Intro to Applied Deep Learning

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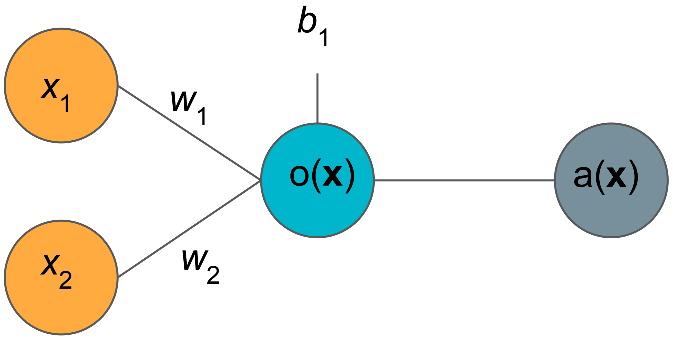
MINER & KASCH
DATA SCIENCE

Contents

What is deep learning?

Deep learning models are essentially large neural networks. Neural networks are basically the function (neuron) below chained together many times.



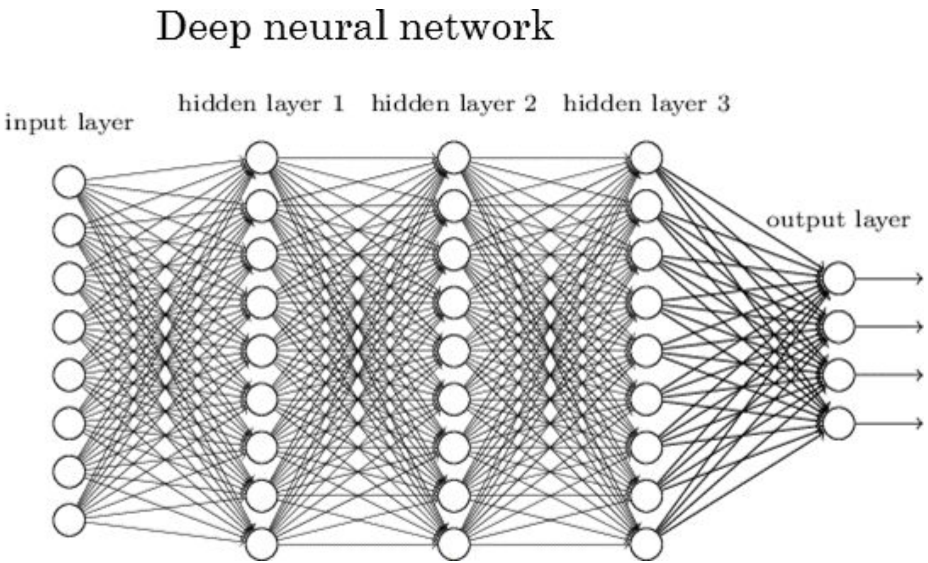
$$a(x) = a(o(x)) = a(b + \sum_{i}^{n} x_i w_i)$$

What is deep learning?

Deep learning models are essentially large neural networks. Neural networks are basically the function (neuron) below chained together many times.

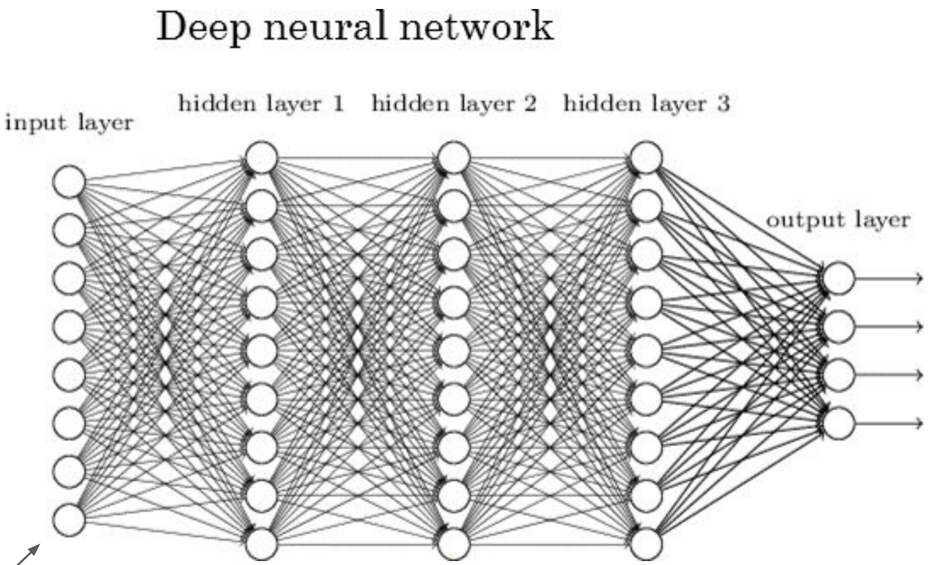
$$f(x) = f^{(3)}(f^{(2)}(f^{(1)}(x)))$$

What is deep learning?



http://www.rsipvision.com/exploring-deep-learning/

What is deep learning?



Input data

http://www.rsipvision.com/exploring-deep-learning/

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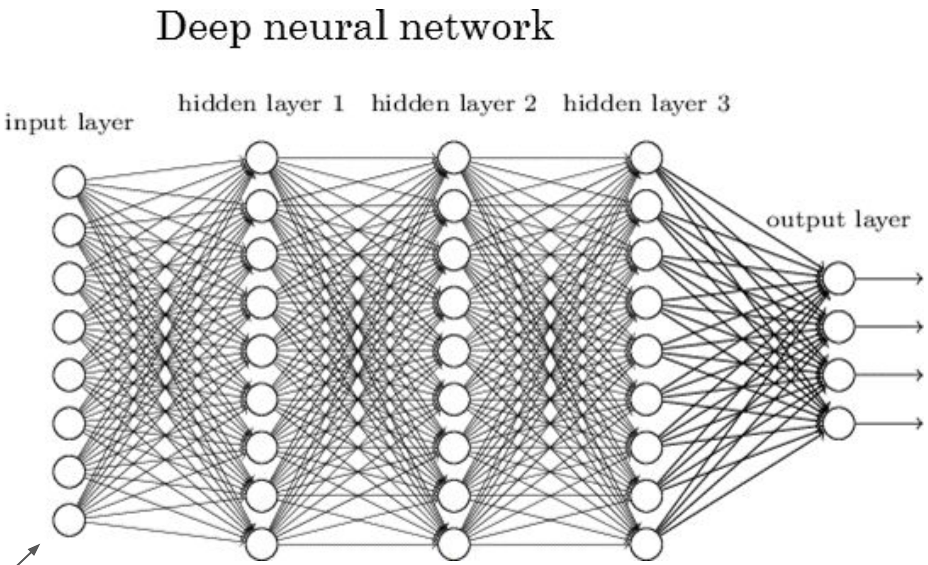

Input data

Data Transformations

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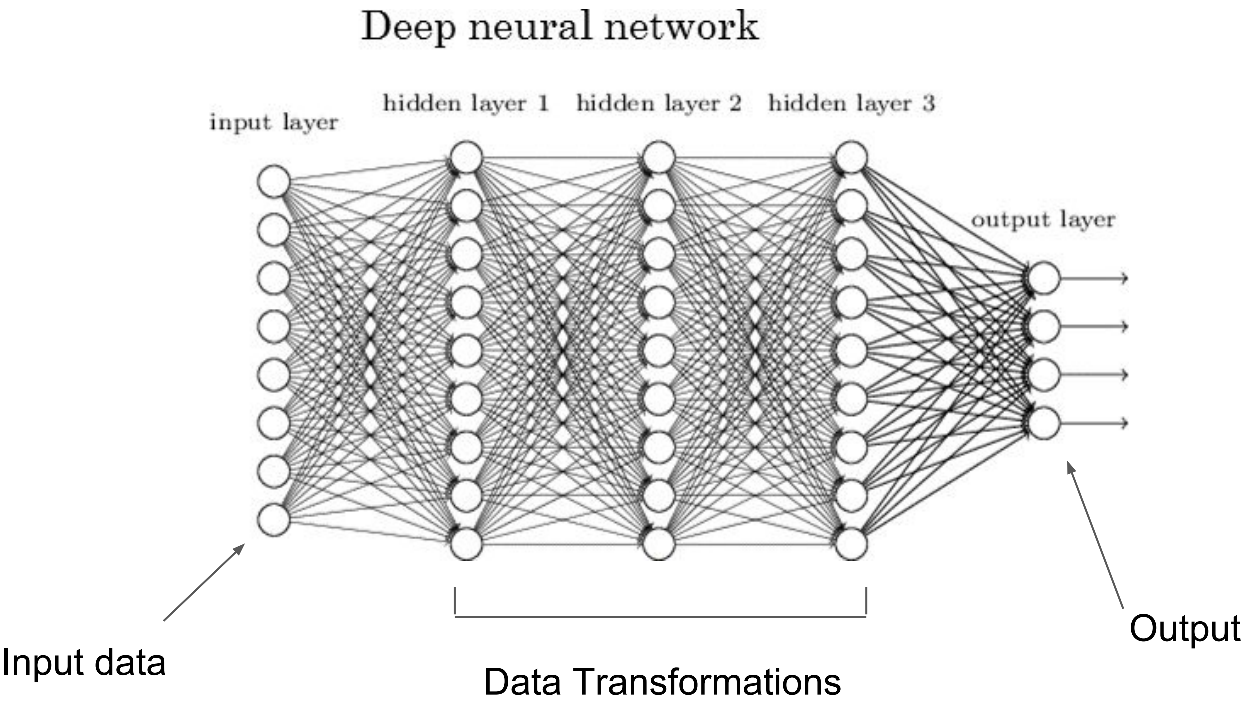

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Representation learning

Deep learning presents us with a unique philosophy for machine learning. Instead of learning the mapping from our features to an output we are learning the best representation of our features.

