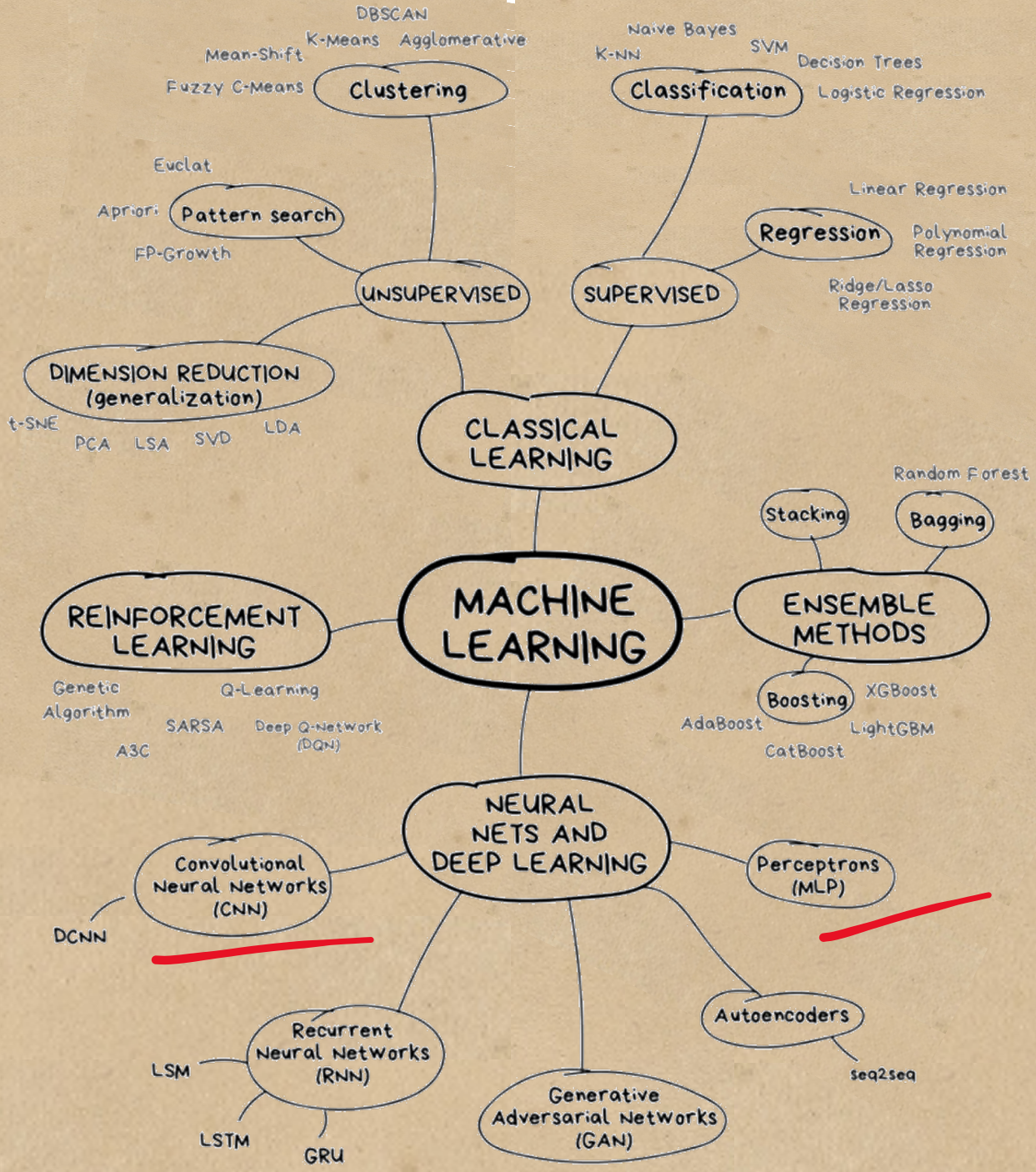
328
MADRID
Guitar 1/3,

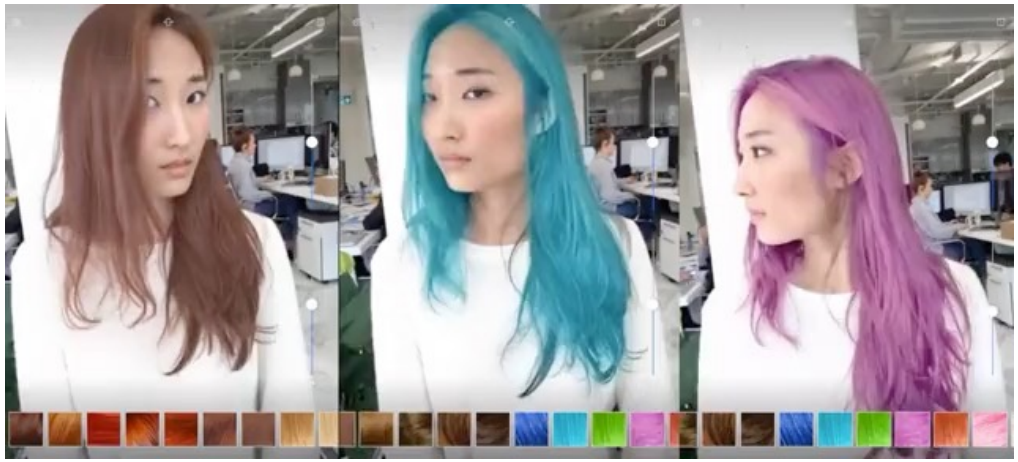
ML Fundamentals – Lecture 9

- Perceptron
- Feedforward nets
- Tensors & Keras
- Architectures
- Training
  - Optimizers
  - Regularization

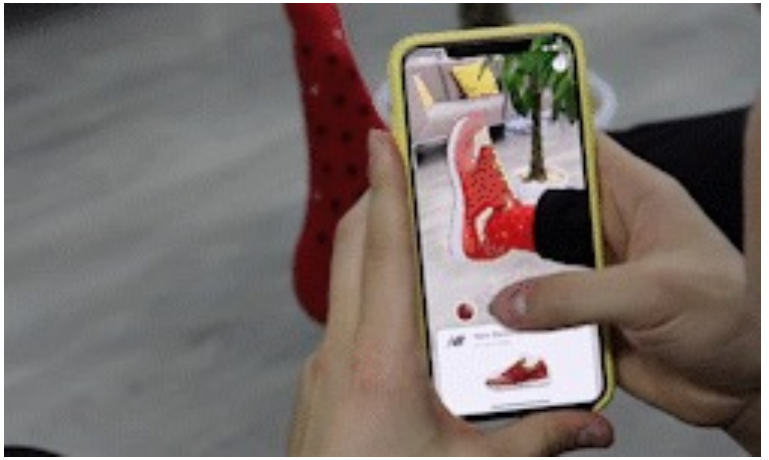



MACHINE LEARNING
CLASSICAL LEARNING
UNSUPERVISED
SUPERVISED
Clustering
DBSCAN
K-Means
Agglomerative
Mean-Shift
Fuzzy C-Means
Classification
Naive Bayes
K-NN
SVM
Decision Trees
Logistic Regression
Pattern search
Euclat
Apriori
FP-Growth
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
DIMENSION REDUCTION (generalization)
t-SNE
PCA
LSA
SVD
LDA
REINFORCEMENT LEARNING
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
ENSEMBLE METHODS
Stacking
Bagging
Random Forest
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
NEURAL NETS AND DEEP LEARNING
Convolutional Neural Networks (CNN)
DCNN
Perceptrons (MLP)
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)
Autoencoders
seq2seq

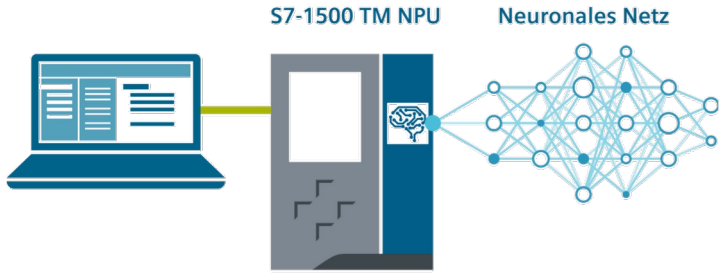
Why Deep Learning?



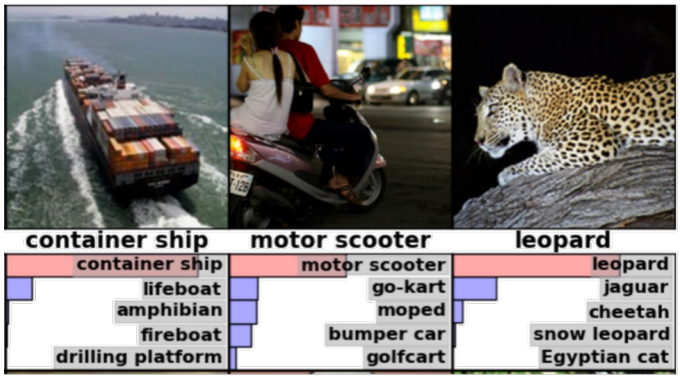
https://news.developer.nvidia.com/3d-real-time-video-hair-coloration/



https://news.developer.nvidia.com/new-app-uses-ai-to-enable-users-to-explore-sneakers-in-ar/



A few Deep Learning milestones

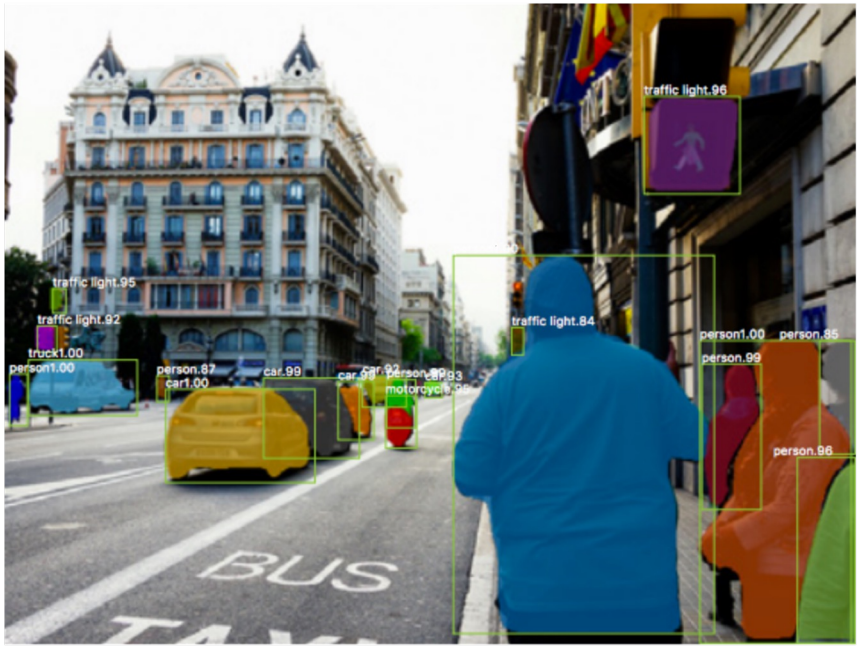


ions a leading CNN architecture made on images from the ImageNet dataset.

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

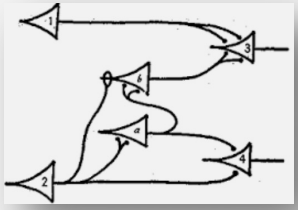


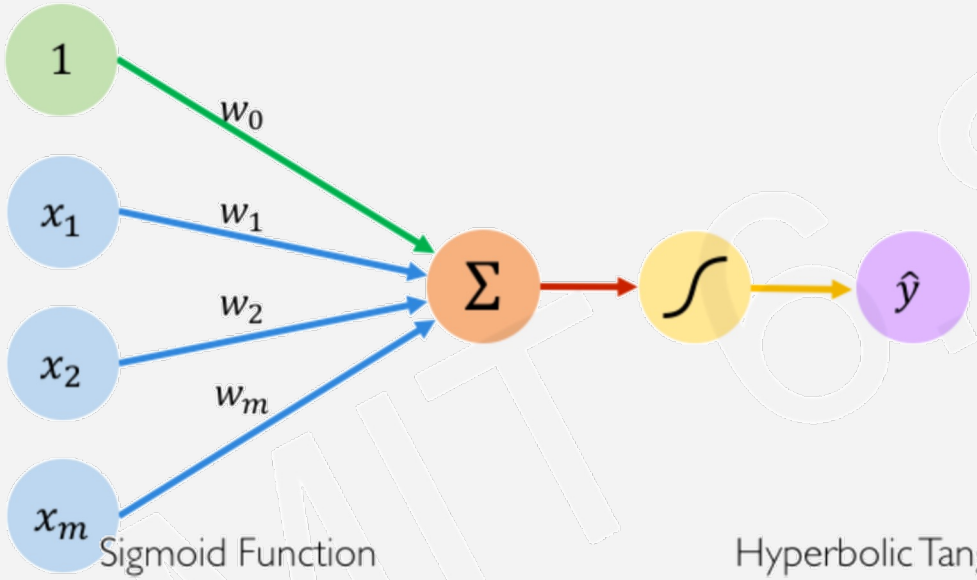
Object detection using "Mask R-CNN". Source

- Near-human-level image classification
- Near-human-level speech transcription
- Near-human-level handwriting transcription
- Dramatically improved machine translation
- Dramatically improved text-to-speech conversion
- Digital assistants such as Google Now and Amazon Alexa
- Near-human-level autonomous driving
- Improved ad targeting, as used by Google, Baidu, or Bing
- Improved search results on the web
- Ability to answer natural-language questions
- Superhuman Go playing

The (single layer) perceptron

McCulloch-Pitts neuron, 1943
Rosenblatt, 1958





Output

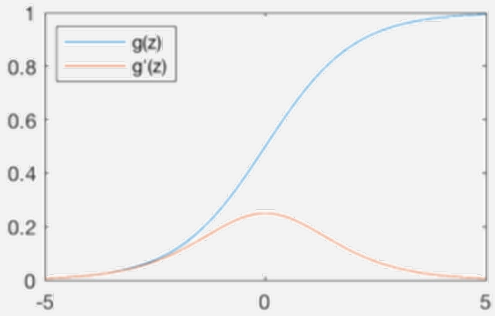
Linear combination of inputs

$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i\, w_i\right)$$

Non-linear activation function

Bias

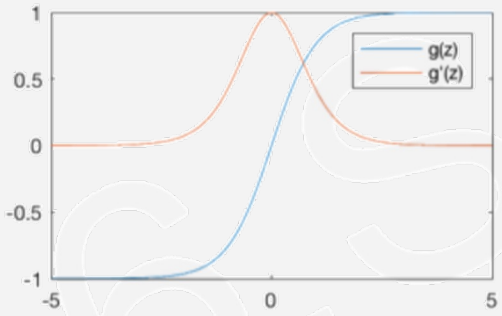
Sigmoid Function



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

$$g'(z) = g(z)(1 - g(z))$$

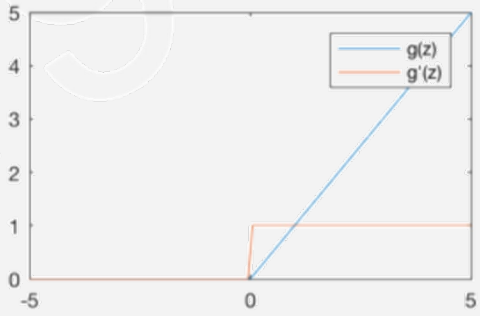
Hyperbolic Tangent



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

$$g'(z) = 1 - g(z)^2$$

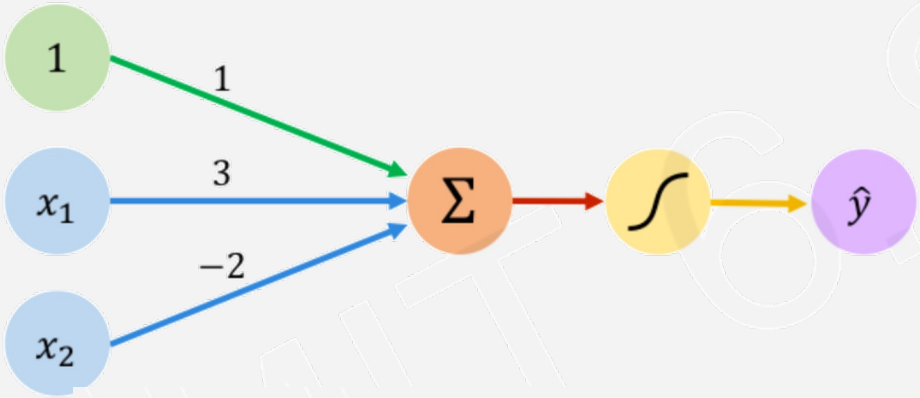
Rectified Linear Unit (ReLU)

