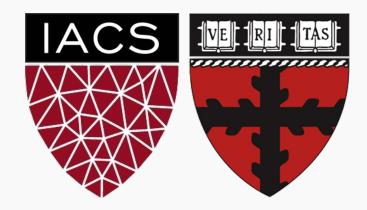
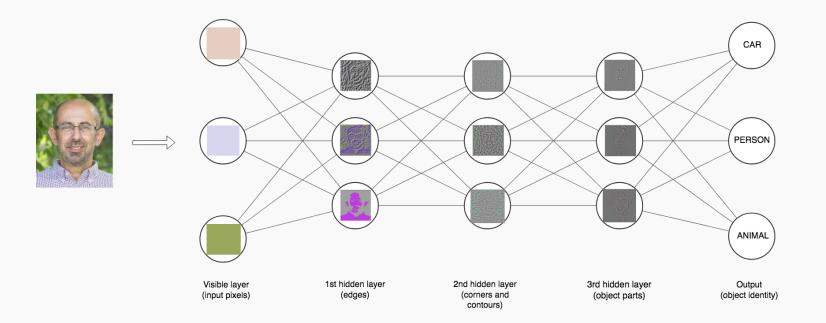
# Lecture 33 : NN Review

## CS109A Introduction to Data Science Pavlos Protopapas, Kevin Rader and Chris Tanner



Deep learning is a mathematical framework for learning **layered representations** from data. Neural networks are models for learning such representations; they are structured in actual layers stacked next to each other.





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Deep learning is not always the right tool for the job.

#### XGBoost, Random Forest or Gradient Boosting is usually a better choice for:

• Tabular data, data with engineered features

#### NNs shine on:

- Image recognition
- Natural language processing
- Autonomous driving
- Speech recognition

Do NNs benefit from feature engineering? Yes, when there is domain knowledge, and/or when there is too few training data.



### INPUT

The input data is a 2D data matrix of shape (batch\_size, features).

All inputs to a NN need to be tensors. Values in the tensors should be small (in the [-1, 1] or [0, 1] range). Heterogeneous data should be normalized. Some feature engineering might benefot small datasets.

We pass the number of features as a parameter to the input layer. If our training data consists of 6000 observations, each with 4 features, then input\_shape = (4,)



### INPUT

Categorical variables should be encoded using one of the options we have learned:

- Integer Encoding: each unique label is mapped to an integer;
- **One Hot Encoding**: each label is mapped to a binary vector;

To input images in a FFN we must flatten them first, that is, reshape the 2D or 3D array of pixel values to a 1D array (these will be the features)



### **LOSS FUNCTION**

**Regression**: **Mean squared error** (mean\_squared\_error)

#### **Classification:** Cross-entropy

- For binary target variables we use binary\_crossentropy.
- For multiclass target variables, integer encoded, we use sparse\_categorical\_crossentropy.
- For multiclass target variables, one-hot encoded, we use categorical\_crossentropy.



### OUTPUT

```
number of features = 4
```

model.add(tf.keras.layers.Dense(4, activation='softmax'))