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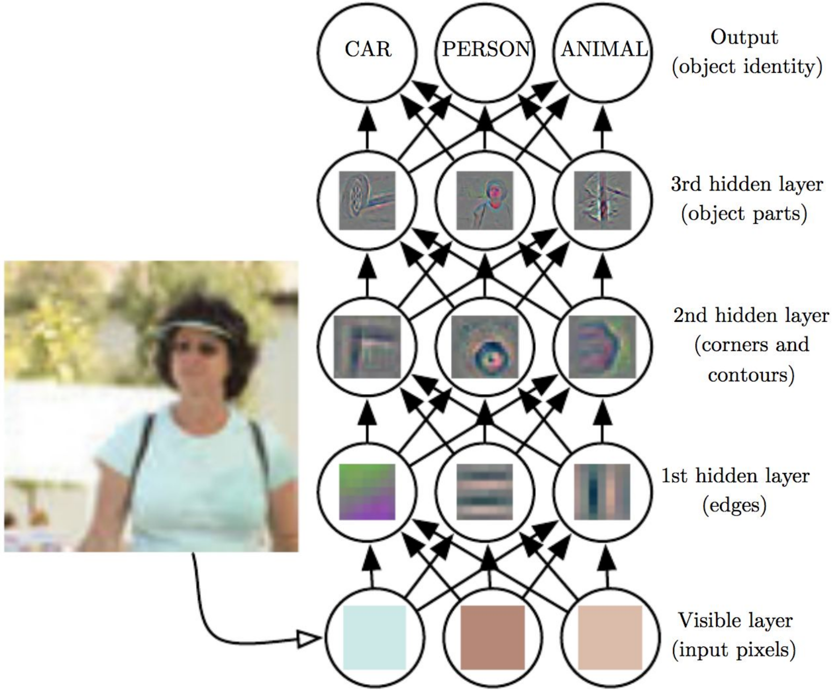
Each layer of a neural network introduces feature representations that are expressed in terms of other more simple representations.

The process has multiple steps, with each layer building on the representations created by the previous layer.

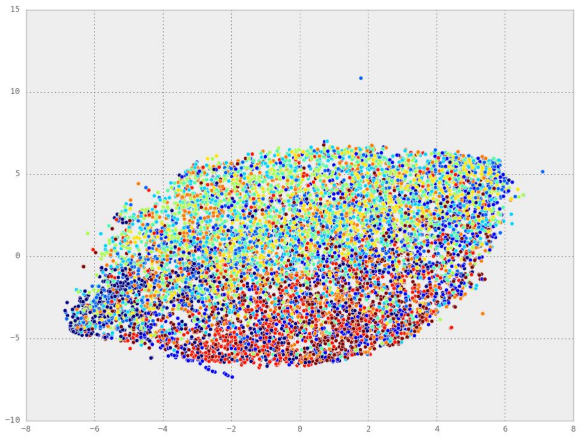
Representation Learning

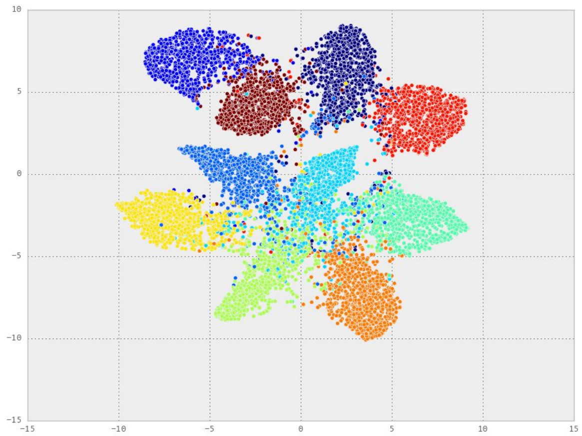


[Deep Learning Book (2016)]

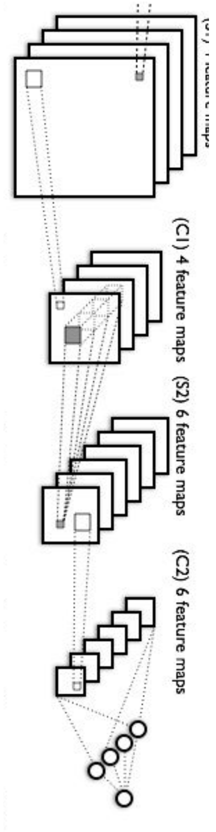
Representation Learning

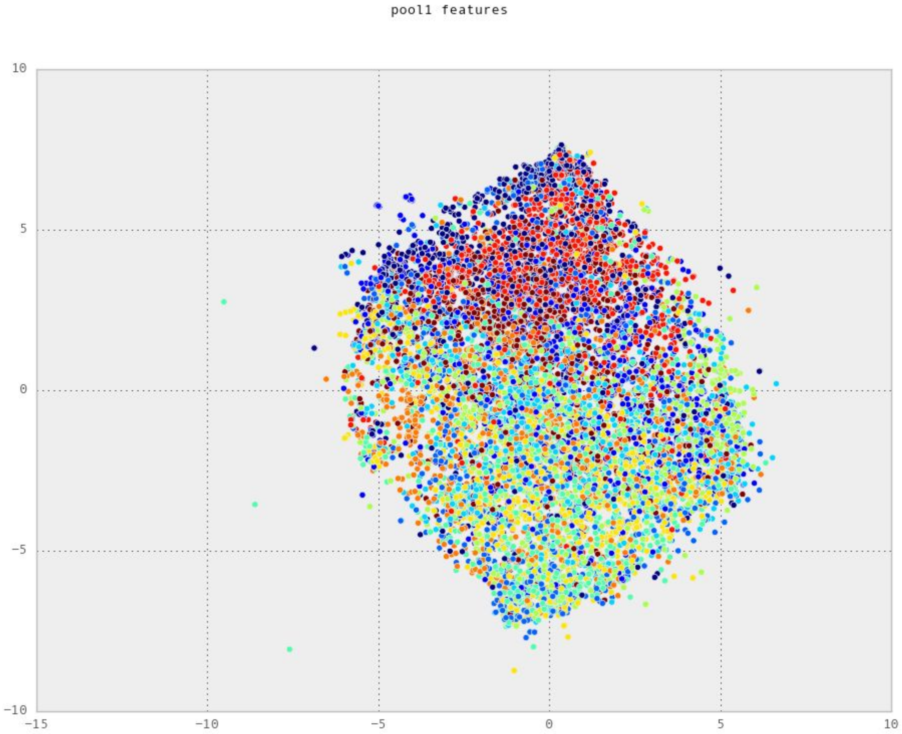
Here is a test with natural images. Unsupervised clustering on the raw images and then again on the features extracted from the final layer of a deep neural network.





Representation Learning





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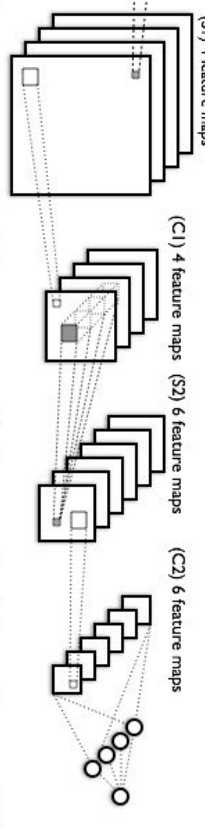