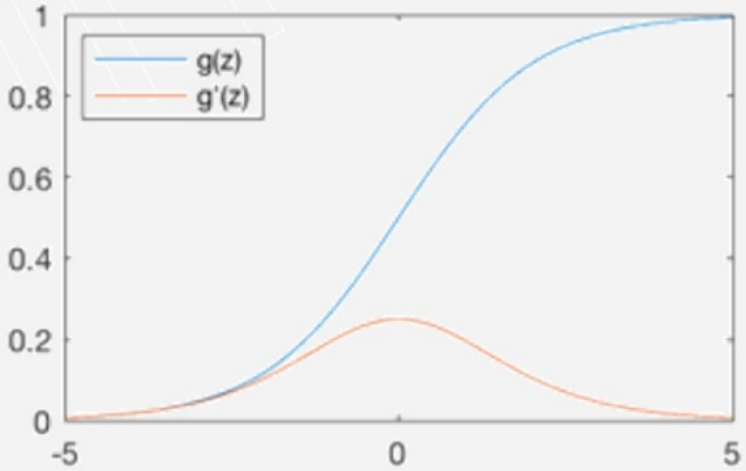


$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

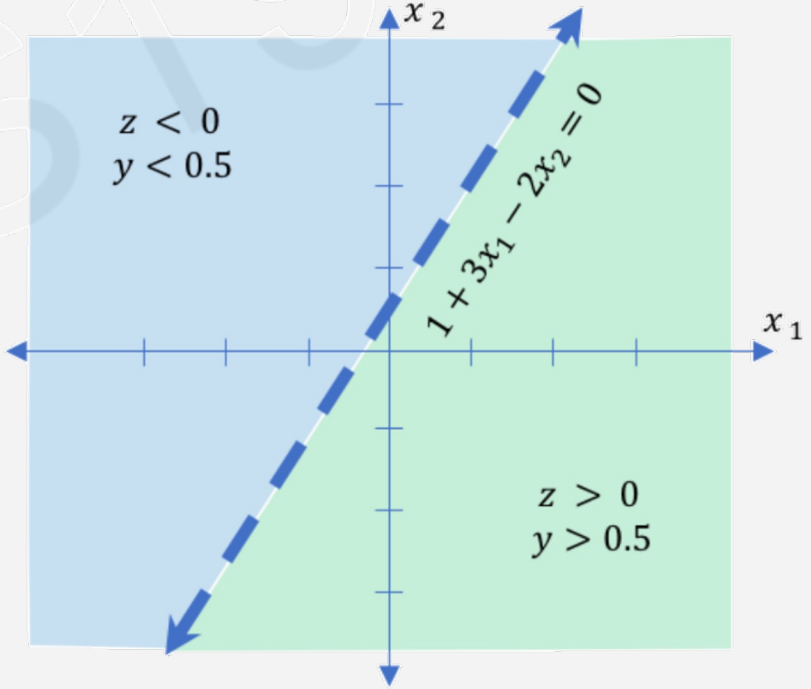
The (single layer) perceptron





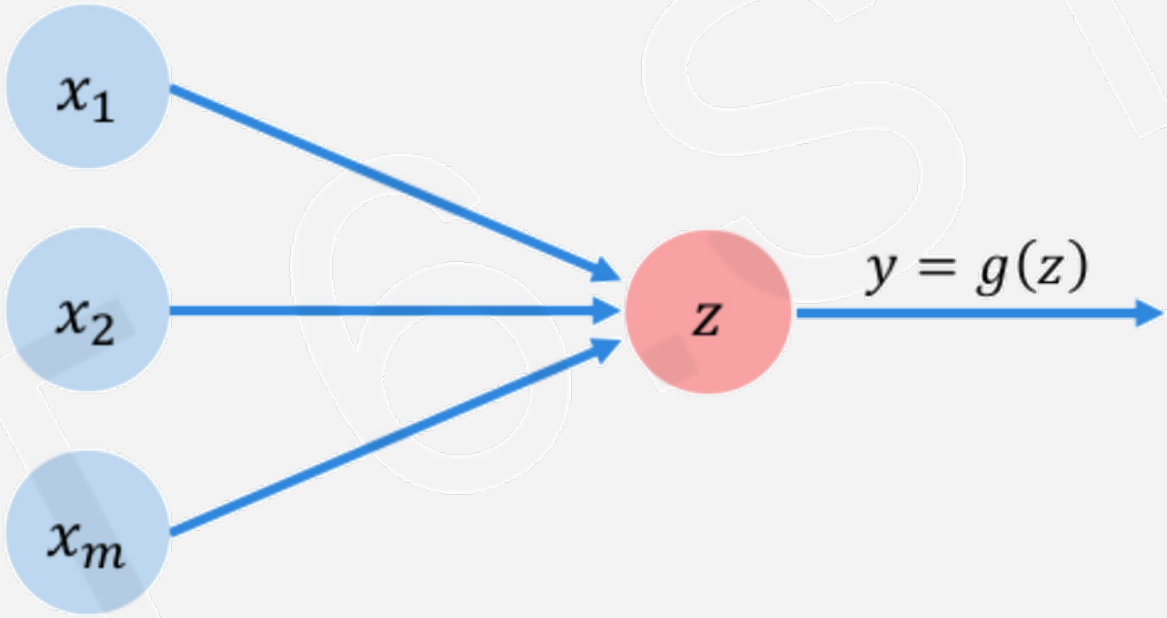
$$g(z) = \frac{1}{1 + e^{-z}}$$

$$\hat{y} = g(1 + 3x_1 - 2x_2)$$



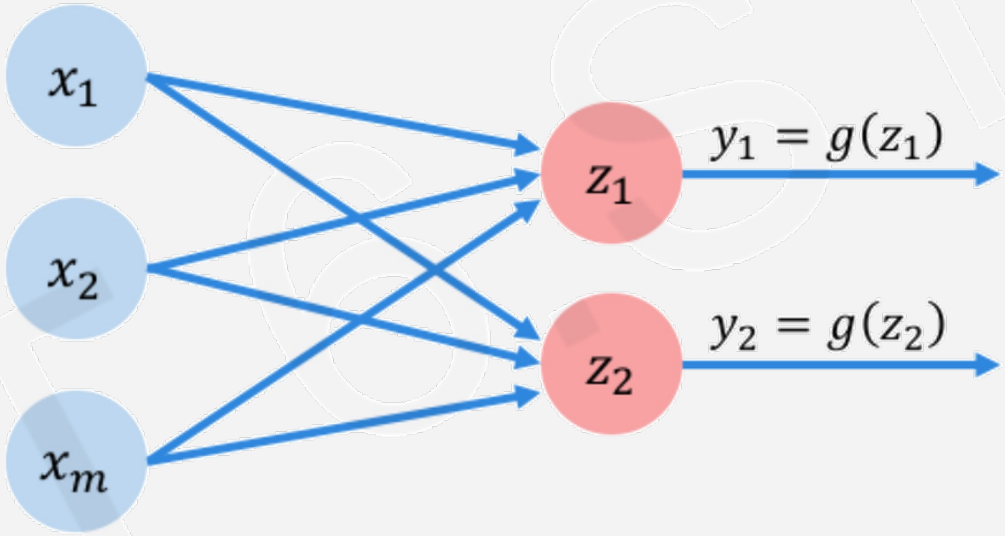
- The preceptron represents a single neuron
- Weights initialized randomly
- Then, updated through optimizer, (e.g. Gradient Descent)

One output



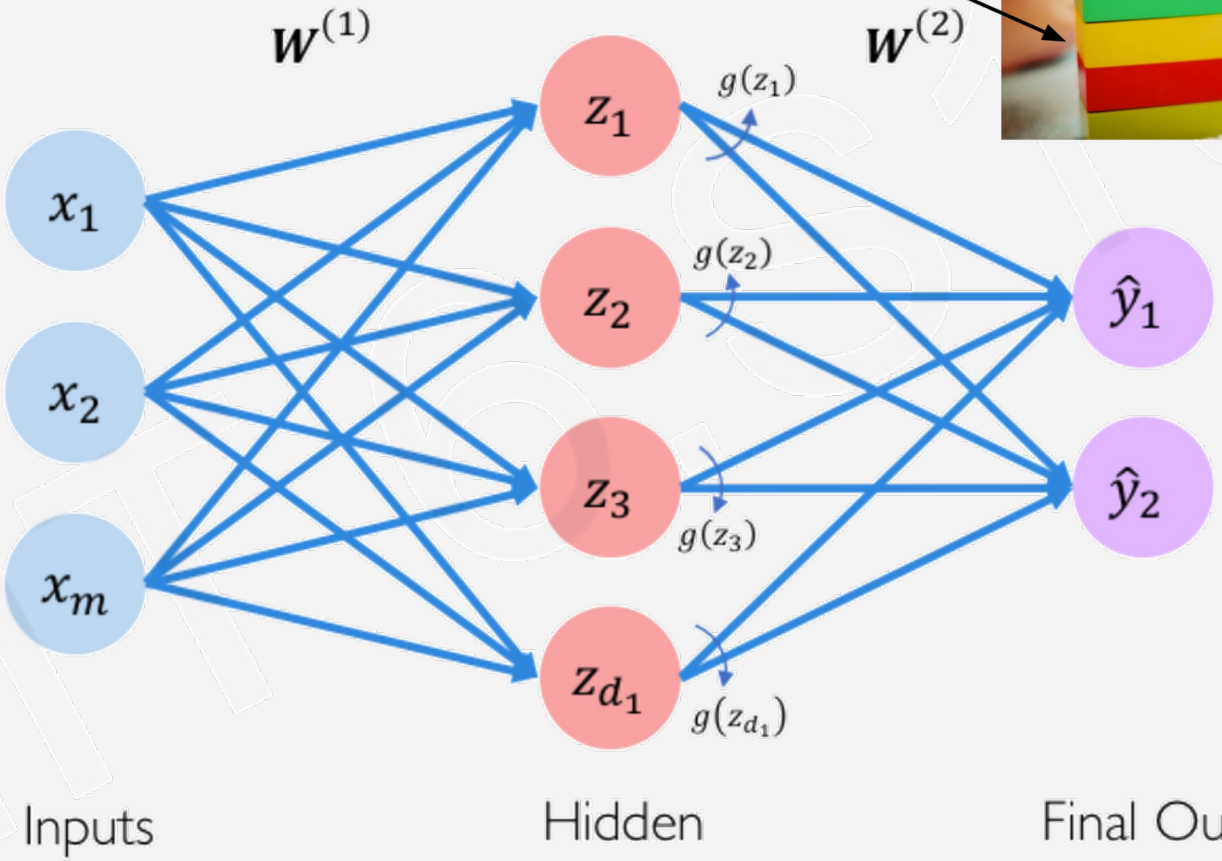
$$z = w_0 + \sum_{j=1}^{m} x_j w_j$$

More than one output



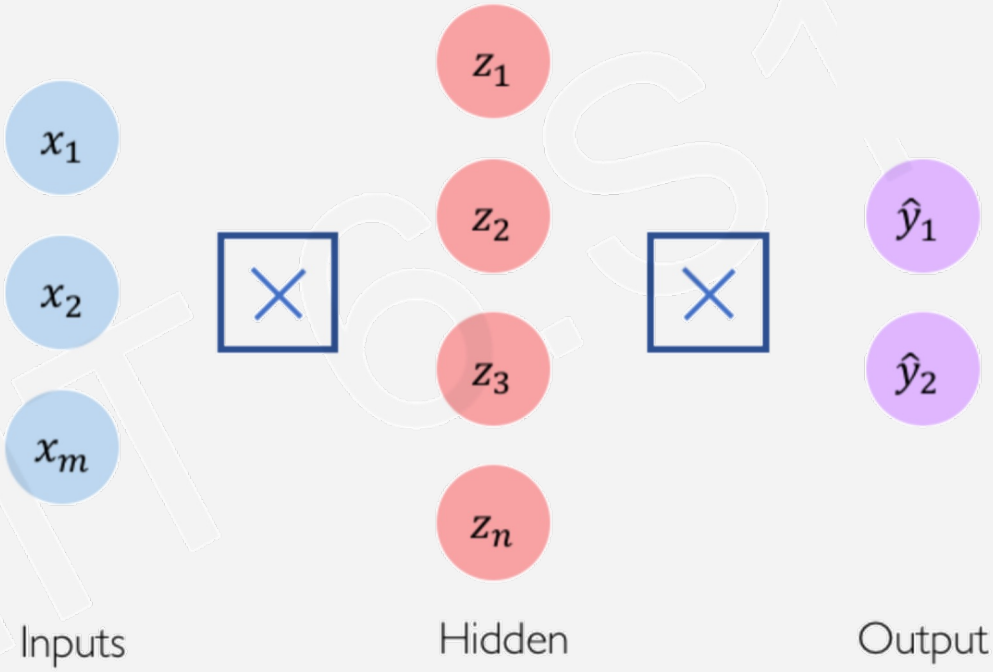
$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

One hidden layer



$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,i}^{(1)} \qquad \hat{y}_i = g\left(w_{0,i}^{(2)} + \sum_{j=1}^{d_1} g(z_j) \, w_{j,i}^{(2)}\right)$$