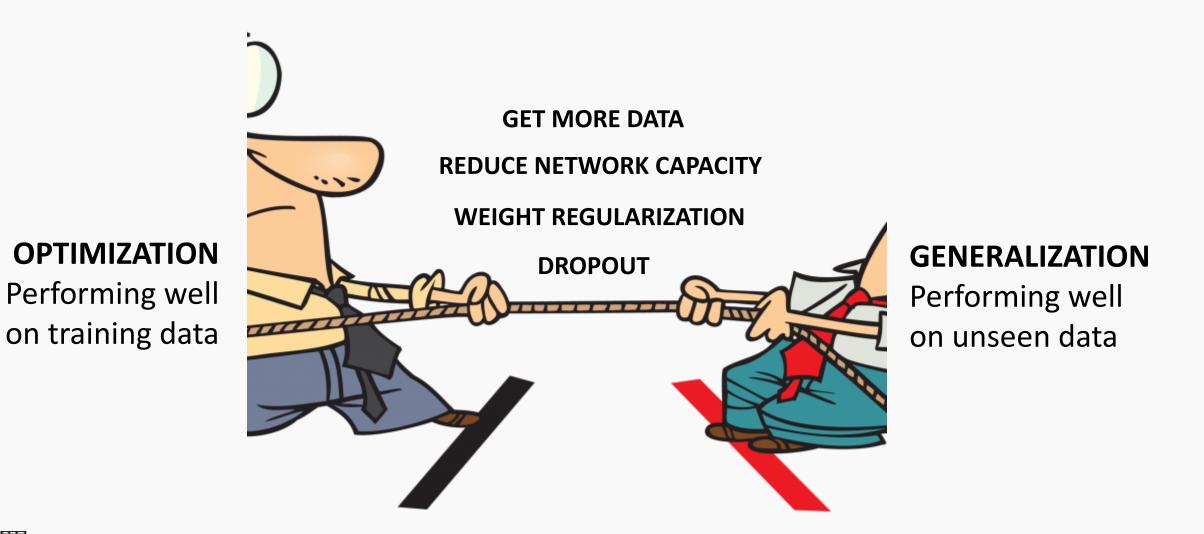
## Design choices for neural networks





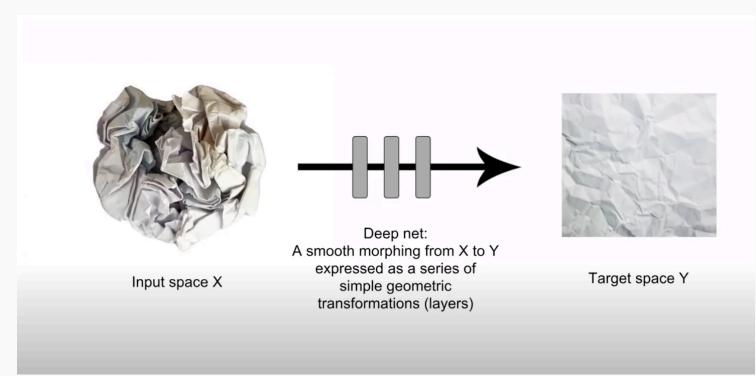
# Unfortunately there is no magic formula







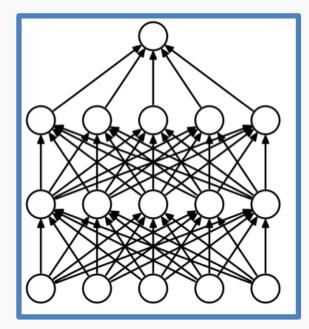
We can think of layers as transformations from the input space of the layer to the output space of the layer; a transformation that involves an affine part followed by a non-linear part (activation function). A mapping to a lower dimensional space, as seen in the figure below, from a talk by Francois Chollet, the creator of keras.

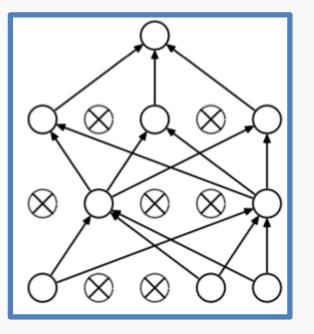




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Dropout was developed by Geoff Hinton and his students at the University of Toronto. It consists of randomly dropping out (setting to zero) a number of output features of the layer during training. For balance during testing, the layer's output values are scaled down by a factor equal to the dropout rate; no units are dropped out in test time.





In a large network many units can collaborate to respond to the input while the weights can remain relatively small. This is called co-adaptation. Dropout prevents overfitting by reducing co-adaptation of neurons. It's like training many random subnetworks.



Its implementation in keras drops a percentage of the input nodes at training time, then scales the values up by the same proportion and does nothing at test time.

model.add(layers.Dropout(0.5))

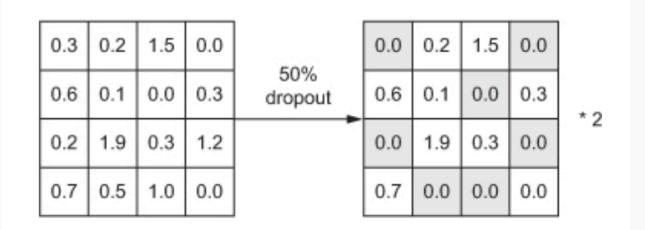
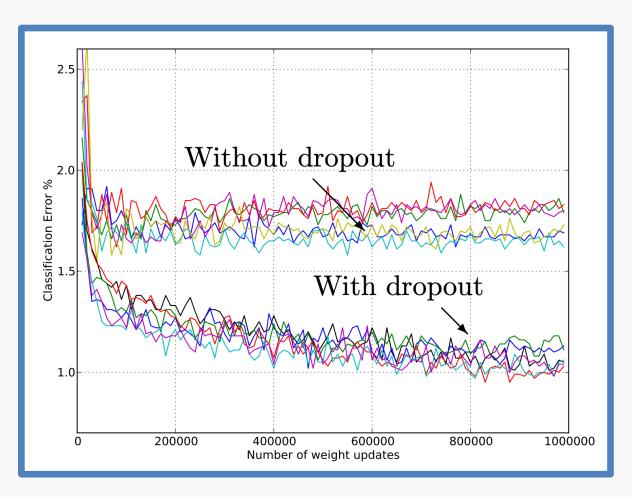


Image: Francois Chollet



## Regularization : Dropout

#### Widely used and highly effective



Test error for different architectures with and without dropout.

The networks have 2 to 4 hidden layers each with 1024 to 2048 units.



## Regularization : Data augmentation





crop-and-pan



flip-ud



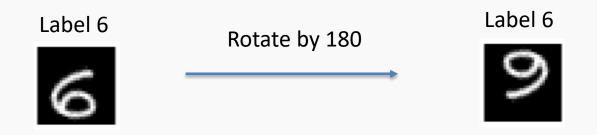
elastic







Carefully choose your transformations. Not all transformations are valid.



Data Augmentation does not work for tabular data and not as nicely for time series.