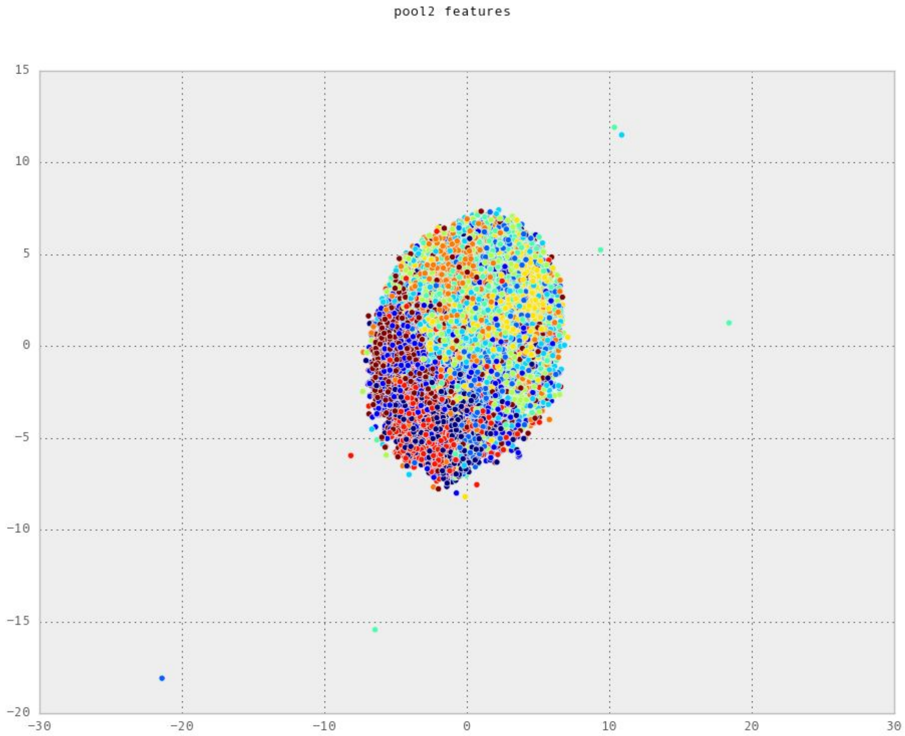

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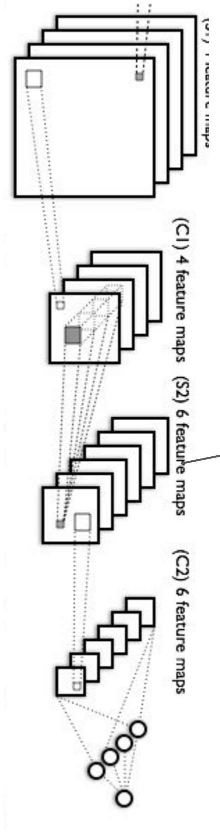
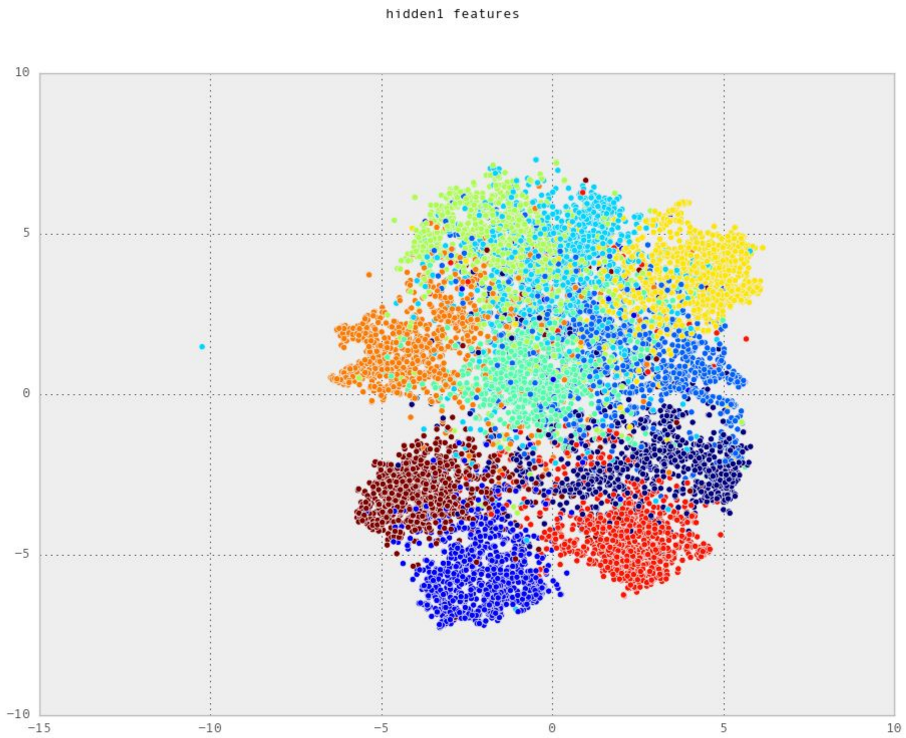
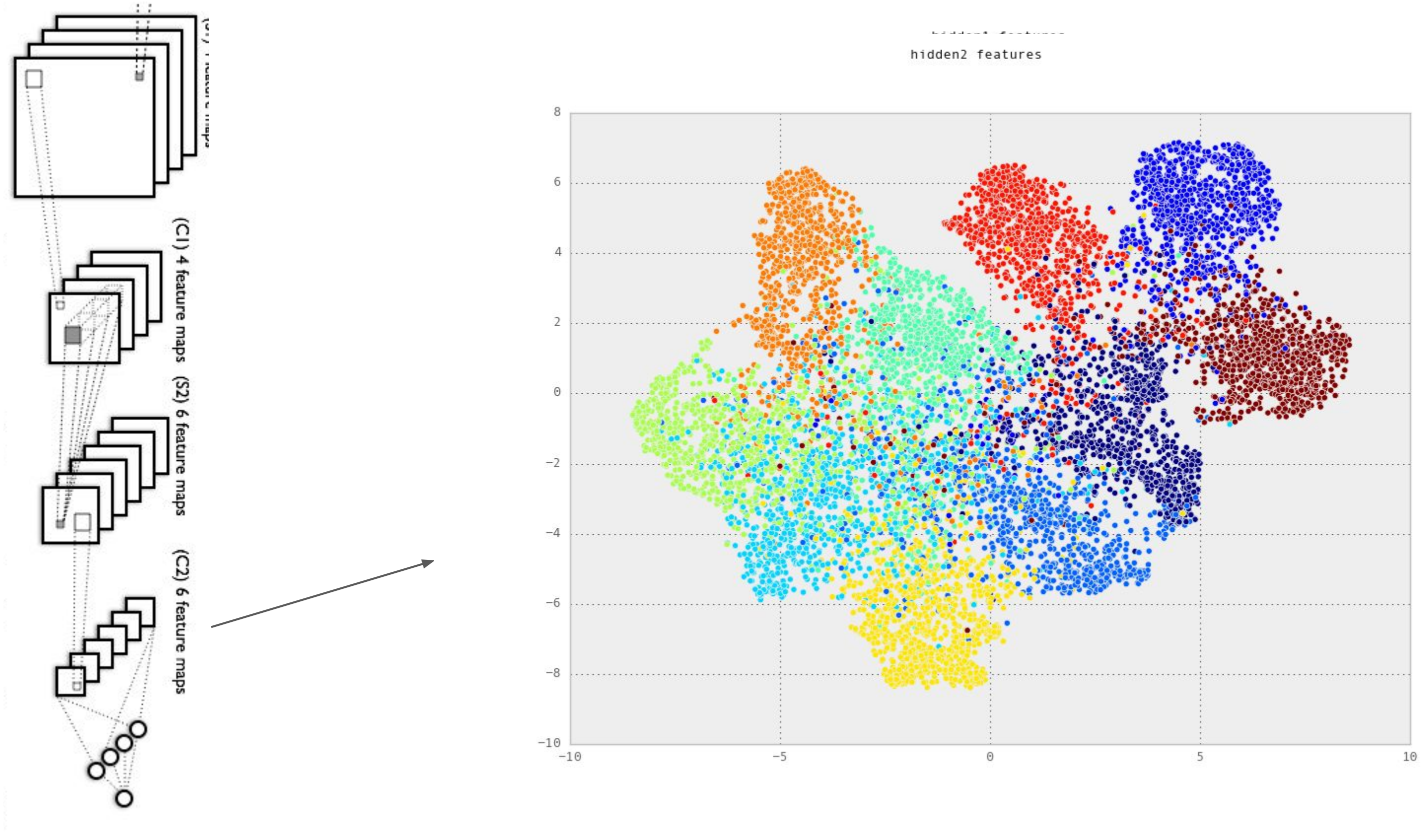




Representation Learning



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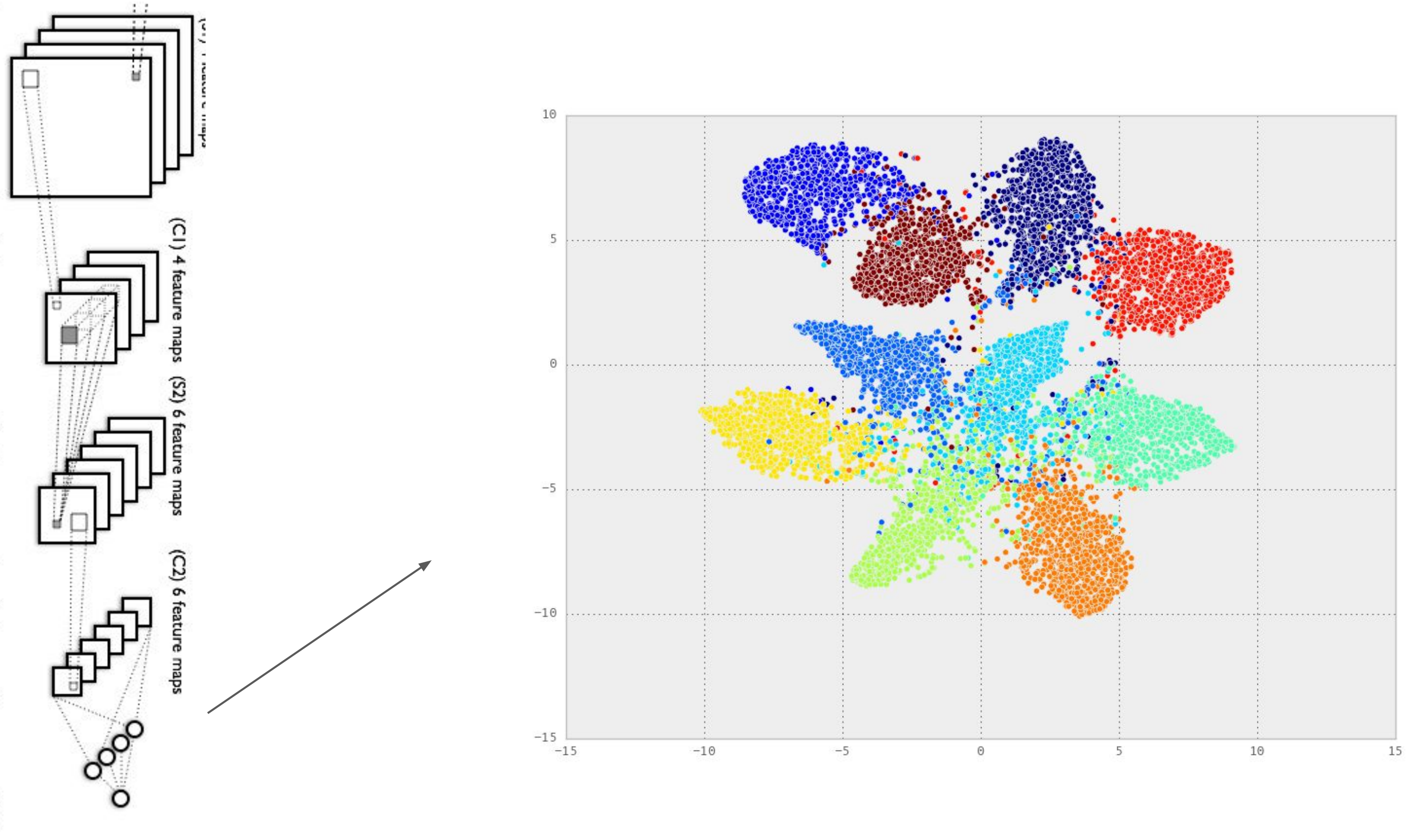


Representation learning

This is an interesting observation!

The ‘deep’ part of this neural network is essentially working to try and make the problem easier.

We will leverage this property to very quickly and effectively make use of the power of deep learning without the headache of training the networks from scratch.

Applied Deep Learning

Most applied deep learning work revolves around two strategies. Both of which utilize neural networks that have already been trained

1. We can take a pretrained network and finetune it on our specific problem.
   a. Ex. A computer vision model already knows how to ‘see’ we just need to finetune it to see whatever our specific problem requires.
2. Using a pretrained network and extract its internal representations of a dataset to use as features for a model.