Same, but simpler

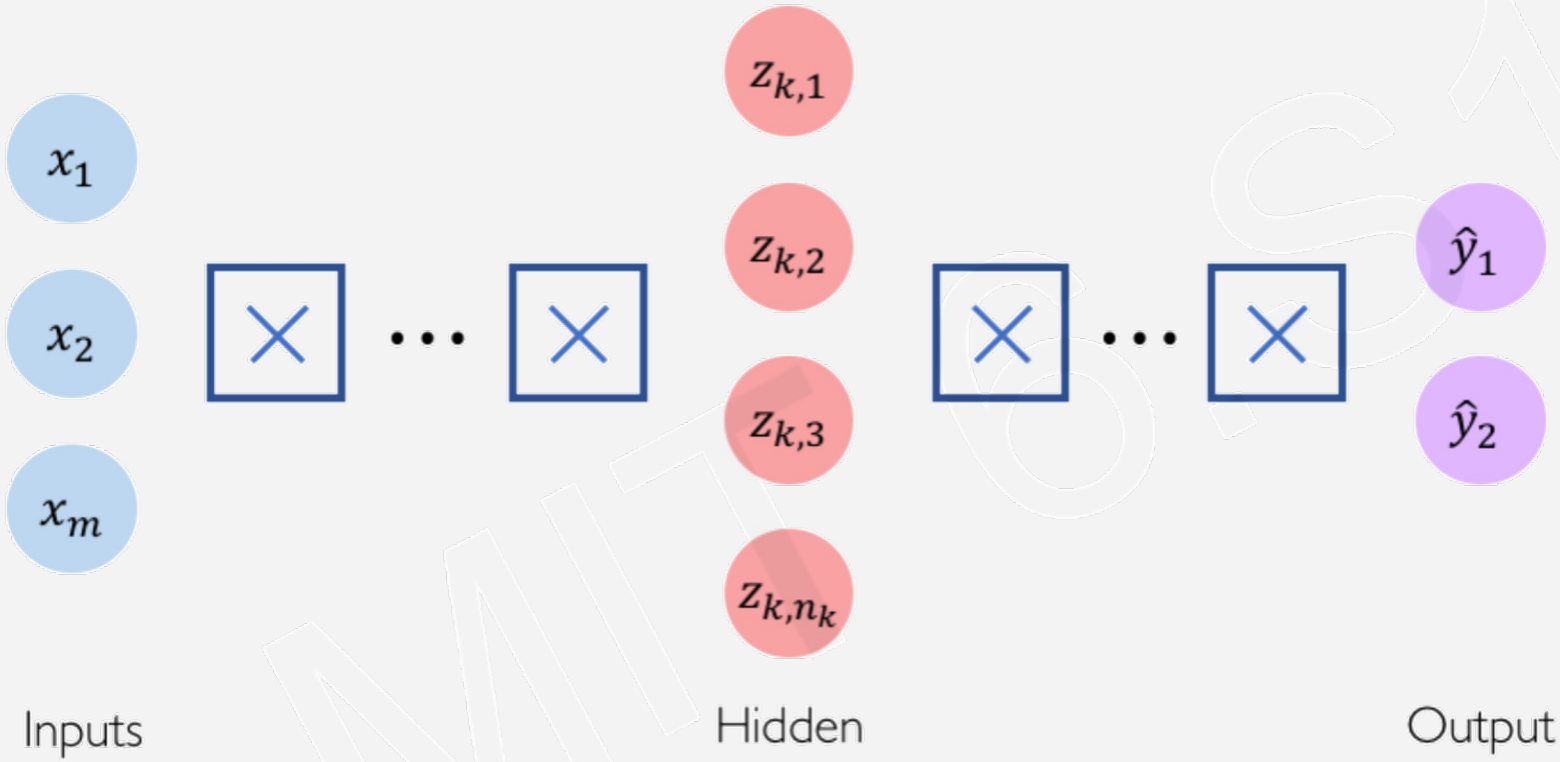


Feedforward Neural Network

- no cycles or loops
- information only moves forward

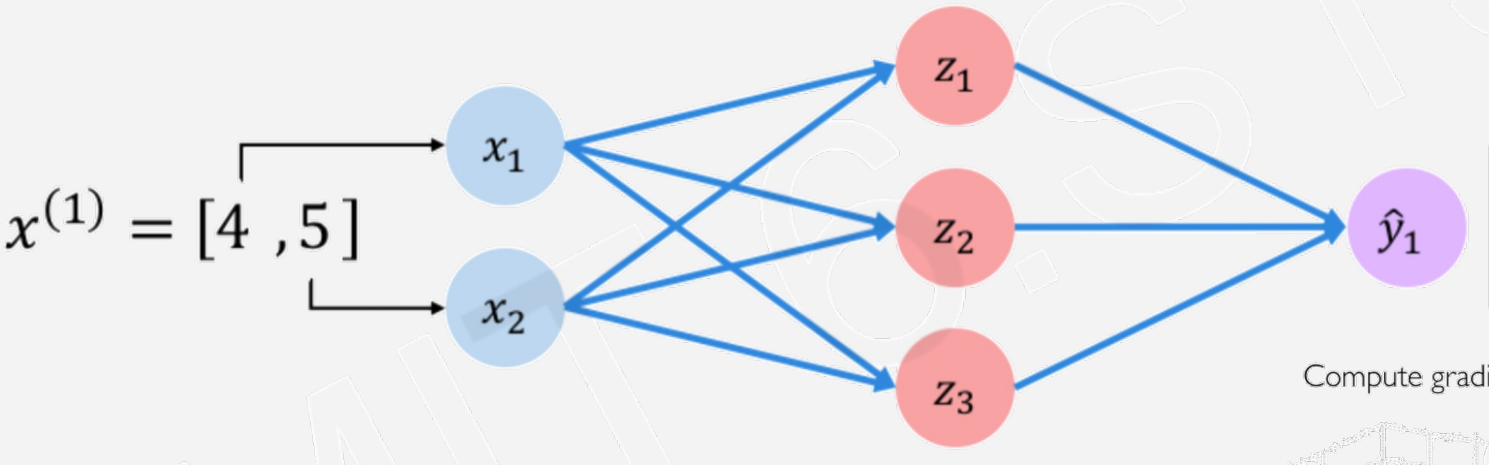
```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(32, input_shape=(784,)))
model.add(layers.Dense(32))
```



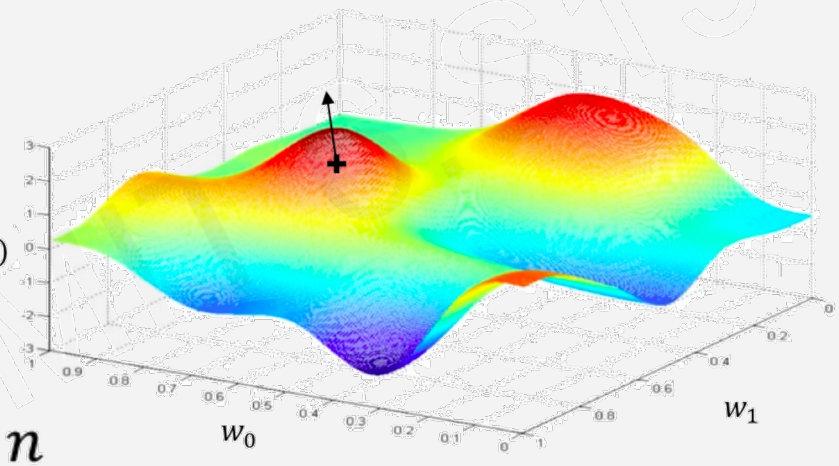
$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Quantifiying the error: the loss function



Predicted: **0.1**
Actual: **1**

Compute gradient, $\frac{\partial J(W)}{\partial W}$



$$\mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

$$\boldsymbol{J(W)} = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Also known as:

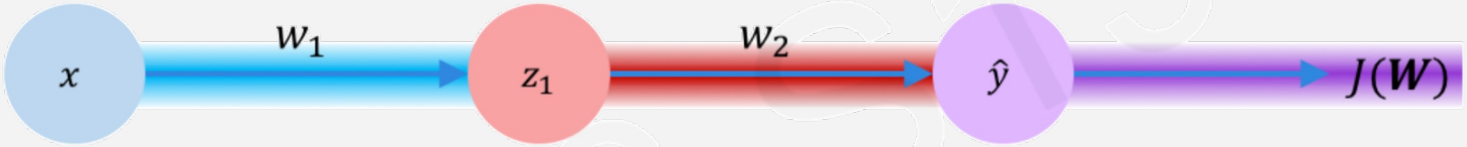
- Objective function
- Cost function
- Empirical Risk

Backpropagation

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton†
& Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

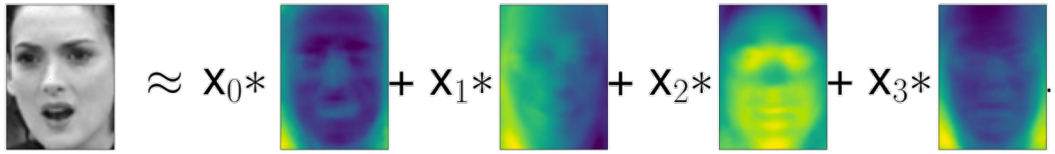


$$\frac{\partial J(\boldsymbol{W})}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

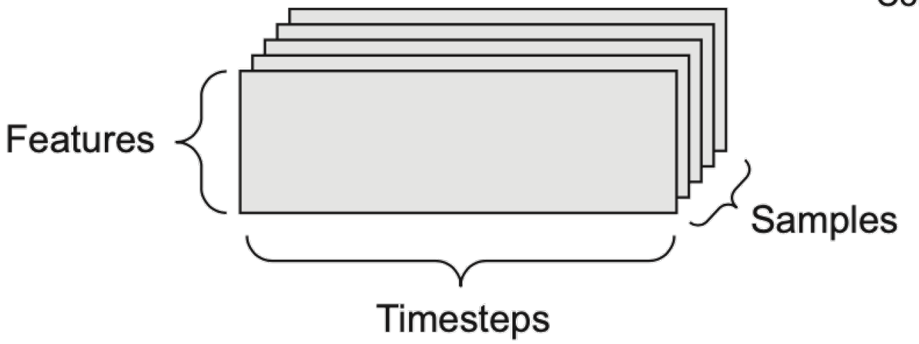
Repeat this for ***every weight in the network*** *using gradients from later layers*

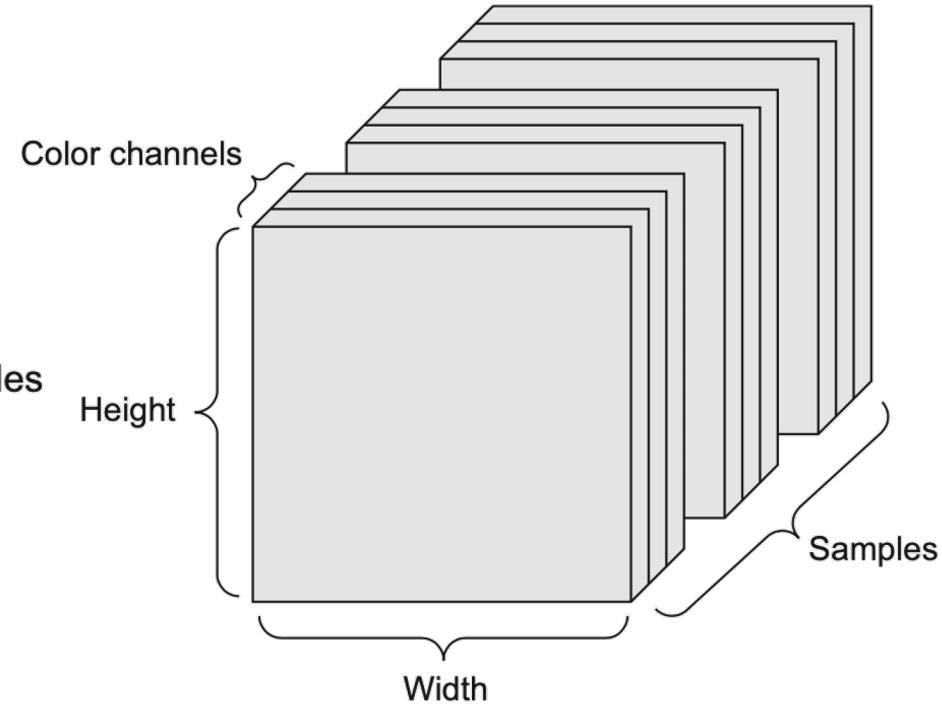
MIT Introduction to Deep Learning, 6.S191 - Alexander Amini

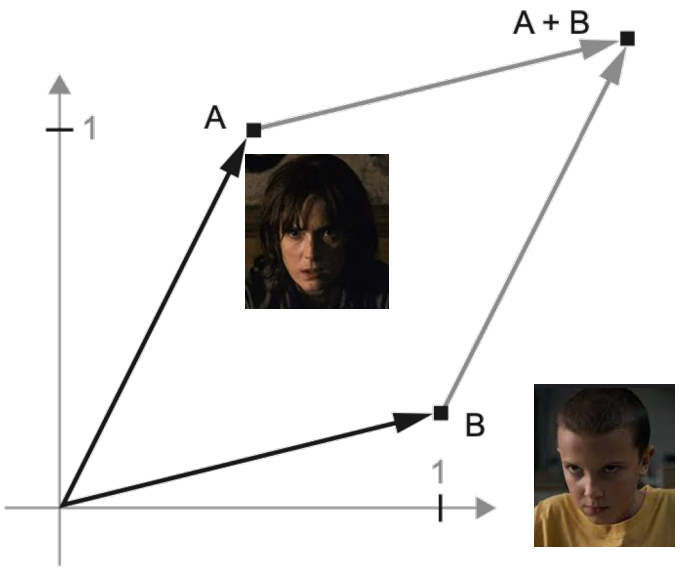
Winona is a dot in feature space



Everything is a tensor



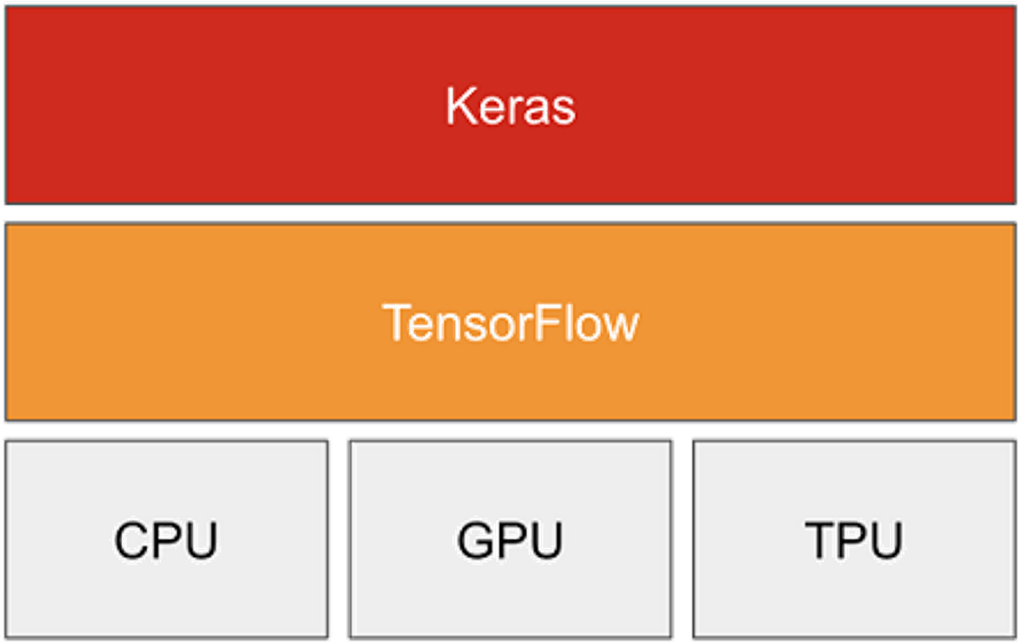




channels-last convention: `(samples, height, width, color_depth)`

Keras & TensorFlow

- **TensorFlow** is an Python ML platform by Google, free and OS.
- **Keras** is a DL API in Python, working as a wrapper over TensorFlow (and others), giving a convenient way to define and train most DL models



Deep learning development: layers, models, optimizers, losses, metrics...

Tensor manipulation infrastructure: tensors, variables, automatic differentiation, distribution...