Transfer Learning

What is transfer learning?

- Transfer learning is taking a neural network that has already been trained and adapting it to a new dataset
- Allows us to use deep learning on problems that we have very little training data for
- Improves the generalization of our network on some novel task
- Let big AI labs do a lot of the hard work for us!

What is transfer learning?

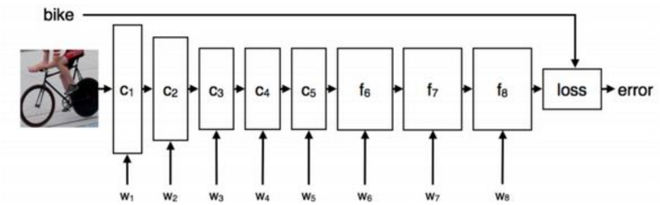
Big research labs typically design and test novel deep learning models on large public benchmark datasets

ImageNet - 1.2 million images across 1000 categories

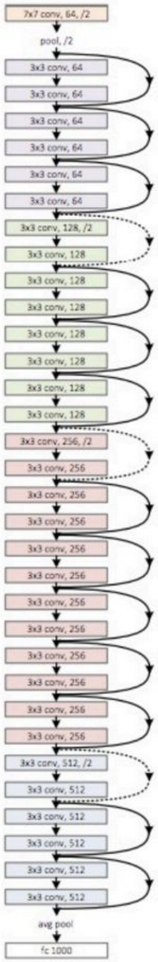
MS COCO - 330k images for things like object detection, image segmentation, and keypoint detection

Pretrained Neural Networks - Classification

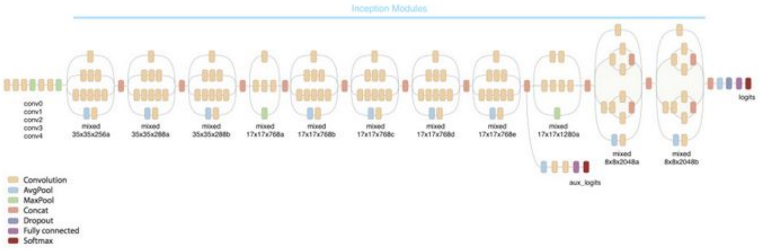
VGG



ResNet



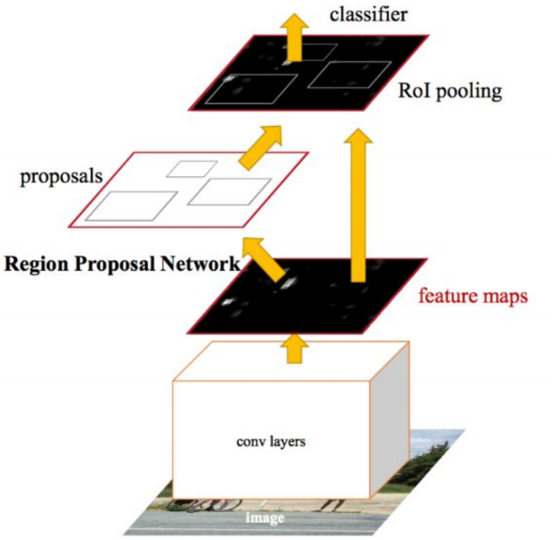
Inception V3



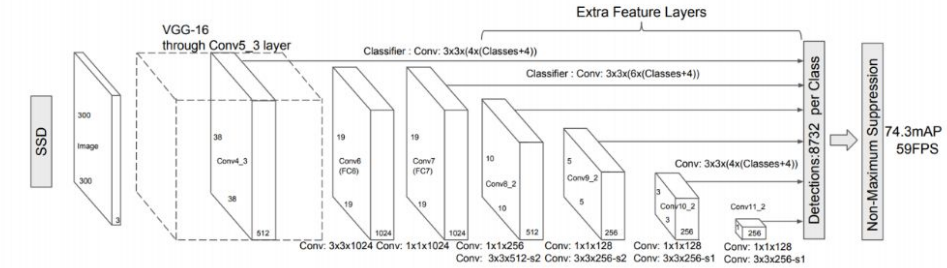
VGG - https://arxiv.org/pdf/1409.1556.pdf, Inception V3 - https://arxiv.org/pdf/1512.00567v3.pdf, ResNet - https://arxiv.org/abs/1512.03385

Pretrained Neural Networks - Detection

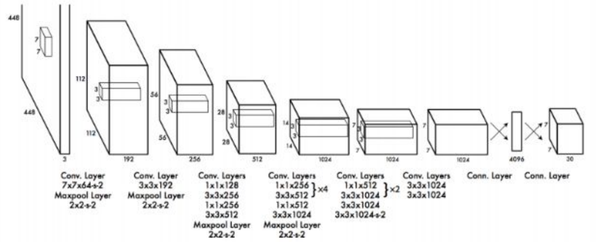
R-CNN



SSD



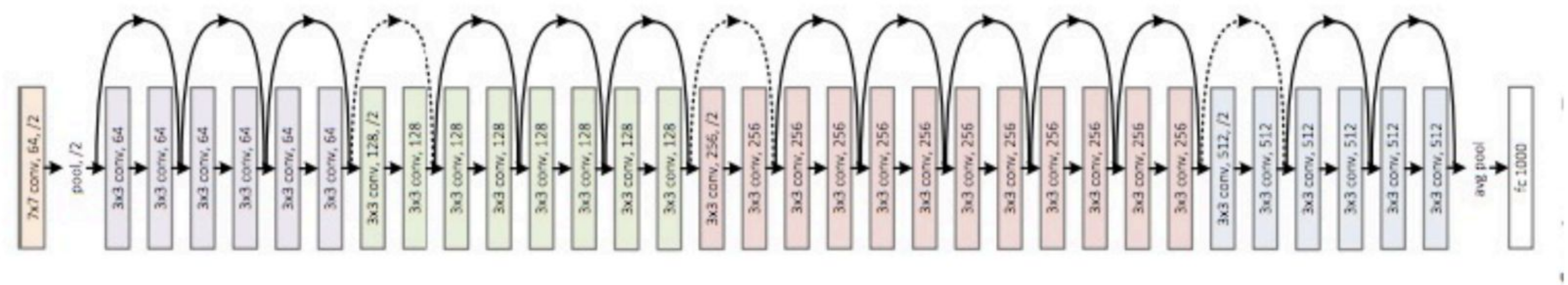
YOLO



RCNN- https://arxiv.org/pdf/1506.01497.pdf, SSD- https://arxiv.org/pdf/1512.02325.pdf, YOLO- https://arxiv.org/abs/1512.03385

Transfer learning - Classification

So we have a state of the art neural network that someone else trained to recognize images and classify them in one of 1000 categories. But, out problem has 5 categories. What do we do?



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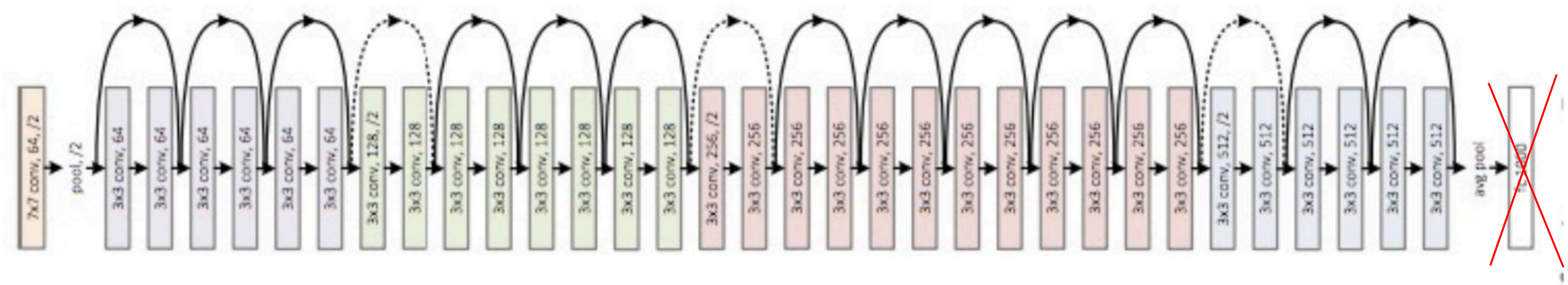

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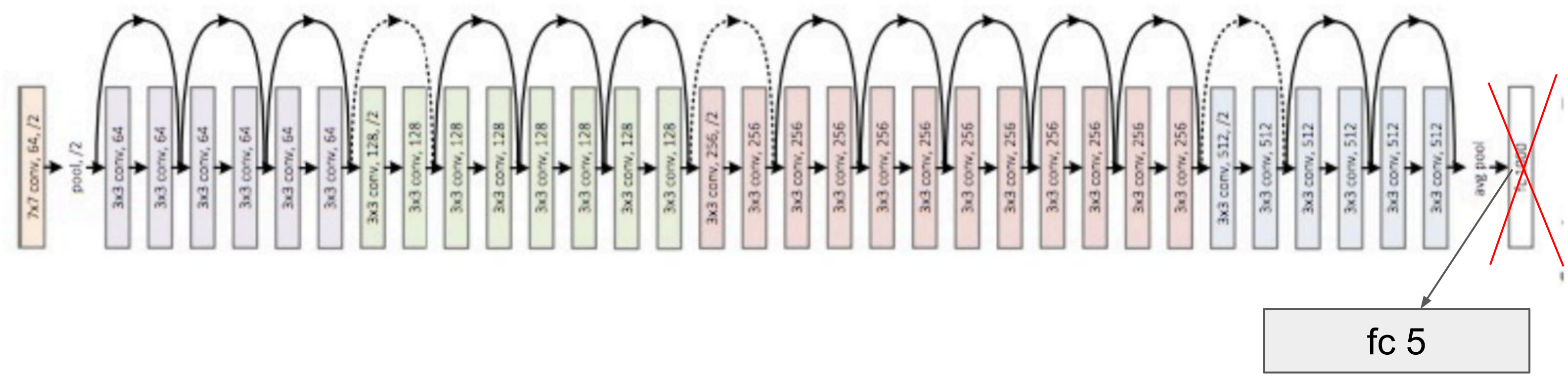


Transfer learning - Classification

Corresponding notebook - `Dogs vs Cats.ipynb`

Transfer learning - How well does it work?

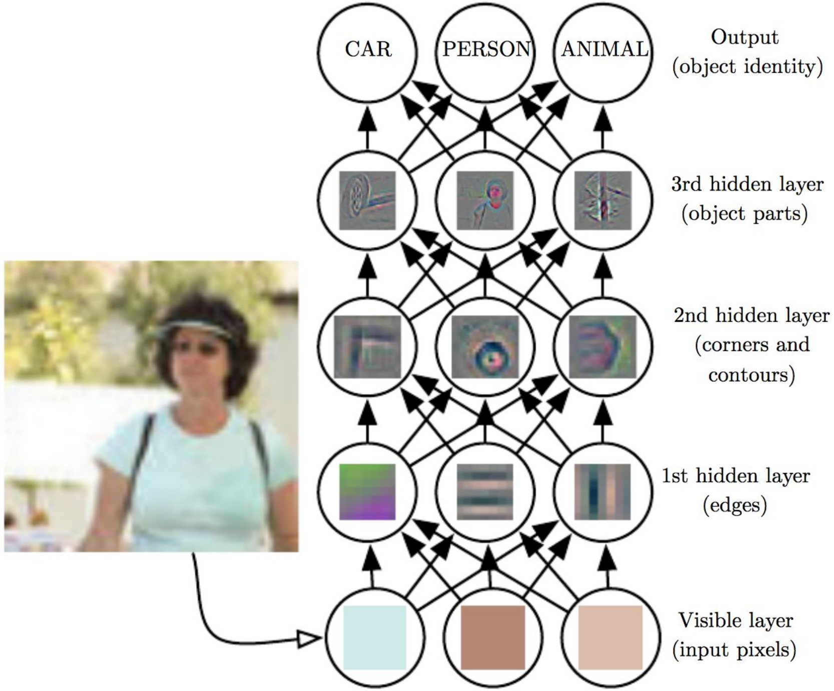
Model	Test top 1 (top 5)	Assoc. train top 1 (top 5)
(a) Bag of visual Words	23.96	–
(b) BossaNova	28.59	–
(c) Overfeat & Extraction	33.91	–
(d) Overfeat & From Scratch	47.46 (69.37)	79.14 (94.49)
(e) Overfeat & Fine Tuning	57.98 (78.86)	89.69 (97.96)
(f) Vgg16 & Extraction	40.21	–
(g) Vgg16 & From Scratch	53.62 (74.67)	88.17 (97.68)
(h) Vgg16 & Fine Tuning	65.71 (82.54)	96.18 (99.39)
(g) InceptionV3 & Fine Tuning	**66.83 (84.53)**	85.34 (95.91)

Remi Cadene's masters thesis - Deep Learning for Visual Recognition

Model type	Test mAP	Train mAP
(a) BoW	53.2	–
(b) BossaNova and FishersVector	61.6	–
(c) Vgg16 from scratch	39.79	99.73
(d) Vgg16 extraction	83.22	–
(e) Vgg16 fine tuned	**85.70**	98.81

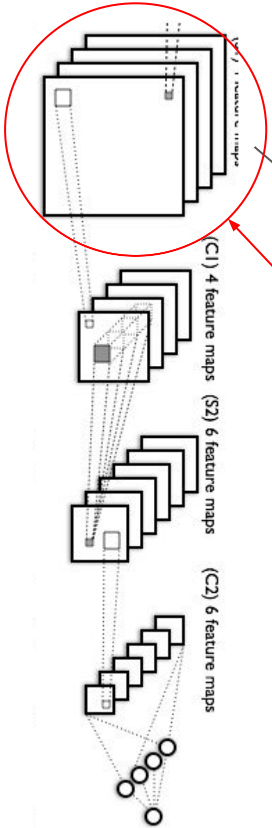
Why does this work?

Representation Learning

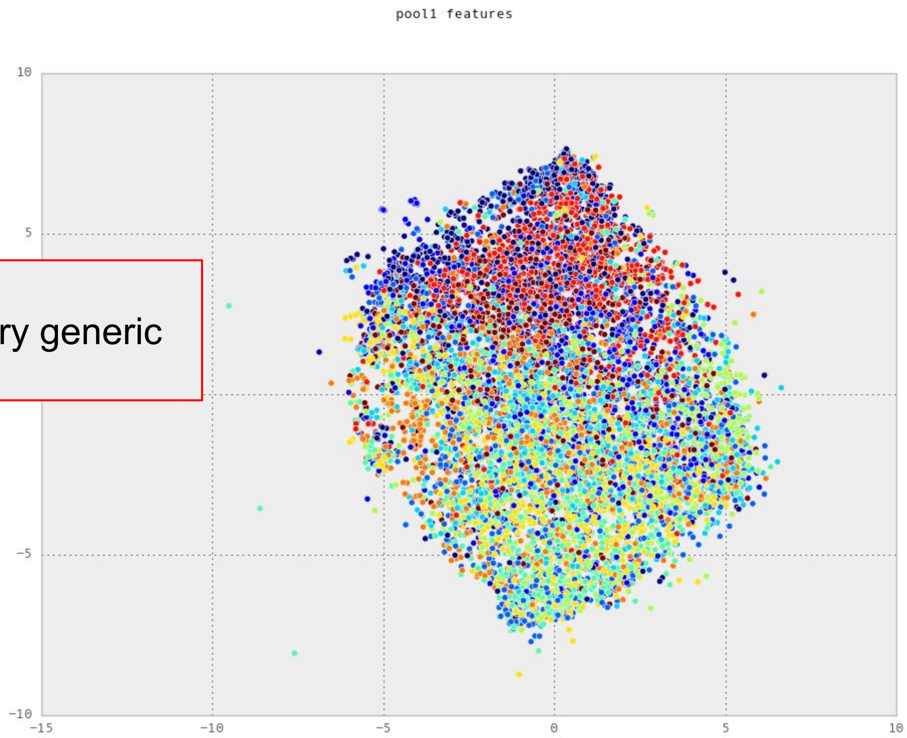


[Deep Learning Book (2016)]