Hardware: execution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Rasti
1000
Rasti A1

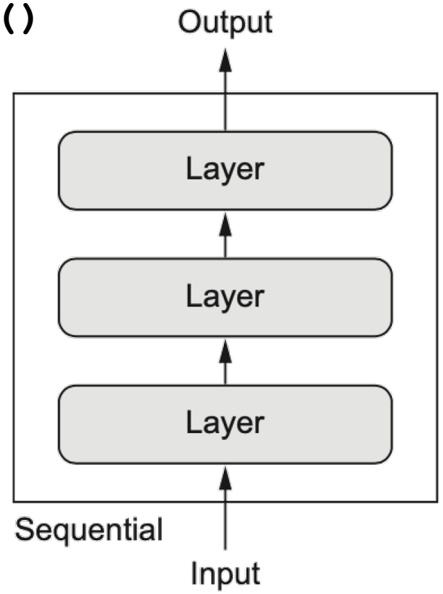
Keras & TensorFlow

```
import tensorflow as tf

mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

#setup simple shallow MLP
model = tf.keras.models.Sequential([
tf.keras.layers.Flatten(input_shape=(28, 28)),
tf.keras.layers.Dense(128, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(10)
])
```




```
model.compile(optimizer='adam',loss=tf.keras.losses.SparseCategoricalCros
sentropy(from_logits=True), metrics=['accuracy'])
model.fit(train_images, train_labels, epochs=10)

test_loss, test_acc = model.evaluate(test_images, test_labels,verbose=2)
```

https://www.tensorflow.org/tutorials/keras/classification

Run in Google Colab

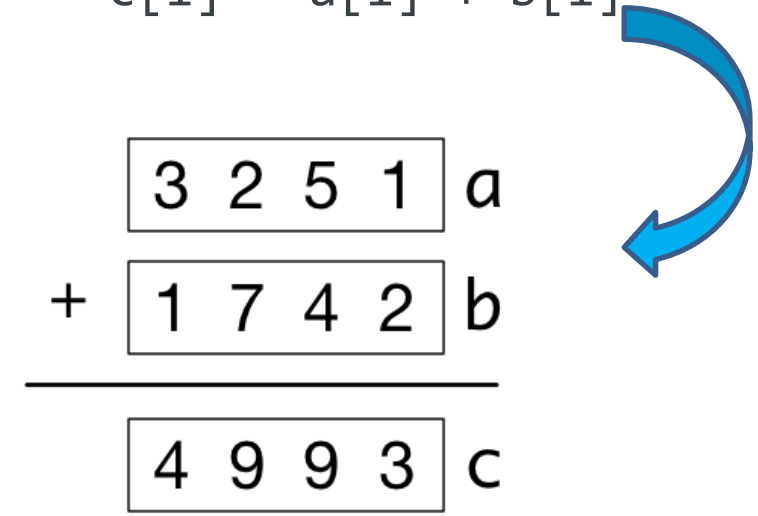
Vectorization

- Use vectors not loops
- For keras/numpy arrays, we can use vector math instead of a loop:

c = a + b

- Gives an opportunity to execute vector addition in parallel
- Same with plenty of operations

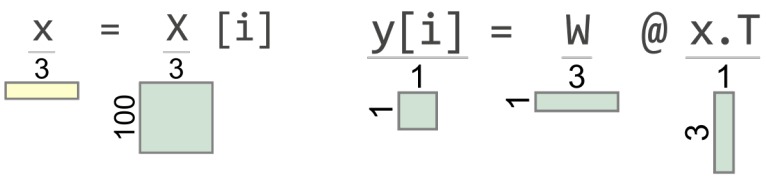
```
for i in range(len(a)):
    c[i] = a[i] + b[i]
```



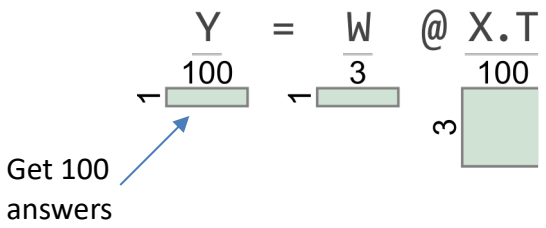
Vectorization in training loop

- Running one instance through network is how we think about it
- In practice, we send a subset or all X instances through the network in one go and compare all $\hat{y}$ predictions to all y
  - Instead of looping through instances, we pass X through to use matrix-matrix multiplies instead of matrix-vector multiplies

```
for epoch in range(nepochs):
    for i in range(n):
        x = X[i]
        y[i] = model(x)
        …
```




```
for epoch in range(nepochs):
    Y = model(X)
    …
```



Assume n=100, m=3, n_neurons=1 in 1x3 weight matrix W

Keras callbacks

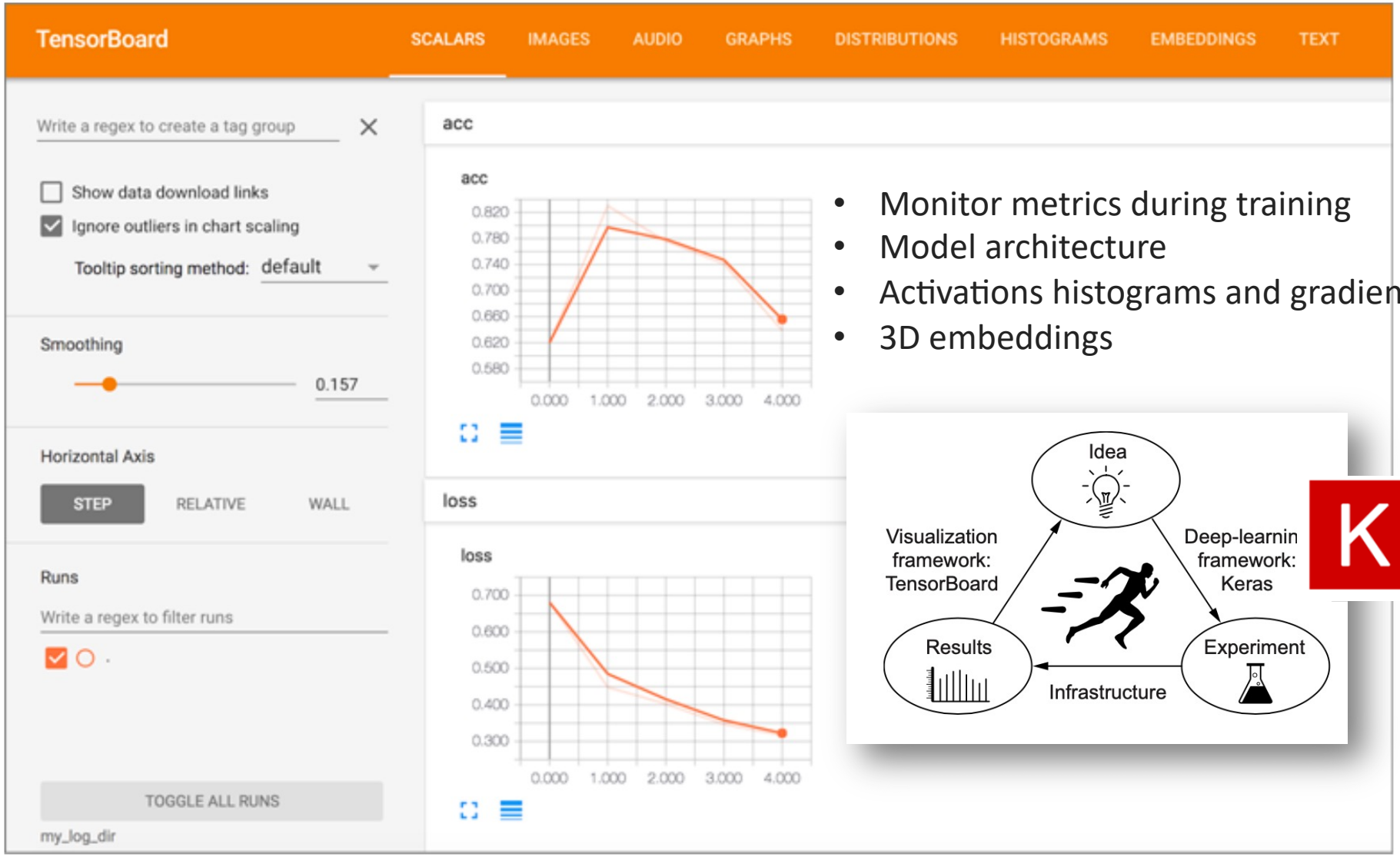
- *Model checkpointing*—Saving the current weights of the model at different points during training.
- *Early stopping*—Interrupting training when the validation loss is no longer improving (and of course, saving the best model obtained during training).
- *Dynamically adjusting the value of certain parameters during training*—Such as the learning rate of the optimizer.
- *Logging training and validation metrics during training*
- *Visualizing the representations learned by the model as they're updated*

Tensorboard

Training metrics

```
$ tensorboard --logdir=my_log_dir
```

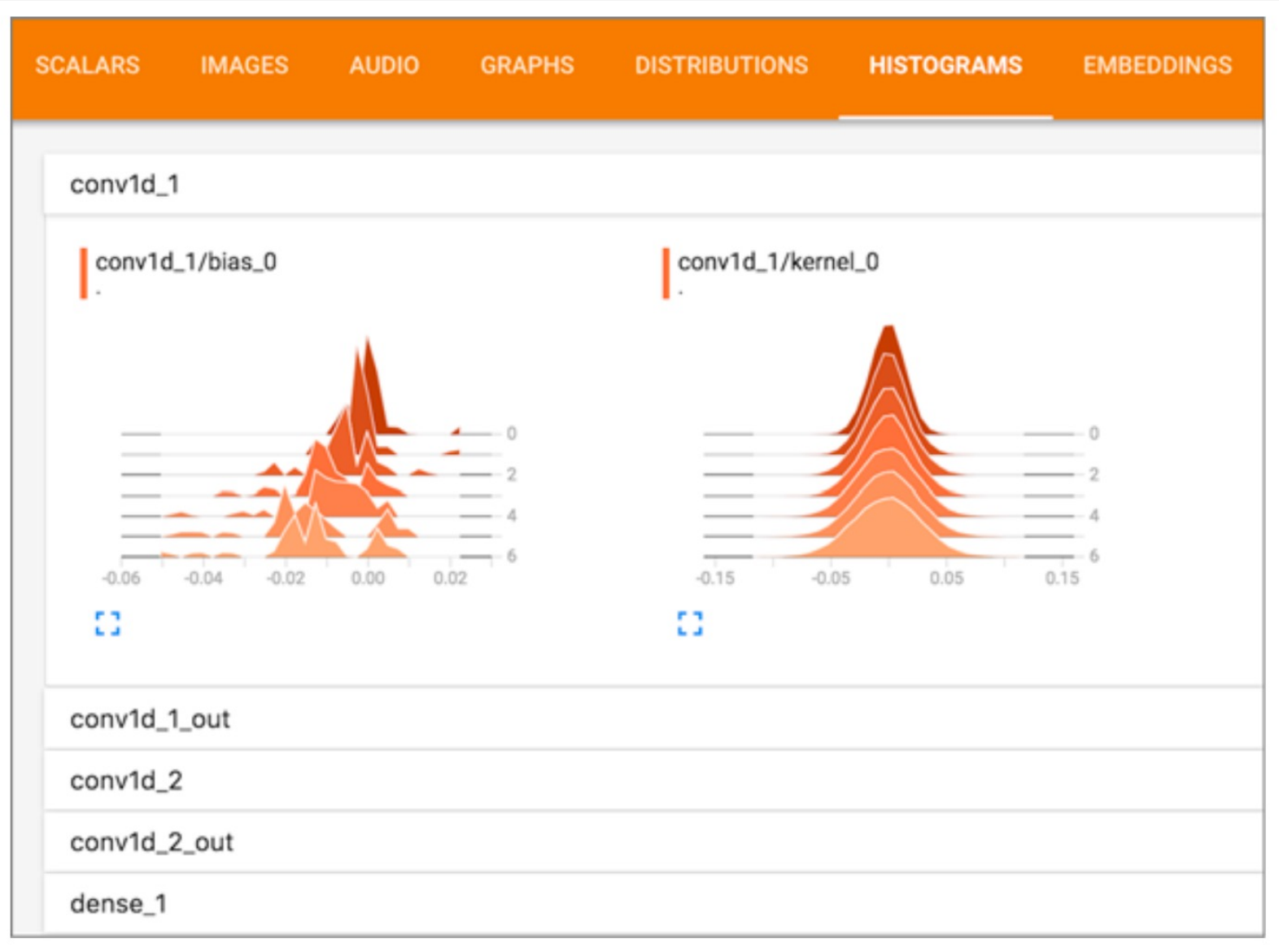
http://localhost:6006



- Monitor metrics during training
- Model architecture
- Activations histograms and gradients
- 3D embeddings

Tensorboard

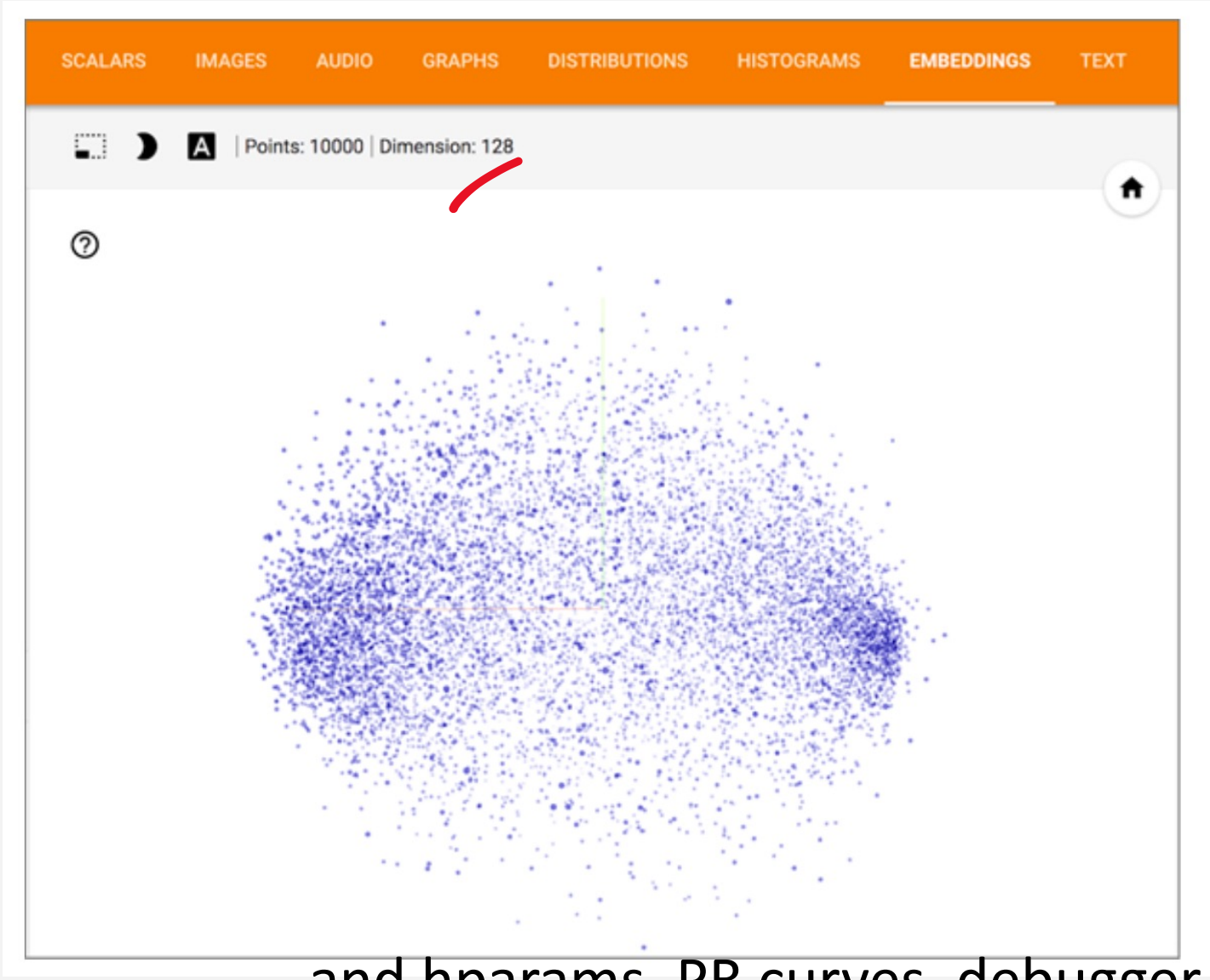
Activation histograms



Tensorboard

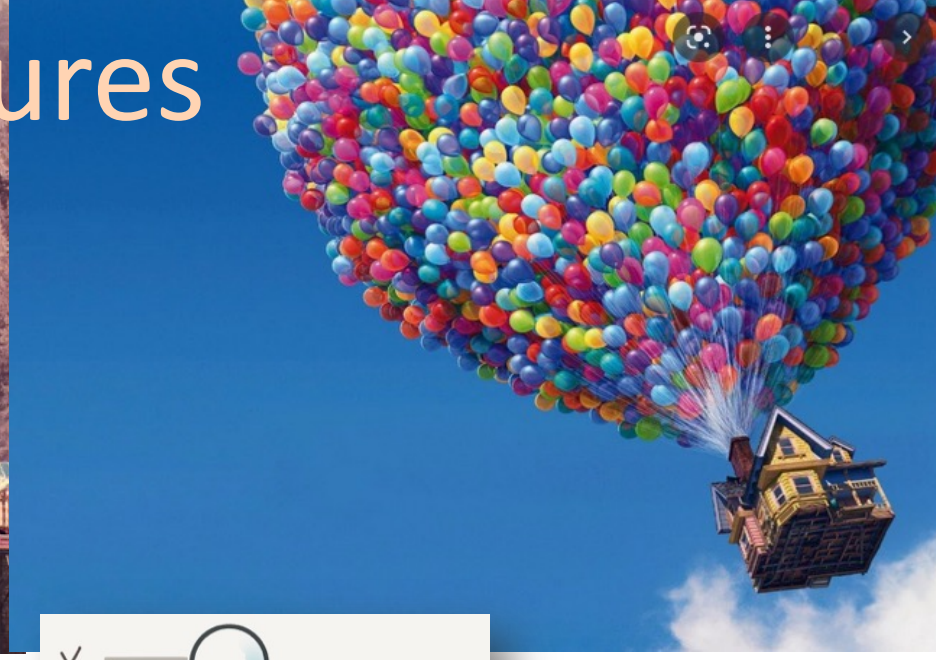
Visualize embedding with PCA or t-SNE

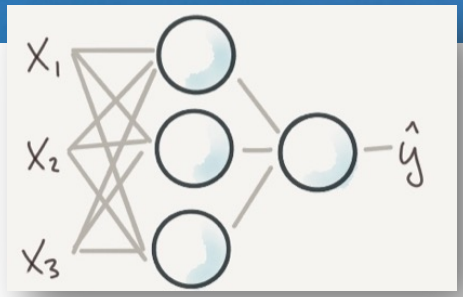
Embeddings



....and hparams, PR curves, debugger, & more

Network architectures

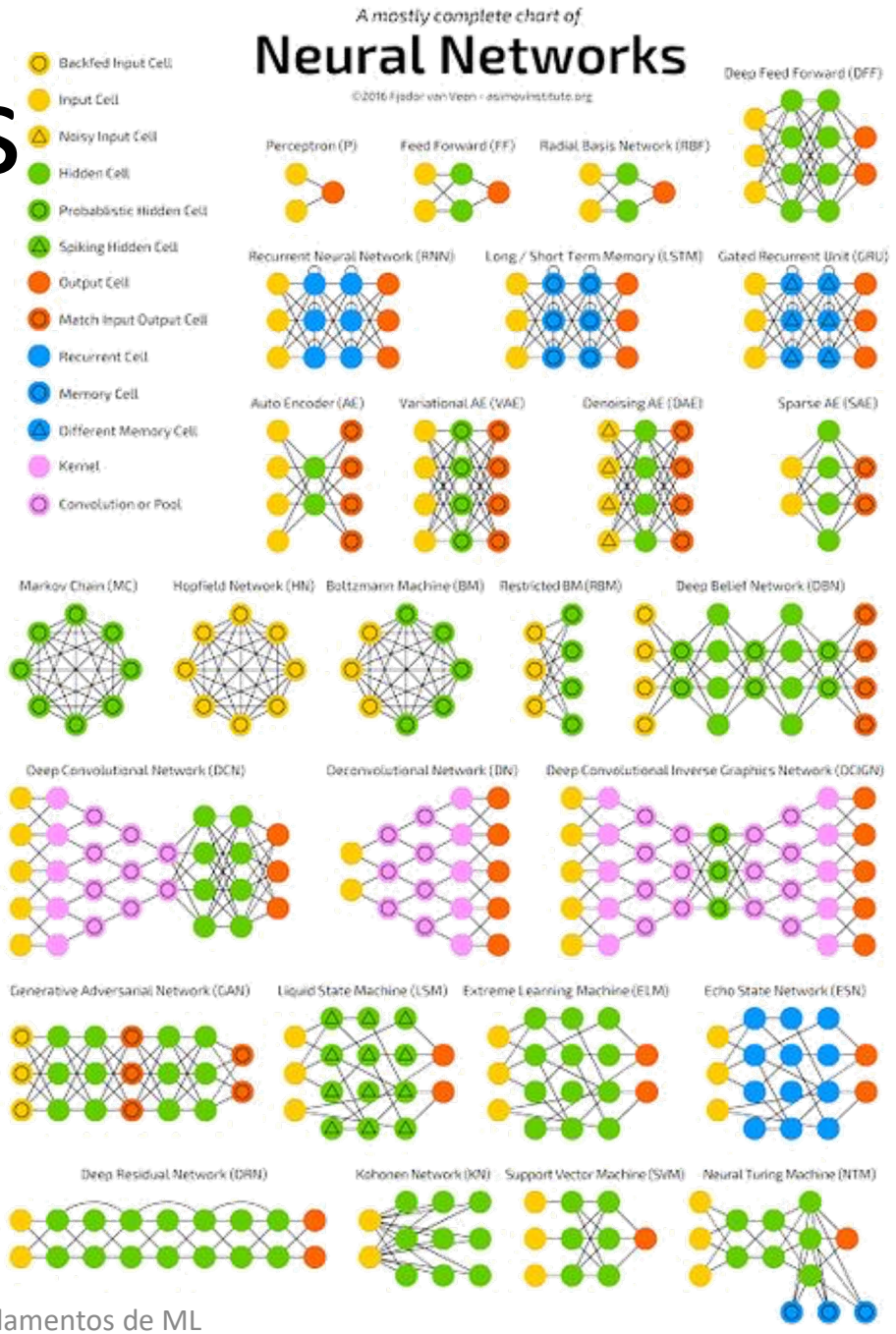




- **Vector data** —Densely connected network (Dense layers).
- **Image data**—2D convnets.
- **Sound data** (for example, waveform)—Either 1D convnets (preferred) or RNNs.
- **Text data**—Either 1D convnets (preferred) or RNNs.
- **Timeseries data**—Either RNNs (preferred) or 1D convnets.
- **Other types of sequence data**—Either RNNs or 1D convnets. Prefer RNNs if data ordering is strongly meaningful (for example, for timeseries, but not for text).
- **Video data**—Either 3D convnets (if you need to capture motion effects) or a combination of a frame-level 2D convnet for feature extraction followed by either an RNN or a 1D convnet to process the resulting sequences.
- **Volumetric data**—3D convnets.

NN architectures

- **Standard**
- **CNN-ConvNets**
  - **images**
- RNN-Recurrent networks
  - sequence of inputs
- GAN-Generative antagonistic networks
  - unsupervised (originally)
- Autoencoders
  - unsupervised (originally)



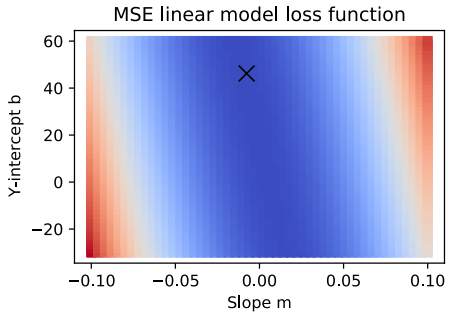
https://www.asimovinstitute.org/neural-network-zoo/

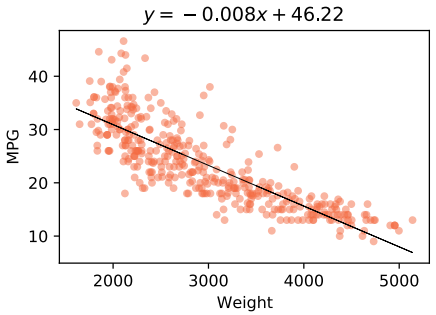
Preparing data

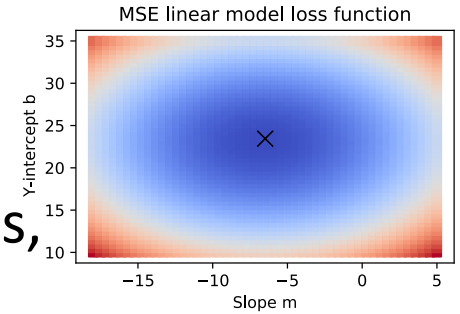
$$X = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

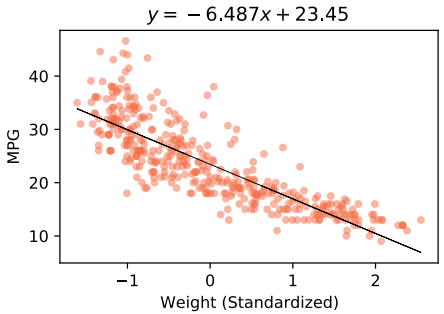
- Everything must be numeric
- No missing values
- Dummy encode categoricals (`pd.get_dummies()`)
- Should normalize numeric features in X to zero-mean, variance one ("whitening")
  - Speeds up training
- Compare regression equations, loss function surfaces

(Cars dataset)

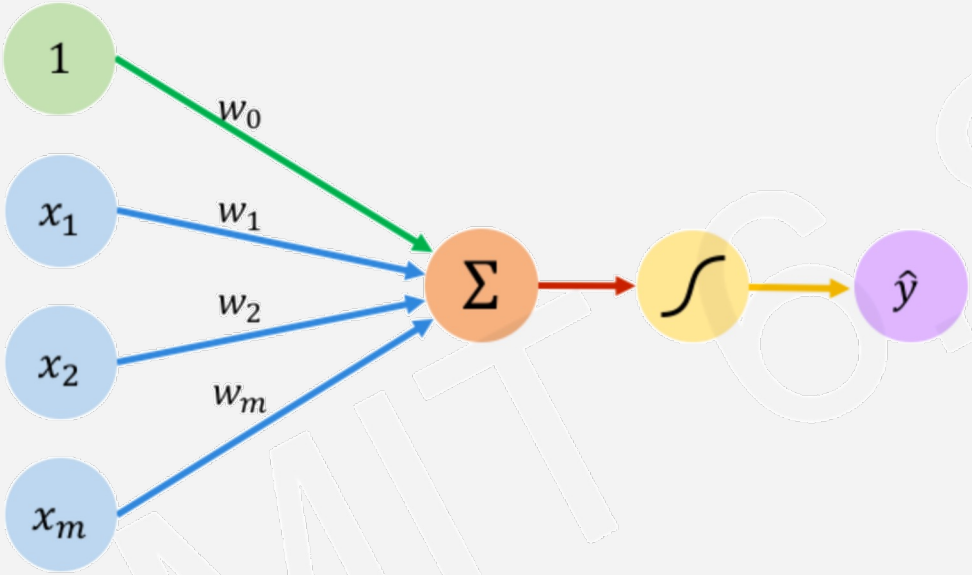


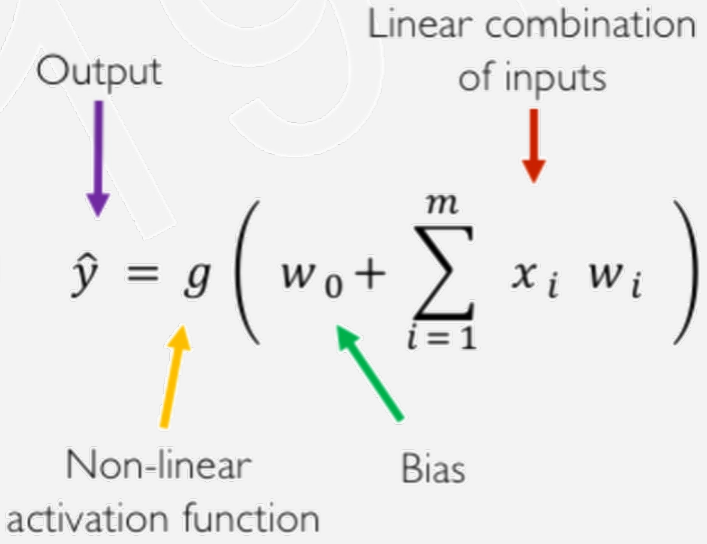


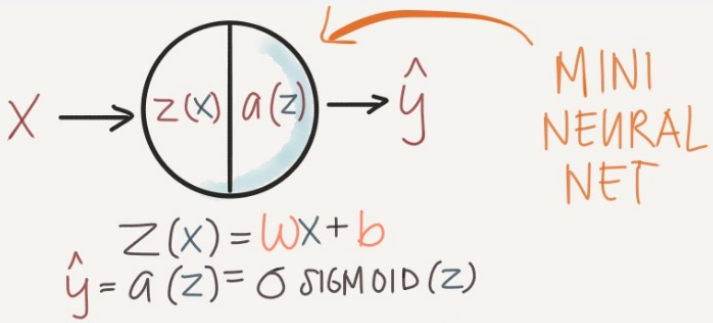


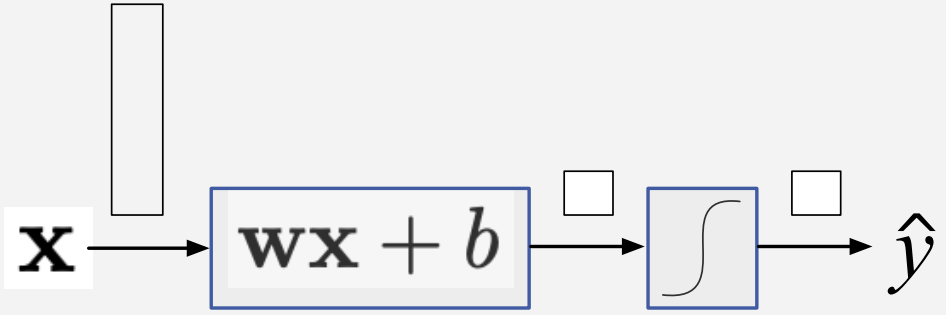


Equivalent Neural Networks illustrations



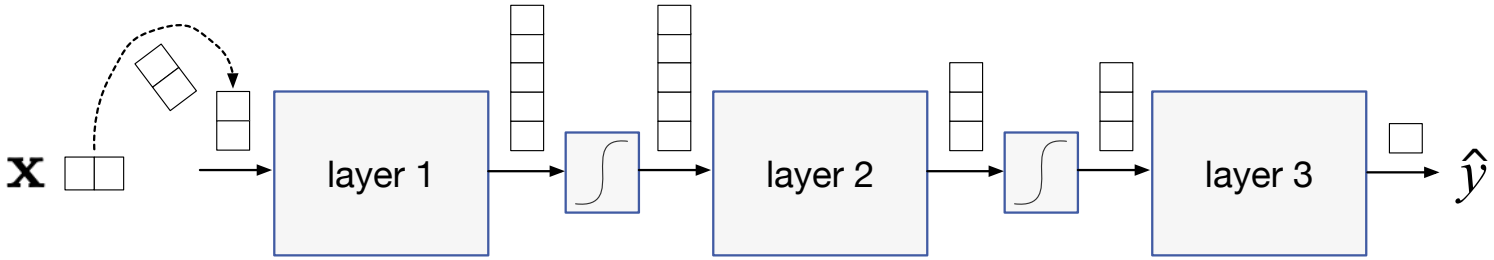






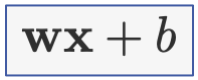
What's a neural network?