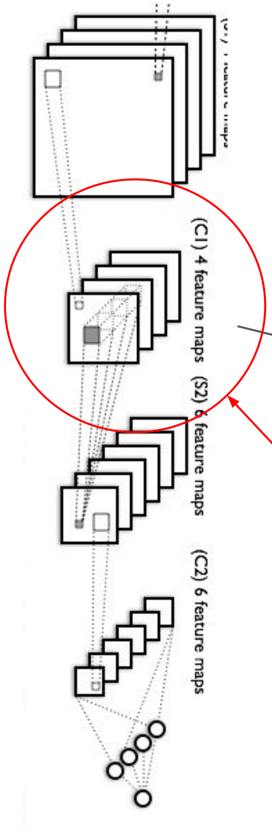
Representation Learning

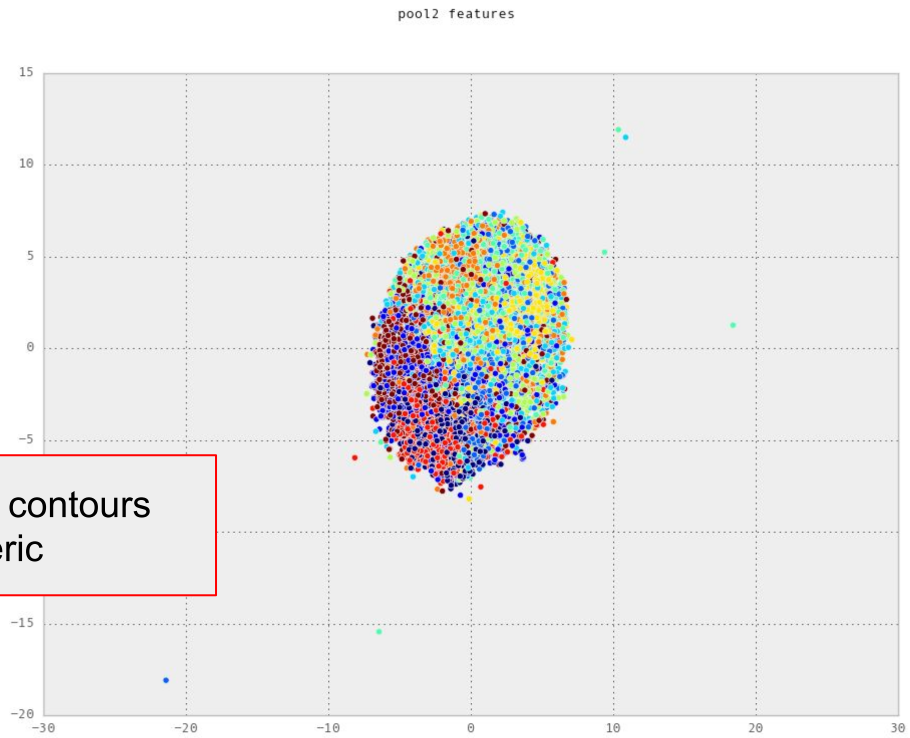


Edges are very generic



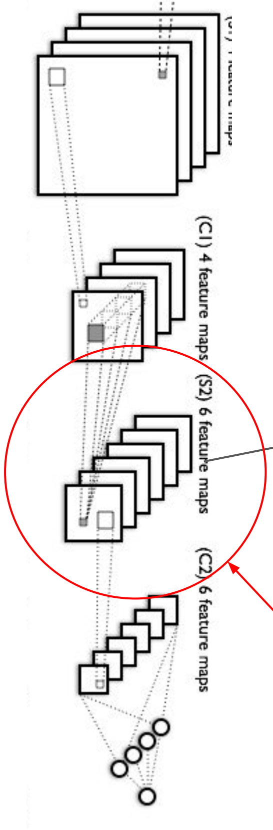
Representation Learning

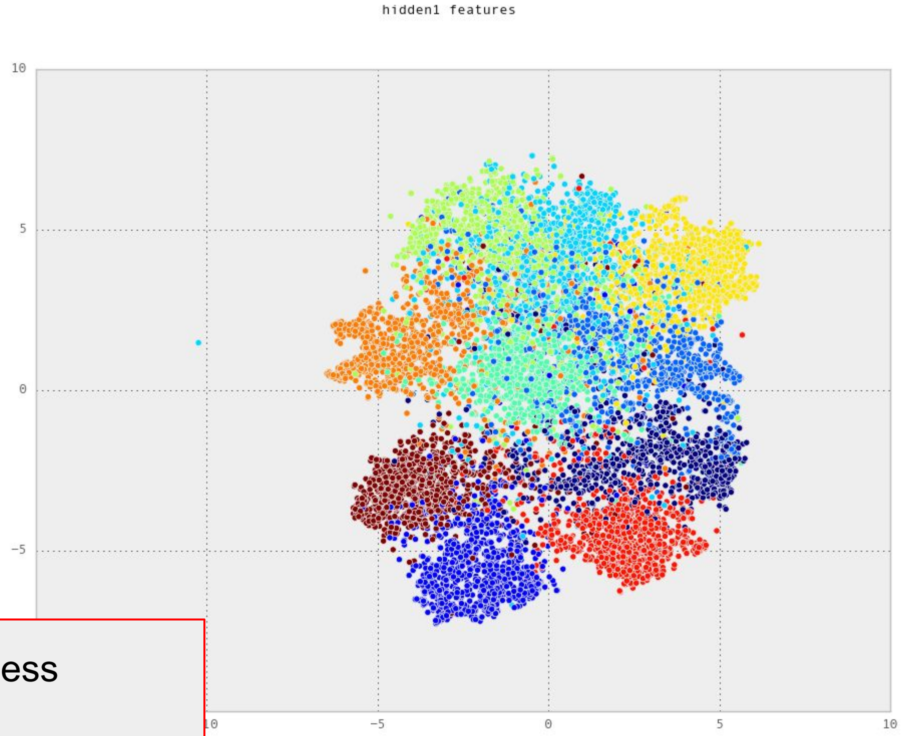




Corners and contours are still generic

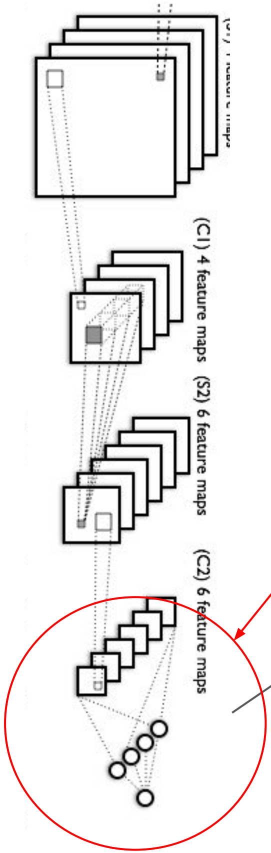
Representation Learning



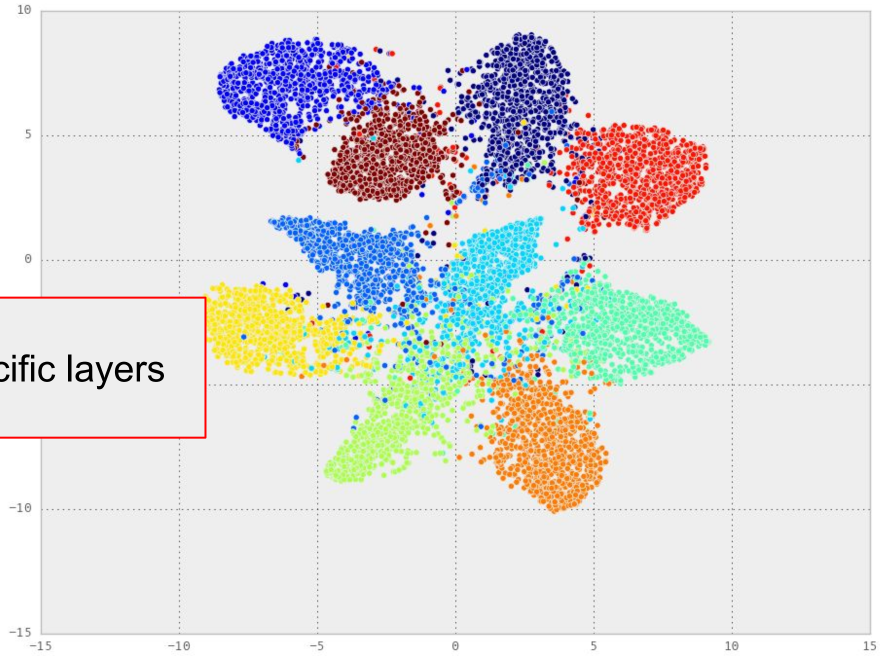


Object parts less generic

Representation Learning



Problem specific layers



Feature Extraction

We will use these networks as feature extractors to represent our data as dense information rich vectors.

We can vectorize the following quite easily:

1. Images
   a. Using Convolutional Neural Networks trained to classify images
2. Words
   a. Using neural networks trained to predict words given their context
3. Sentences
   a. Using neural networks that are trained to reconstruct sentences given their context

What about text

Transfer learning with text

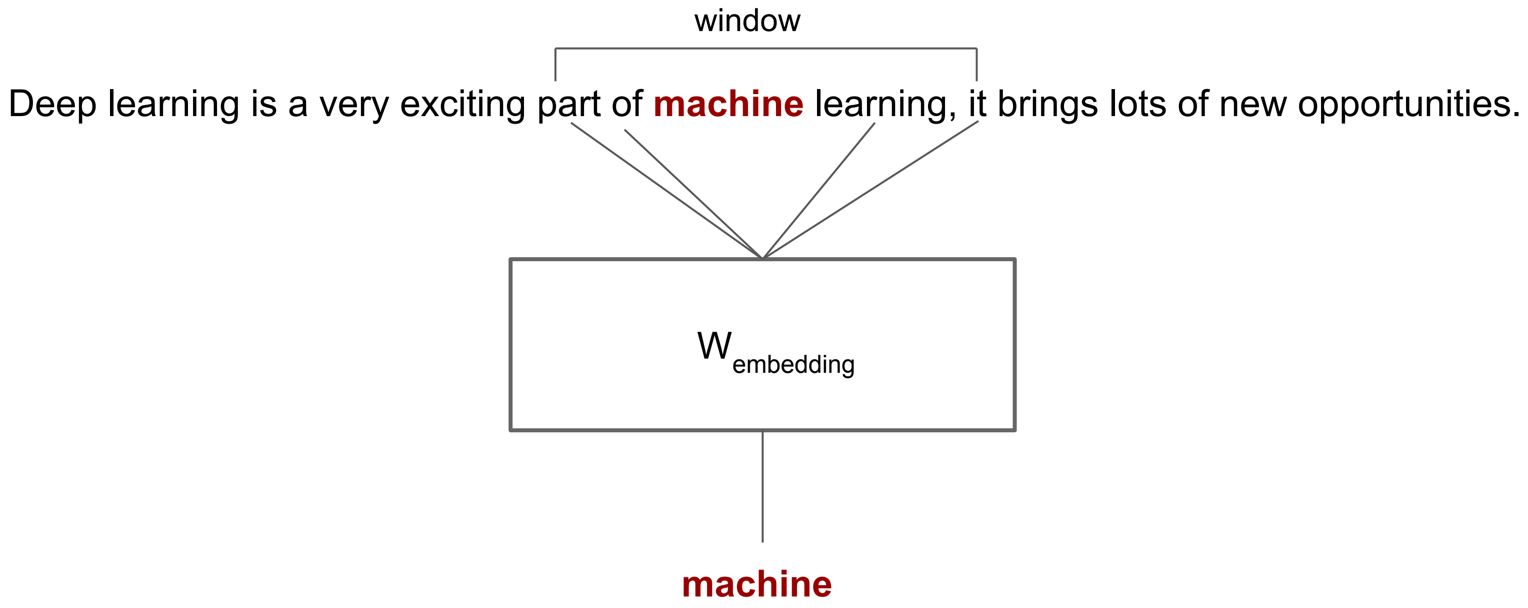
- Transfer learning within NLP is a little bit less straightforward
  - Don’t seem to get universal ‘deep’ features
  - Repurposing an RNN trained on one task to another doesn’t give us the same performance like we see with CNNs in computer vision applications

- Transfering word level representations learning is much more widespread

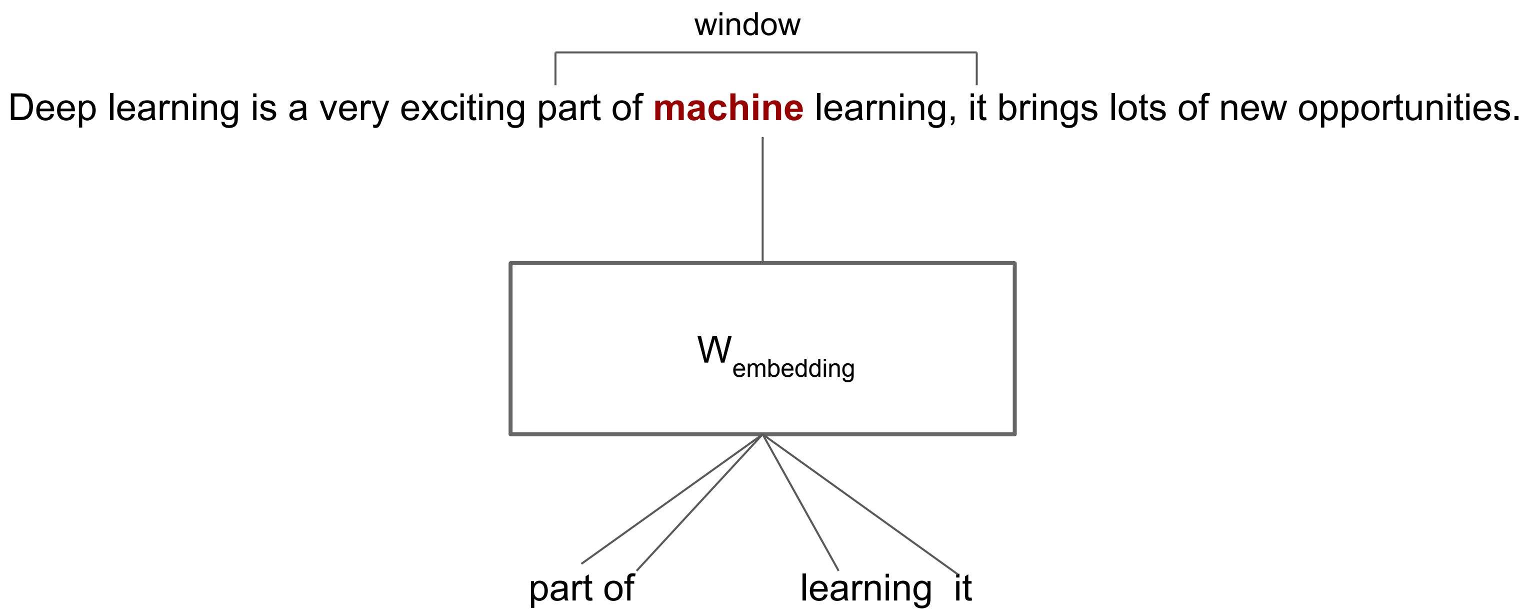
Word Embeddings

- Takes the approach of trying to learn semantic representations of words based on their context.
- Word2Vec
- GloVe

Word2Vec - Continuous Bag of Words



Word2Vec - Skip Gram



GloVe

- Build a co-occurrence matrix for all of the words in your dataset

- Factorize it to yield matrices of word vectors

Transfer learning with text

- Once you have these word embeddings you can use them in place of any word representation that you want to give to a machine learning system:
    - Inputs for an RNN
    - Text similarity metrics for words, phrases, or documents

Putting it into practice

Fine Tuning a Network

To finetune a network we typically choose a network that was already trained on a similar problem to our own.

We then train the network in much the same way that it was originally trained with a few differences.

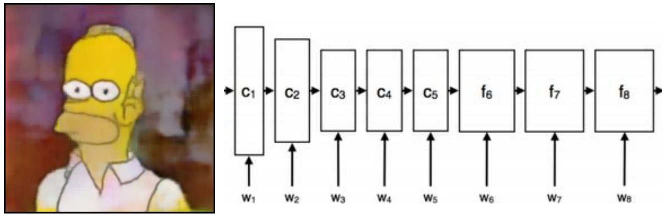
1. Use a much smaller learning rate
2. Only train for a handful of iterations

Fine Tuning a Network - Checking what we learned

When you fine tune a network on a much smaller dataset you risk introducing bias into the network.

You want to make sure that your network did not learn to cheat your task in some way.

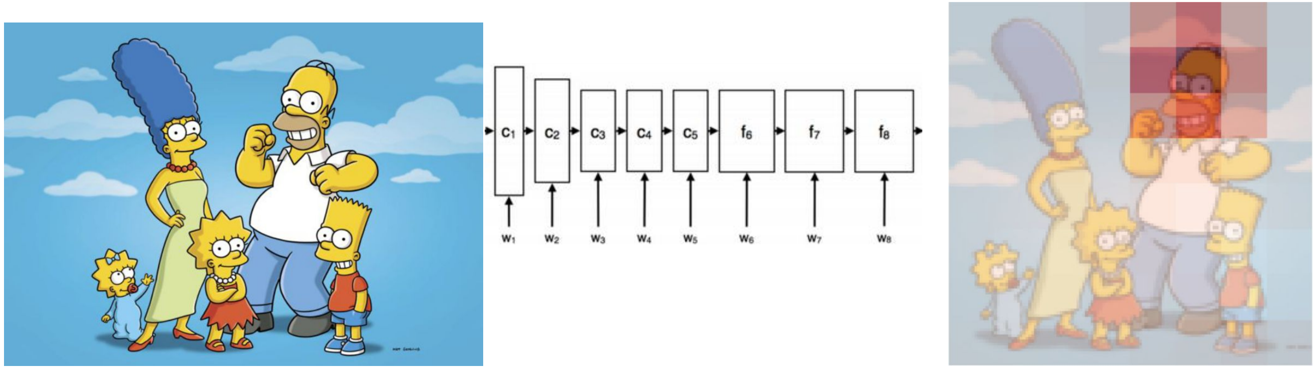
Fine Tuning a Network - Checking what we learned



Homer
Marge
Maggie
Bart
Lisa
...

Network has an output which corresponds to probability of certain character given some image

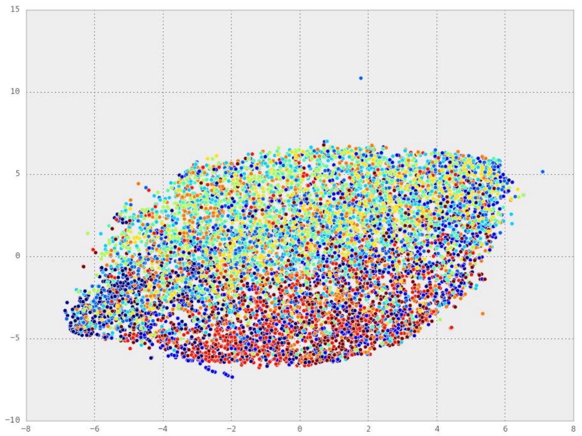
Fine Tuning a Network - Checking what we learned

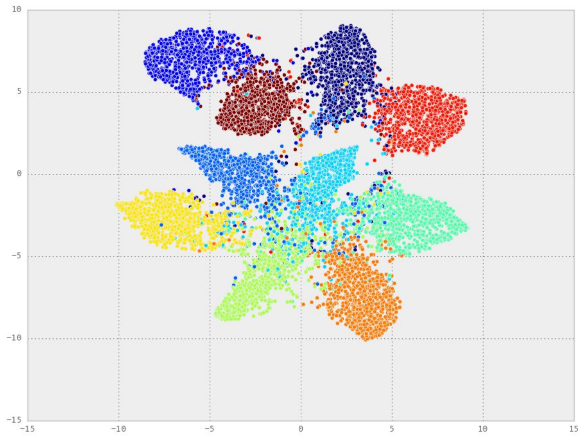


We trace back through the output for homer to see which regions of some image activate most for the ‘homer’ specific output.

Using deep learning without any retraining

You can make use of learned representations without even retraining a deep learning model on your dataset.





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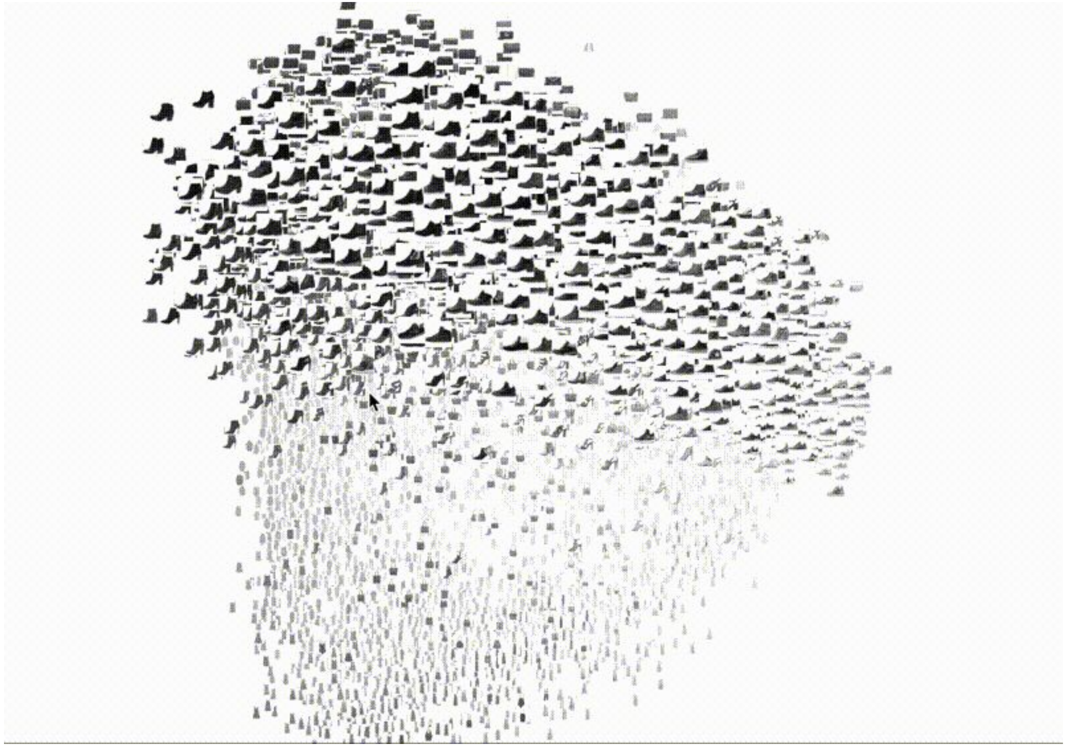

https://github.com/zalandoresearch/fashion-mnist

Using deep learning without any retraining

A pretrained network on 1.2 million images across 1000 categories should have learned some pretty good generic representations of common objects.

The extracted vectors of these representations will essentially be a measure of what objects are in an image, where they are, and what details are present.