- Ignore the neural network metaphor, but know the terminology
- A combination of linear and nonlinear transformations
  - Linear: $z^{[layer]} = W^{[layer]}\boldsymbol{x}^{\boldsymbol{T}} + \boldsymbol{b}^{[layer]}$
  - Nonlinear: $\boldsymbol{g}^{[layer]} = \boldsymbol{\sigma}\left(z^{[layer]}\right)$; called *activation function*
- Networks have multiple *layers*; layer is a stack of *neurons*



- Transform raw $\boldsymbol{x}$ vector into better and better features, final linear layer can then make excellent prediction

DL Building blocks

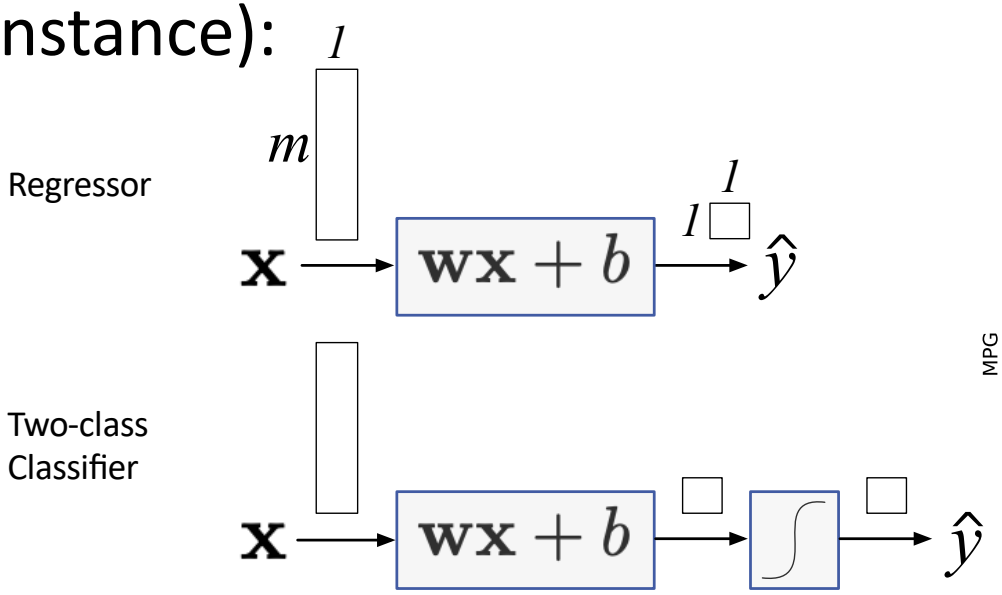


linear

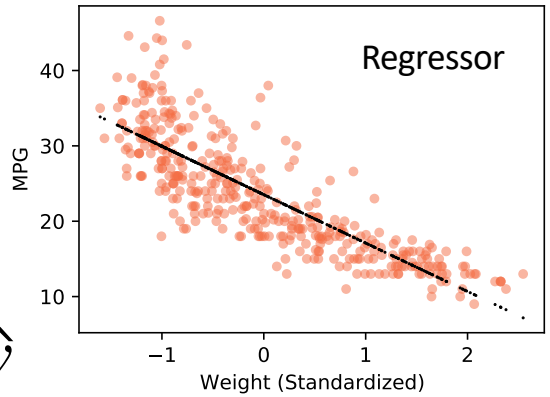

sigmoid


ReLU (rectified linear unit)

- $\hat{y} = w_1 x_1 + w_2 x_2 + \ ... + w_m x_m + b = \boldsymbol{w}\boldsymbol{x}^{\boldsymbol{T}} + b$ for n x m dimensional X
- Linear/logistic regression equivalents (one $\boldsymbol{x}$ instance):



Assume we magically know $\boldsymbol{w}$ and b



Underfitting a bit here
(need more of a quadratic)

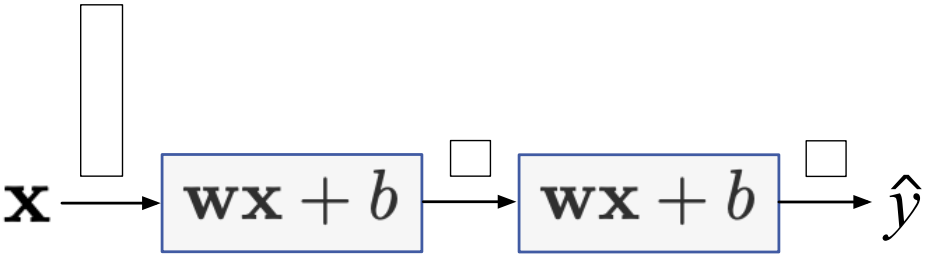
(For simplicity, we are using proper $\boldsymbol{w}\boldsymbol{x}^{\boldsymbol{T}}$ in math but omitting transpose in diagrams)

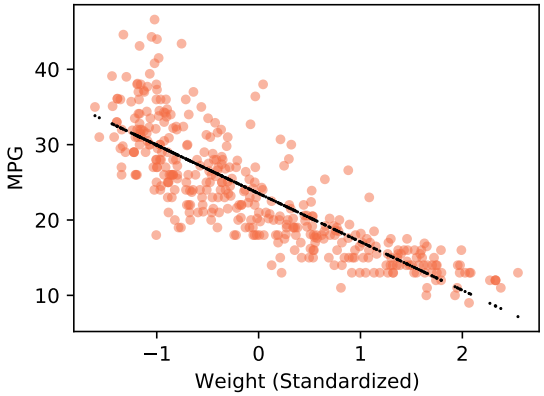
Try adding layers to get more power

- But, sequence of linear models is just a linear model

$$\hat{y} = w'(\mathbf{w}\mathbf{x}^T + b) + b' = w'\mathbf{w}\mathbf{x}^T + w'b + b' = \mathbf{w}''\mathbf{x}^T + b''$$

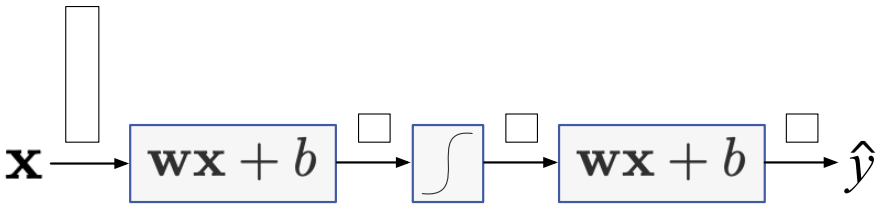
(w' is scalar since $\boldsymbol{wx^T} + b$ is scalar)

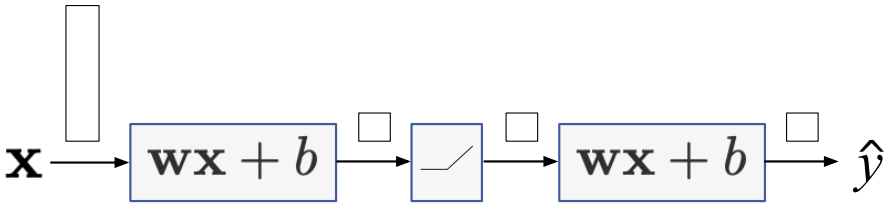


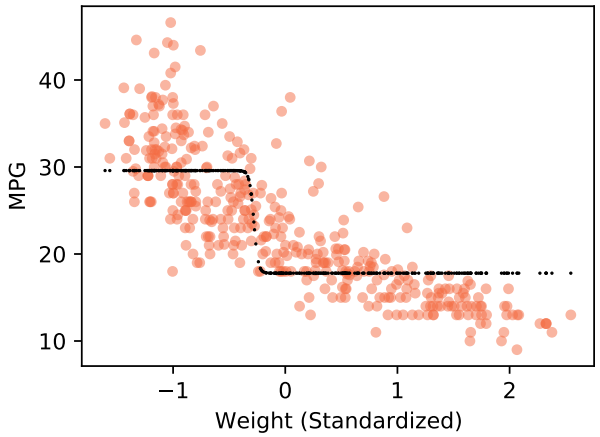


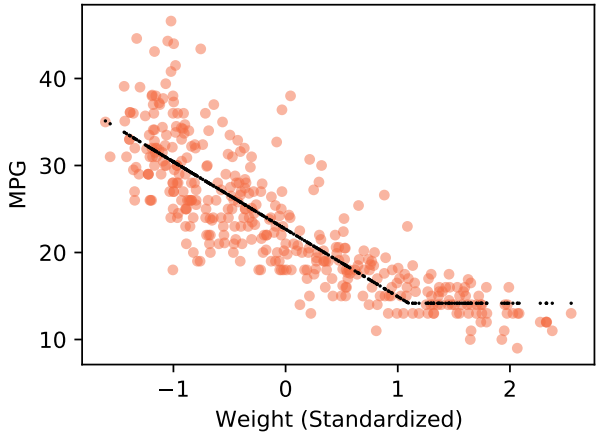
Still just a line

Must introduce nonlinearity







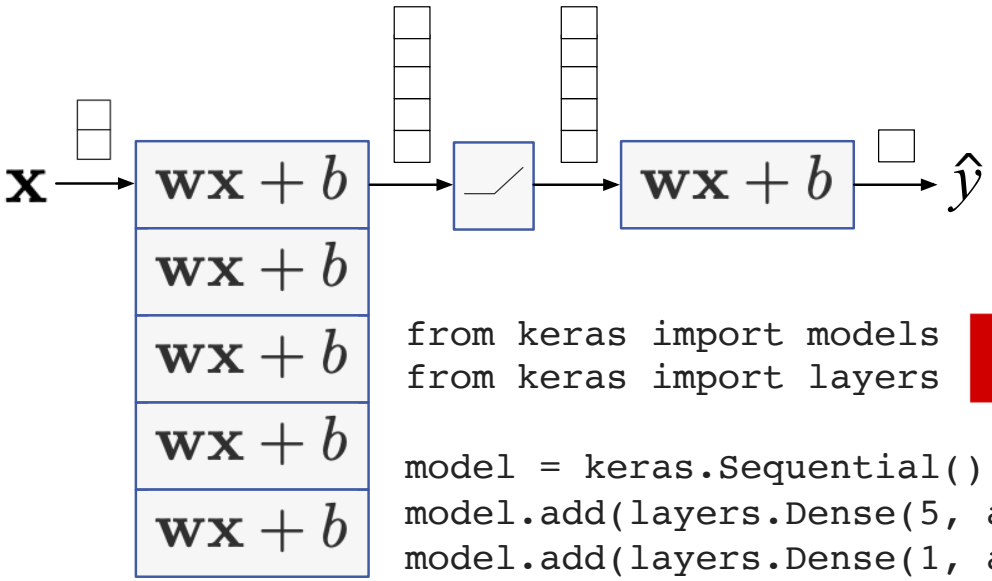


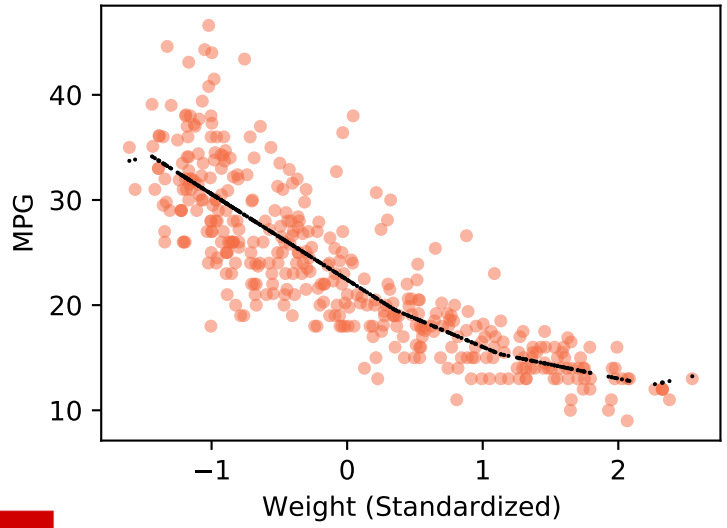

```
from keras import models
from keras import layers
model = keras.Sequential()

model.add(layers.Dense(1, activation='sigmoid', input_shape=(1,)))
{model.add(layers.Dense(1, activation='relu', input_shape=(1,)))}
model.add(layers.Dense(1, activation='linear'))
```

Stack linear models (neurons) for more power

- Stack gives layer: W matrix and $\boldsymbol{b}$
- $\boldsymbol{g}^{[1]} = relu\left(W^{[1]}\boldsymbol{x}^{\boldsymbol{T}} + \boldsymbol{b}^{[1]}\right)$
- $\hat{y} = \boldsymbol{g}^{[2]} = W^{[2]}\boldsymbol{g}^{[1]} + \boldsymbol{b}^{[2]}$



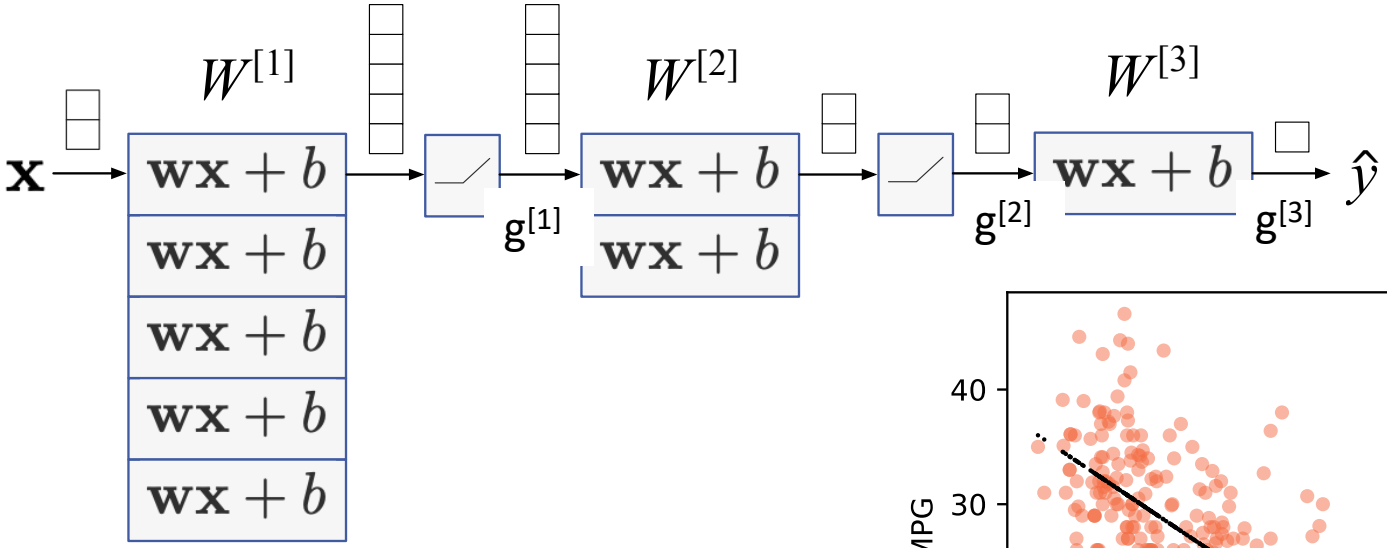


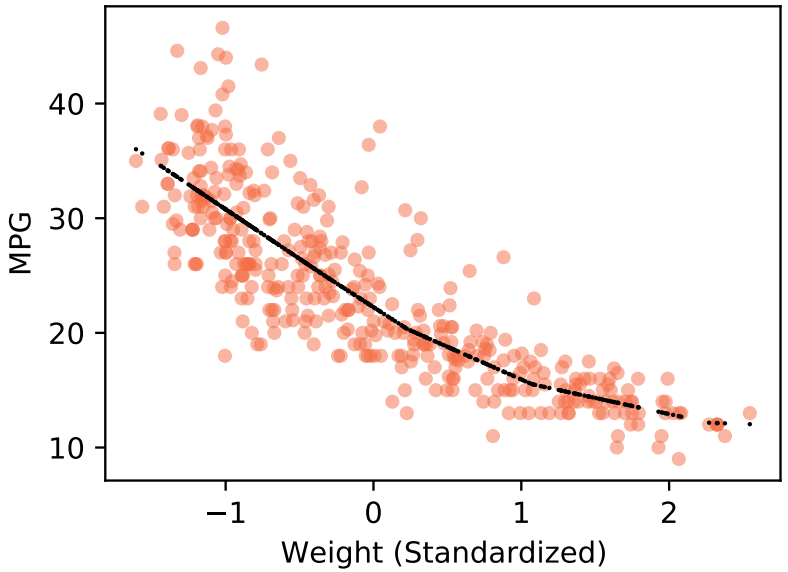

```
from keras import models
from keras import layers

model = keras.Sequential()
model.add(layers.Dense(5, activation='relu', input_shape=(m,)))
model.add(layers.Dense(1, activation='linear'))
```

All these $\boldsymbol{w}$ and b are different
(how many in total?)

Math for dataset 1D: weight→MPG



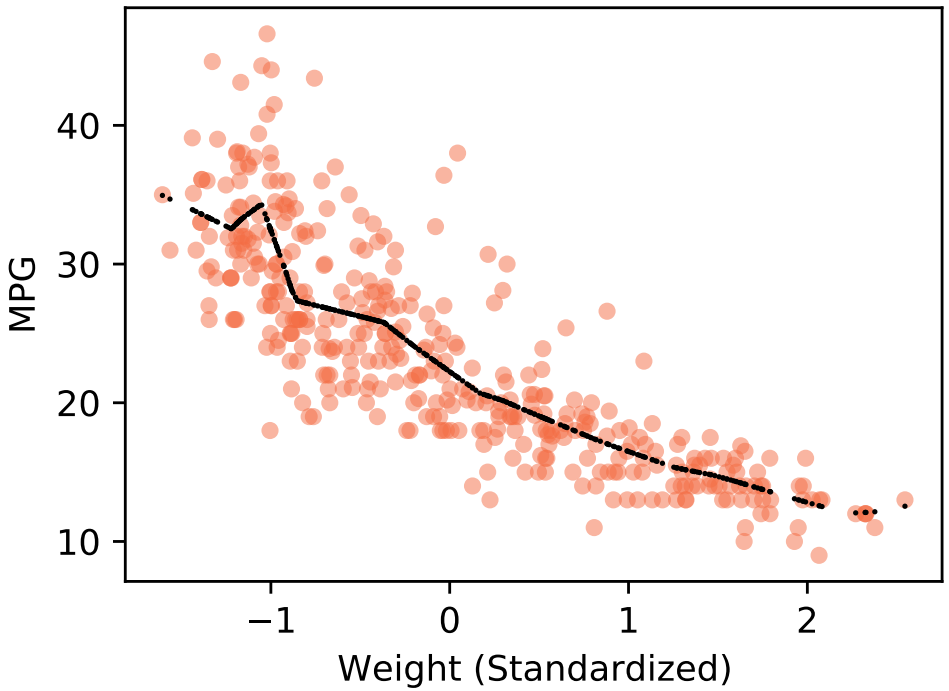



```
from keras import models
from keras import layers

model = keras.Sequential()
model.add(layers.Dense(5, activation='relu', input_shape=(m,)))
model.add(layers.Dense(2, activation='relu'))
model.add(layers.Dense(1, activation='linear'))
```

Too much capacity can overfit

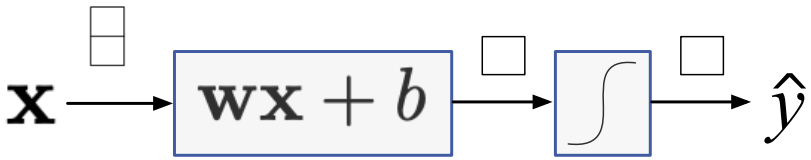
- Models with too many parameters will overfit easily, if we train a long time
- Needs regularization



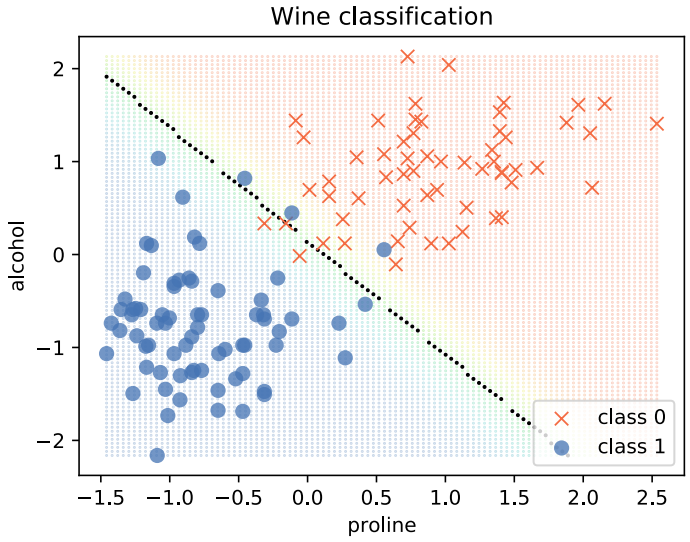

```
from keras import models
from keras import layers

model = keras.Sequential()
model.add(Dense(1000, activation='relu', input_shape=(m,)))
model.add(layers.Dense(1, activation='linear'))
```

Binary classifiers



- Add sigmoid to regressor and we get a two-class classifier
- Prediction $\hat{y}$ is probability of class 1
- One-layer (hidden) network with sigmoid activation function is just a logistic regression model
- Provides hyper-plane decision surfaces



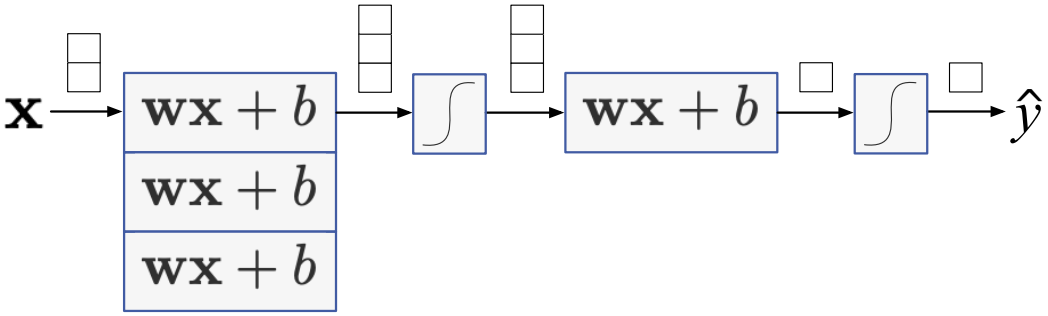

```
from keras import models
from keras import layers
model = keras.Sequential()

model.add(layers.Dense(1, activation='sigmoid', input_shape=(m,)))
```

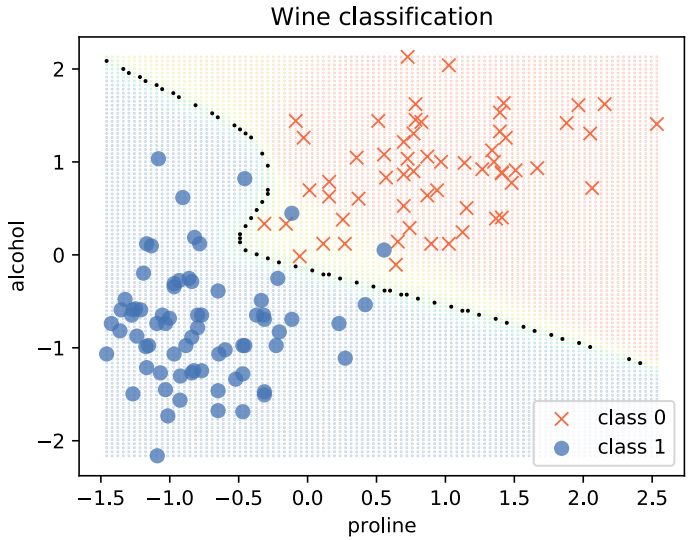
Stack neurons, add layer

See https://github.com/parrt/fundamentals-of-deep-learning/blob/main/notebooks/5.binary-classifier-wine.ipynb

- We get a nonlinear decision surface



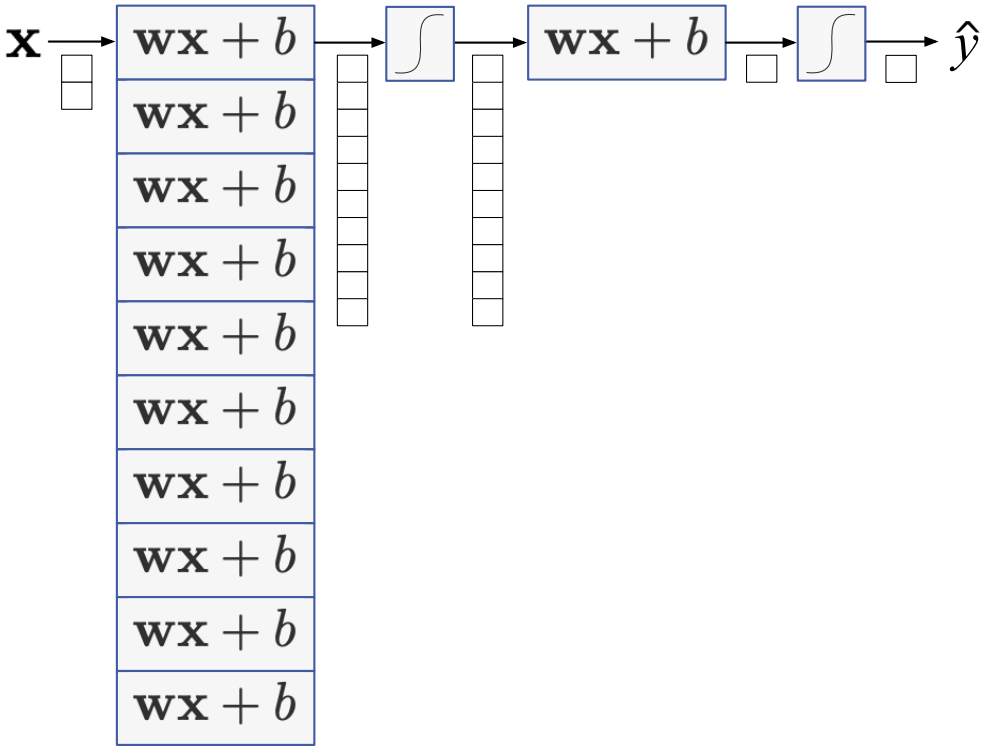
All these $\boldsymbol{w}$ and b are different

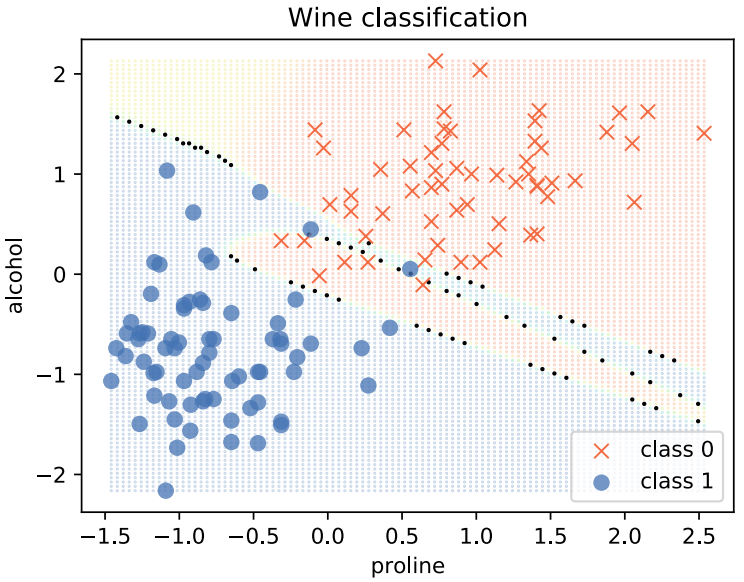



```
from keras import models
from keras import layers

model = keras.Sequential()
model.add(layers.Dense(3, activation='sigmoid', input_shape=(1,)))
model.add(layers.Dense(1, activation='sigmoid'))
```

More neurons: more complex decision surface

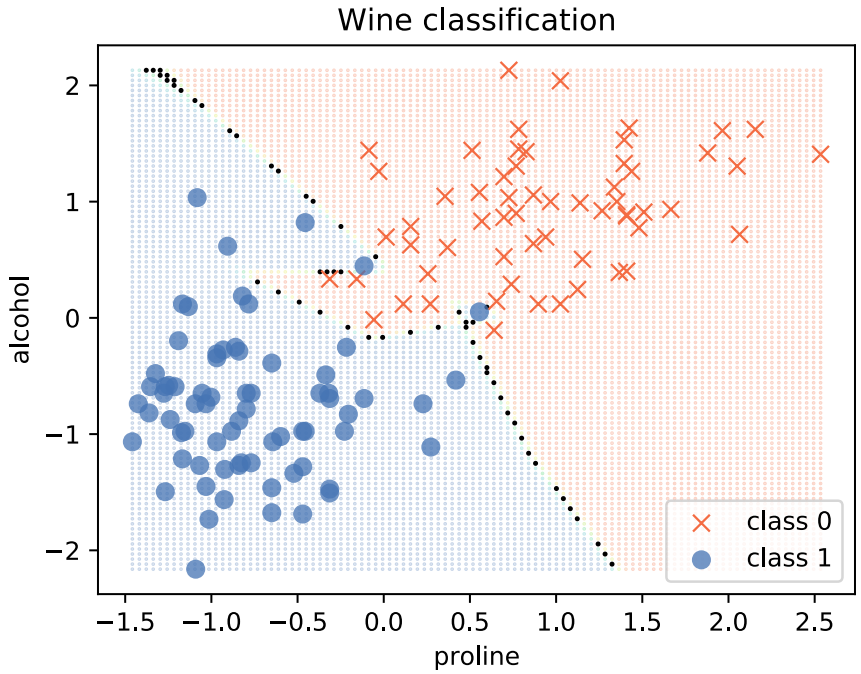




Likely overfit

Not only more complex than hyperplane but non-contiguous regions

Even ReLUs can get "curvy" surfaces



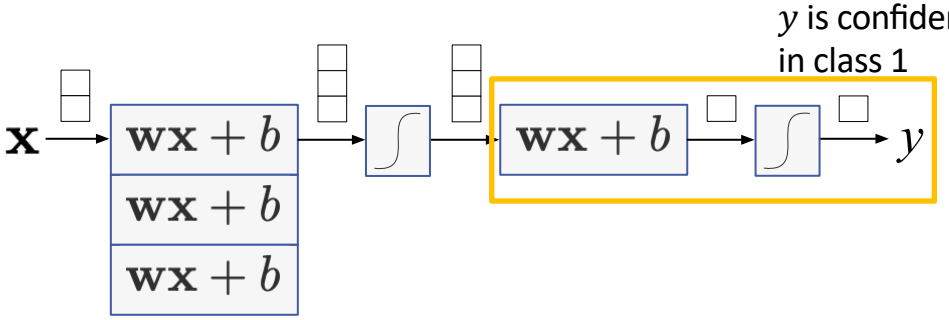

```
from keras import models
from keras import layers

model = keras.Sequential()
model.add(Dense(10, activation='relu', input_shape=(m,)))
model.add(Dense(10, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

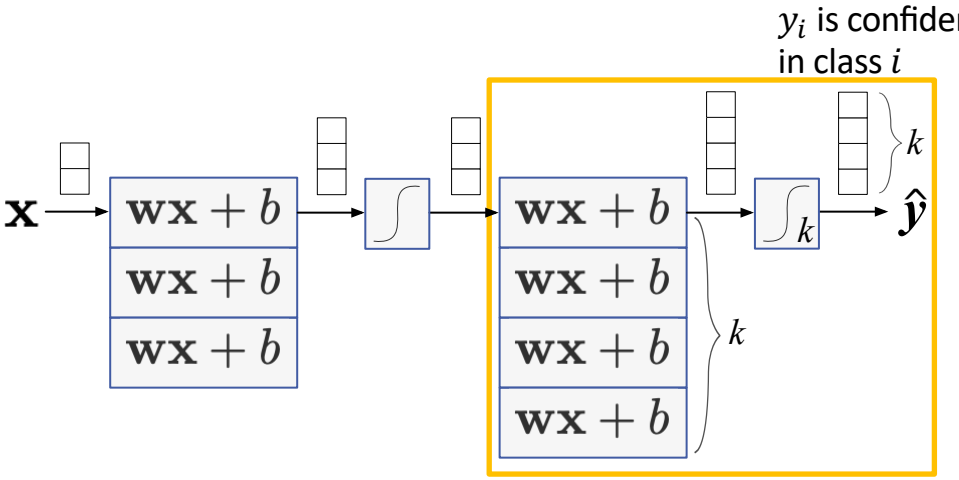
(Last activation function still must be sigmoid)

k-class classifiers

- **2-class problems**: final 1 neuron linear layer + sigmoid layer



- ***k*-class problems**: final k-neuron linear layer + *softmax*




```
from keras import models
from keras import layers
model = keras.Sequential()
model.add(Dense(3, activation='signoid', input_shape=(2,)))
{model.add(Dense(1 activation=sigmoid'))}
model.add(Dense(4, activation=softmax'))
```

(Last activation function still must be softmax)

k-class classifiers

- Instead of one neuron in last layer, we use k for k classes
- Last layer has vector output: $\boldsymbol{z}^{[layer]} = W^{[layer]}\boldsymbol{x}^{\boldsymbol{T}} + \boldsymbol{b}^{[layer]}$
- Instead of sigmoid, we use softmax function
- Vector of k probabilities as activation: $\hat{\boldsymbol{y}} = softmax\left(\boldsymbol{z}^{[layer]}\right)$
- Normalized probabilities of k classes

$$softmax(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

Sample softmax computation

- For layer output vector $\boldsymbol{z}$:
  - Any number gets mapped to positive values

$$softmax(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

  - max gets inflated respect to others, thus, normalization acts as a max function, but 'softer' (i.e., is continuous).
- Similar to the Boltzmann distribution,
  - thus, suceptible of a T parameter, to modulate the impact of smaller values (T >> 1 tends to equiprobability).