Using deep learning without any retraining

- Cosine/Euclidean distance metrics will work to compare the vectors
  - Create image similarity searches by comparing vector distances between query image and database
  - Cluster images into categories

$$\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Using deep learning without any retraining

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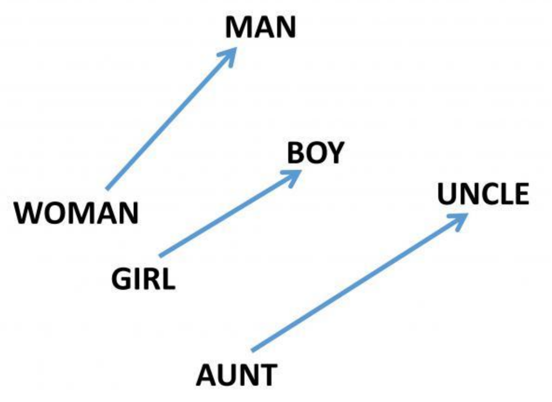
    - Word embeddings are an attempt to capture semantic representations of words within vectors

Using deep learning without any retraining

- Works with word embeddings
  - Word embeddings are an attempt to capture semantic representations of words within vectors
  - Can find similar words using distance metrics
  - Can do math on words
    - `woman + king - man = queen`



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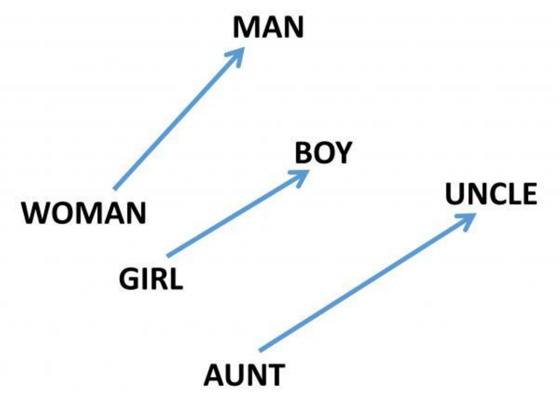
  - Aggregate word embedding statistics over sentence or paragraph capture the semantic meaning of that text



Using deep learning without any retraining

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  - Can find similar words using distance metrics
  - Can do math on words
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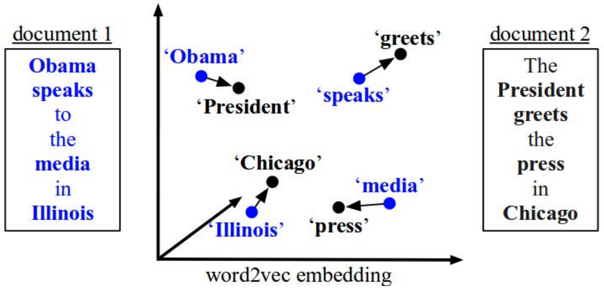
  - Aggregate word embedding statistics over sentence or paragraph capture the semantic meaning of that text
  - Can do document semantic similarity search using aggregate statistics or specialized algorithms (word movers distance)



http://proceedings.mlr.press/v37/kusnerb15.pdf

Using deep learning without any retraining

- Practice notebooks
  - `Reverse Image Search.ipynb`
  - `Word Embeddings for Document Similarity.ipynb`

Code Introduction

Applied Deep Learning Practice

In the notebooks today we will do:

1. Reverse Image search
2. Semantic Document Matching
3. Image Classification

Keras

“Keras is a minimalist, highly modular neural networks library, written in Python and capable of running on top of either TensorFlow or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research.

Use Keras if you need a deep learning library that:

Allows for easy and fast prototyping (through total modularity, minimalism, and extensibility).

Supports both convolutional networks and recurrent networks, as well as combinations of the two.

Supports arbitrary connectivity schemes (including multi-input and multi-output training).

Runs seamlessly on CPU and GPU.”

Source: https://keras.io/

Keras

Sequential api?

Functional api?

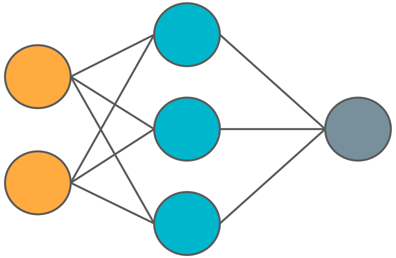
Sequential Models

```python
from keras.models import Sequential

model = Sequential()

model.add(Dense(output_dim=3, input_dim=2, activation='relu'))
model.add(Dense(output_dim=1, activation = 'sigmoid'))

model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```



With the sequential model you start by declaring your model as a sequential. That gives you a blank canvas to start working.

From there you can add anything you want using model.add(). The data will flow through the model in the order that you declare each layer.

The example on the left builds the small neural network that we looked at the in the beginning.

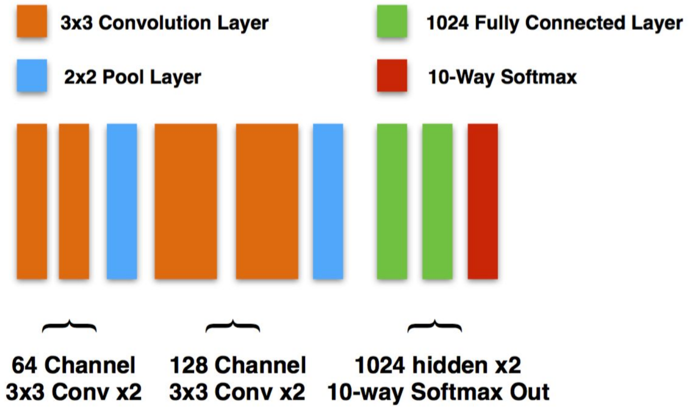
Sequential Models

```python
from keras.models import Sequential

model = Sequential()
# first group of convolution layers
model.add(Convolution2D(64, 3,3, activation='relu', input_shape=(3,100,100)))
model.add(Convolution2D(64, 3,3, activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
# second group of convolution layers
model.add(Convolution2D(128, 3,3, activation='relu', input_shape=(3,100,100)))
model.add(Convolution2D(128, 3,3, activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
# fully connected layers
model.add(Dense(1024, activation='relu'))
model.add(Dense(1024, activation='relu'))
# output layer
model.add(Dense(10, activation='softmax'))

model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```

A slightly more complicated and modern looking ConvNet.

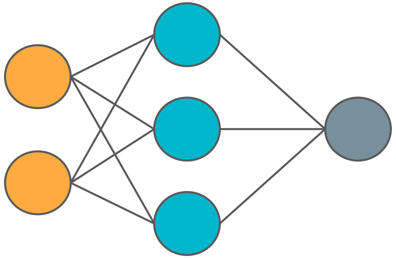


Functional Models

```python
from keras.models import Model
from keras.layers import Input, Dense

model_in = Input(shape=(2,))
hidden = Dense(3, activation='sigmoid')(model_in)
out = Dense(1, activation='sigmoid')(hidden)

model = Model(input=model_in, output=out)
model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```



With the functional model you give each computational layer a name instead of just stacking them up with model.add().

This is key, because you also explicitly provide the input to each layer. This allows you more freedom to try some different architectures with no extra effort to hack the sequential models.

For example some architectures could have multiple independent branches of neurons coming off of the input. This method makes setting that up a breeze.

Functional Models

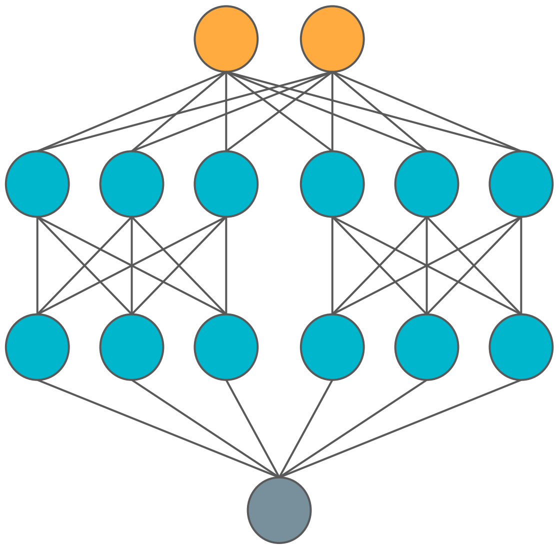
```python
from keras.models import Model
from keras.layers import Input, Dense

model_in = Input(shape=(2,))
hidden1_a = Dense(3, activation='sigmoid')(model_in)
hidden1_b = Dense(3, activation='sigmoid')(hidden1_a)

hidden2_a = Dense(3, activation='sigmoid')(model_in)
hidden2_b = Dense(3, activation='sigmoid')(hidden2_a)

combined = merge([hidden1_b, hidden2_b], mode='concat')
out = Dense(1, activation='sigmoid')(combined)

model = Model(input=model_in, output=out)
model.compile(loss='mse', optimizer='sgd', metrics=['accuracy'])
```



Using Models

```
model.fit(X_train, y_train, nb_epoch=20, batch_size=8)

for _ in range(20):
    for X_dat, y_dat in data_generator:
        model.train_on_batch(X_dat, y_dat)
```

Training a network is an iterative process, so basically we'll be creating loops that stream the data into each model.

We can use Keras built in methods or create our own. The 'data_generator' would just be some function that would loop through the data, dividing it up into batches to stream into the model.

Using Models

```
model.fit(X_train, y_train, validation_split=0.1, nb_epoch=20, batch_size=8)

model.evaluate(X_test, y_test)

for _ in range(20):
    for X_dat, y_dat in data_generator:
        model.test_on_batch(X_dat, y_dat)
```

With .fit() we don’t have to split the data into training and testing before using it. Just tell Keras what percentage of data we want to use to evaluate the model with.

With .evaluate() we split the data before training and use it the same way that we use .fit(). Except this time it won’t update parameters it will just return evaluation metrics.

Using Models

```
model.predict(new_img)

model.predict(bunch_of_new_imgs)

preds = []
for new_img in range(new_imgs):
    preds.append(model.predict(new_img))
```

Each model has a .predict(), it can be used in a variety of ways. Similar to how training and evaluating had a variety of methods, except each one of these will be called with .predict().

You can pass a single new point of data, a numpy array of new data.

You could also loop through the data and make a prediction on each data point.

Other Frameworks

Torch (Lua)

http://torch.ch

MXNet (everything?)

https://github.com/dmlc/mxnet

Theano (Python)

http://deeplearning.net/software/theano/

TensorFlow (Python, C++)

https://www.tensorflow.org