```
z = np.array([0.1, 1, 5])
np.exp(z)
```

```
array([  1.10517092,   2.71828183, 148.4131591 ])
```

```
np.exp(z) / np.sum(np.exp(z))
```

```
array([0.00725956, 0.01785564, 0.9748848 ])
```


@txolerfx

Loss functions

- **Regression**: typically mean squared error (MSE); should have smooth derivative, though mean absolute error works despite discontinuity (it's derivative is a V shape)

```
>>> mse = tf.keras.losses.MeanSquaredError()
>>> mse(y_true, y_pred).numpy()
```

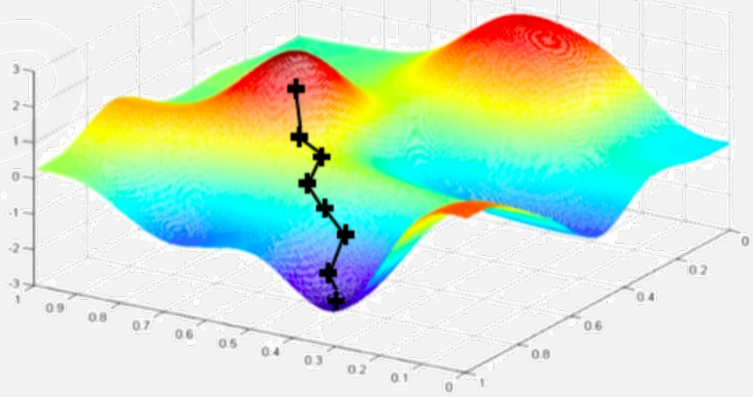
- **Classification**: log loss (also called cross entropy)
  - Penalizes very confident misclassifications strongly
  - Function of actual y and estimated probabilities, not predicted class
  - Perfect score is 0 log loss, imperfection gives unbounded scores

```
>>> bce = tf.keras.losses.BinaryCrossentropy(from_logits=True)
>>> bce(y_true, y_pred).numpy()
```

Gradient descent

Algorithm

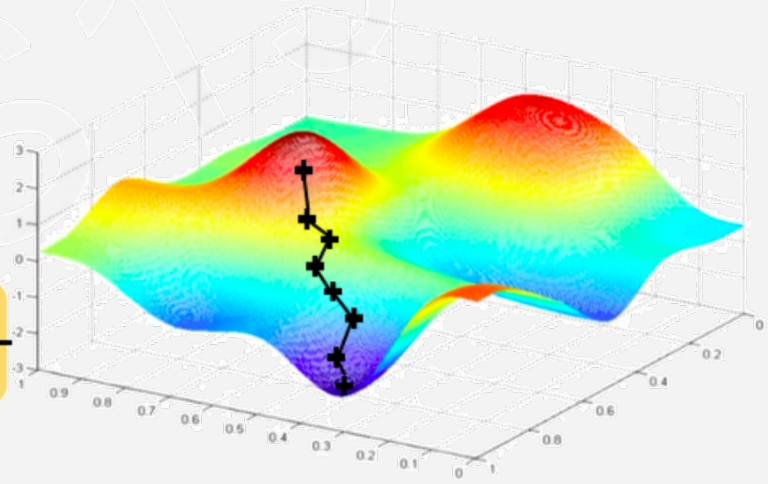
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights



Mini-Batch gradient descent

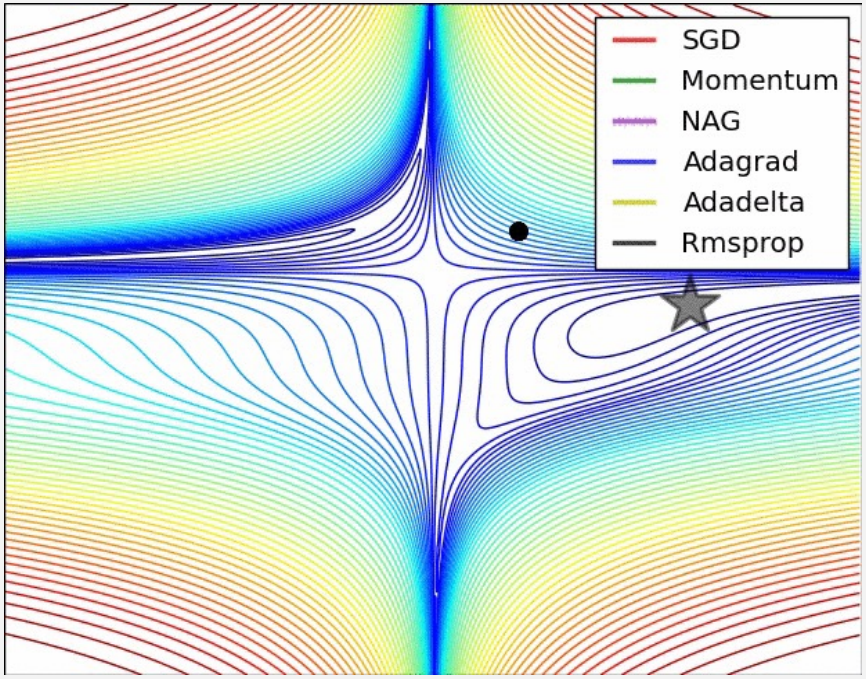
Algorithm

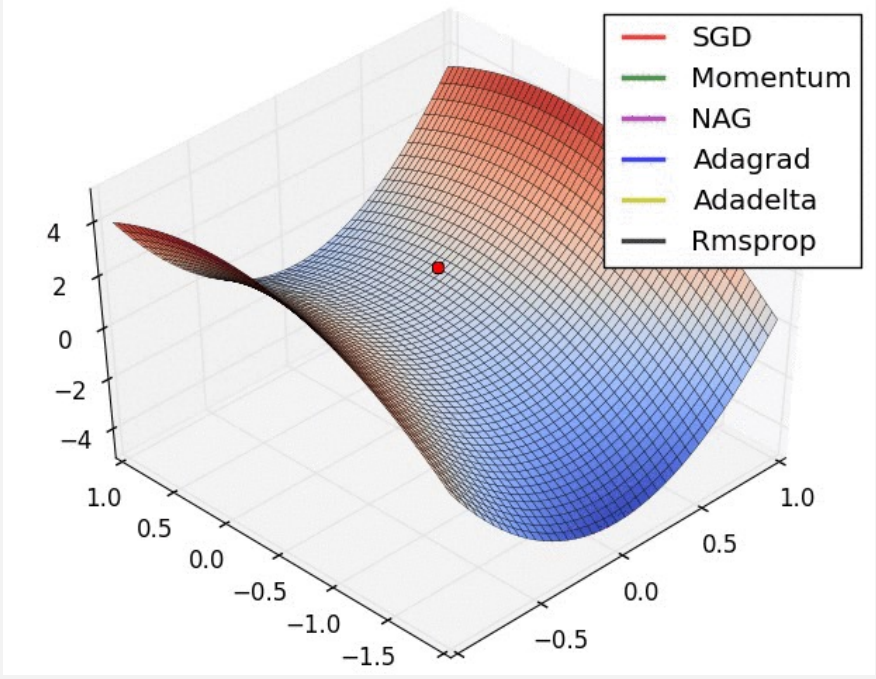
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick batch of B data points
4. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}} = \frac{1}{B} \sum_{k=1}^{B} \frac{\partial J_k(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
6. Return weights



Fast to compute and a much better estimate of the true gradient!

Optimization algorithms





https://cs231n.github.io/neural-networks-3/

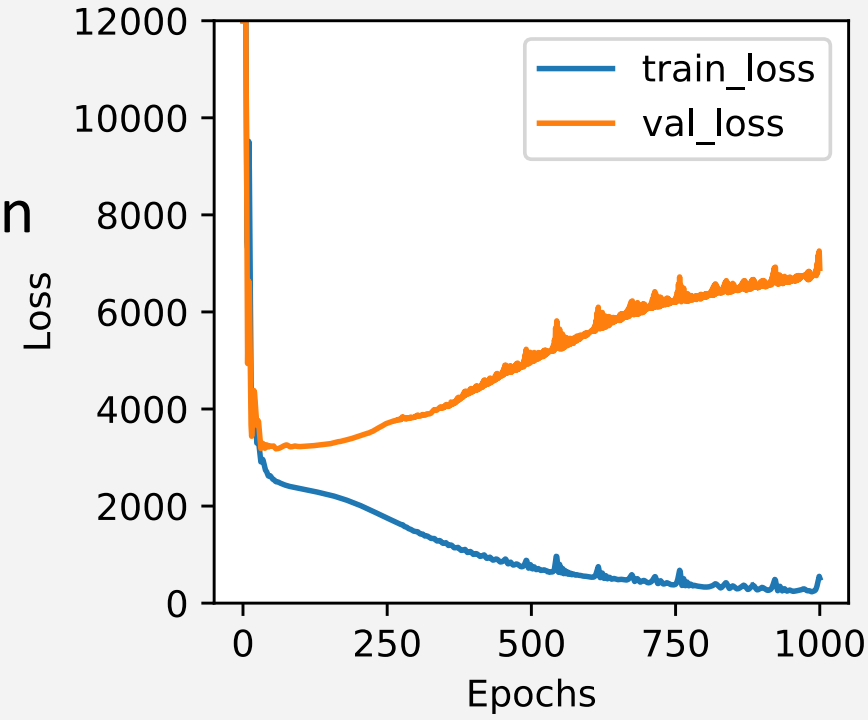
Optimizers in Keras

- SGD
- RMSprop
- Adam
- Adadelta
- Adagrad
- Adamax
- Nadam
- Ftrl

```
>>> opt = tf.keras.optimizers.SGD(learning_rate=0.1)
>>> var = tf.Variable(1.0)
>>> loss = lambda: (var ** 2)/2.0         # d(loss)/d(var1) = var1
>>> step_count = opt.minimize(loss, [var]).numpy()
>>> # Step is `- learning_rate * grad`
>>> var.numpy()
0.9
```

Common train vs validation loss behavior

- DL networks have so many parameters, we can often get training error down to zero!
- But, we care about generalization
- Unfortunately, validation error often tracks away from training error as the number of epochs increases
- This model is clearly overfitting
- Need to use regularization to improve validation loss



Training process

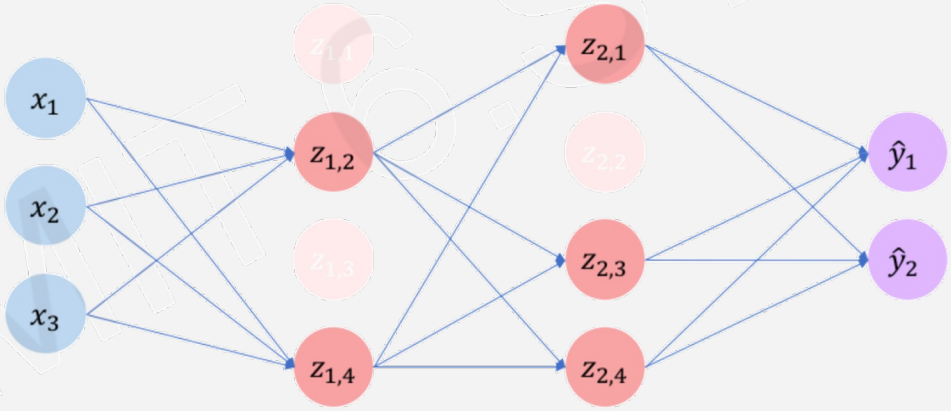
1. Prepare data
   - normalize numeric variables
   - dummy vars for categoricals
   - conjure up values for missing values
2. Split out at least a validation set from training set
3. Choose network architecture, appropriate loss function
4. Choose hyper-parameters, such as dropout rate
5. Choose a learning rate, number of epochs (passes through data)
6. Run training loop (until validation error goes up or num iterations)
7. Goto 3, 4, or 5 to tweak; iterate until good enough

Regularization

Dropout

- During training, randomly set some activations to 0
  - Typically 'drop' 50% of activations in layer
  - Forces network to not rely on any 1 node

```
tf.keras.layers.Dropout(p=0.5)
```



Early stop

- Stop training before we have a chance to overfit

Regularization techniques

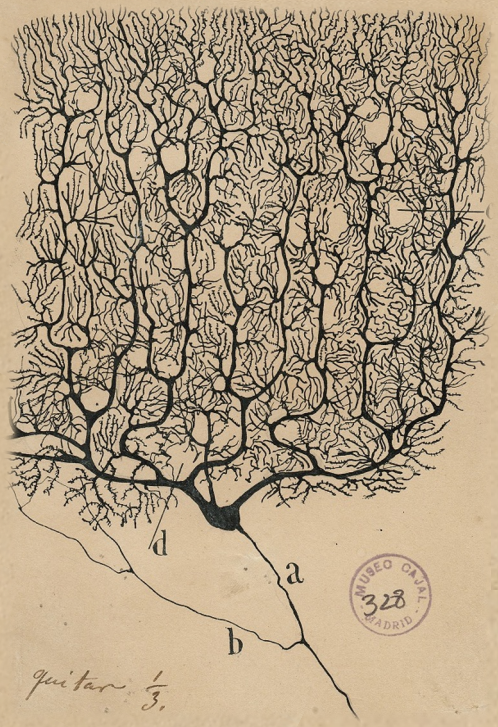
- Get more training data; can try augmentation techniques
  (more data is likely to represent population distribution better)
- Reduce number of model parameters (i.e., simplify it)
  (reduce power/ability to fit the noise)
- Add drop out layers (randomly kill some neurons)
- Weight decay (L2 regularization on model parameters,
  restrict model parameter search space)
- Early stopping, when validation error starts to go up
  (generally we choose model that yields the best validation error)
- Batch normalization has some small regularization effect
  (Force layer activation distributions to be 0-mean, variance 1)
- Stochastic gradient descent tends to land on better
  generalizations

Summary

- Vanilla deep learning models are layers of linear regression models glued together with nonlinear functions such as sigmoid/ReLUs
- Regressor: final layer transforms previous layer to single output
- Classifier: add sigmoid to last regressor layer (2-class) or add softmax to last layer of k neurons (k-class)
- Training a model means finding optimal (or good enough) model parameters as measured by a *loss* (cost or error) function; hyper parameters describe architecture and learning rate, amount of regularization, etc.
- We train using (stochastic) gradient descent; tuning model and hyper parameters is more or less trial and error ☹ but experience helps a lot

ML Fundamentals – Lecture 9

- Perceptron
- Feedforward nets
- Tensors & Keras
- Architectures
- Training
  - Optimizers
  - Regularization



Next:
Deep learning II