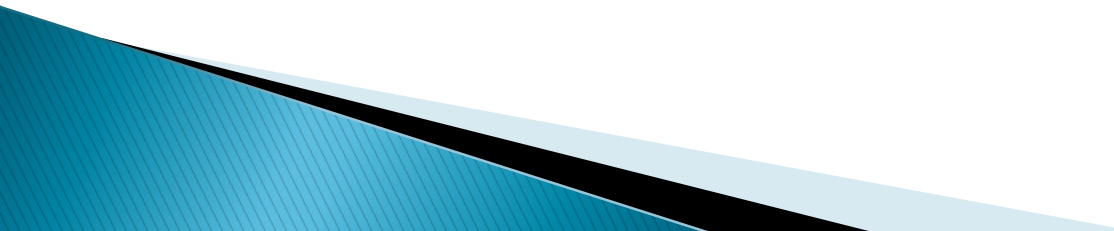


Keras

Lecture 6

Subir Varma

Keras <https://keras.io>

- ▶ High Level API for TensorFlow
 - ▶ Can run on CPU/GPU/TPU
 - ▶ Built in support for ConvNets, RNNs and Transformers
 - ▶ Supports arbitrary network architectures
 - ▶ Can be freely used in commercial projects
 - ▶ Over a million users
- 

A Keras Program (Model Setup)

```
1 import keras
2 keras.__version__
```

```
1 from keras.datasets import mnist
2
3 (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

Import Dataset
(already in Tensor form)

```
1 train_images = train_images.reshape((60000, 28 * 28))
2 train_images = train_images.astype('float32') / 255
3
4 test_images = test_images.reshape((10000, 28 * 28))
5 test_images = test_images.astype('float32') / 255
```

Data Reshaping
+
Data Normalization

```
1 from keras.utils import to_categorical
2
3 train_labels = to_categorical(train_labels)
4 test_labels = to_categorical(test_labels)
```

Label Conversion from Sparse to
Categorical (1-Hot Encoded)

```
1 from keras import models
2 from keras import layers
3
4 network = models.Sequential()
5 network.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
6 network.add(layers.Dense(10, activation='softmax'))
```

Define the Network

```
1 network.compile(optimizer='sgd',
2                 loss='categorical_crossentropy',
3                 metrics=['accuracy'])
```

Compile the Model

Learning Rate specified here

Today's Class → How can I import Raw Data (Image, Text, Tabular)?

```
1 import keras
2 keras.__version__
```

```
1 from keras.datasets import mnist
2
3 (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

```
1 train_images = train_images.reshape((60000, 28 * 28))
2 train_images = train_images.astype('float32') / 255
3
4 test_images = test_images.reshape((10000, 28 * 28))
5 test_images = test_images.astype('float32') / 255
```

```
1 from keras.utils import to_categorical
2
3 train_labels = to_categorical(train_labels)
4 test_labels = to_categorical(test_labels)
```

```
1 from keras import models
2 from keras import layers
3
4 network = models.Sequential()
5 network.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
6 network.add(layers.Dense(10, activation='softmax'))
```

```
1 network.compile(optimizer='sgd',
2                 loss='categorical_crossentropy',
3                 metrics=['accuracy'])
```

```
1 history = network.fit(train_images, train_labels, epochs=20, batch_size=128, validation_split=0.2)
```

In Future Classes

```
1 import keras
2 keras.__version__
```

```
1 from keras.datasets import mnist
2
3 (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

```
1 train_images = train_images.reshape((60000, 28 * 28))
2 train_images = train_images.astype('float32') / 255
3
4 test_images = test_images.reshape((10000, 28 * 28))
5 test_images = test_images.astype('float32') / 255
```

How can I feed in 2D/3D Tensor Data directly without Reshaping?

```
1 from keras.utils import to_categorical
2
3 train_labels = to_categorical(train_labels)
4 test_labels = to_categorical(test_labels)
```

How Can I define Other Types of Networks (ConvNets, RNNs, Transformers)?

```
1 from keras import models
2 from keras import layers
3
4 network = models.Sequential()
5 network.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
6 network.add(layers.Dense(10, activation='softmax'))
```

```
1 network.compile(optimizer='sgd',
2                 loss='categorical_crossentropy',
3                 metrics=['accuracy'])
```

- What are some Faster Optimizers?
- Specifying User Defined Metrics

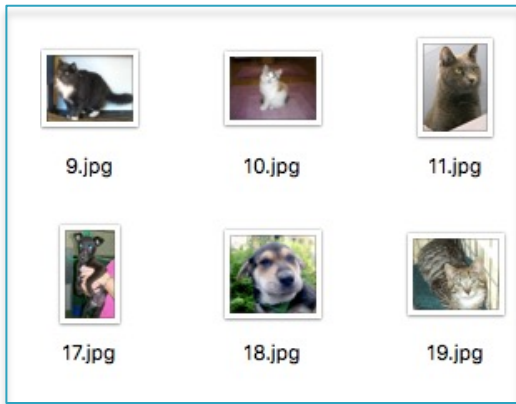
```
1 history = network.fit(train_images, train_labels, epochs=20, batch_size=128, validation_split=0.2)
```

How long should I run the Model?
How to interrupt the Execution?

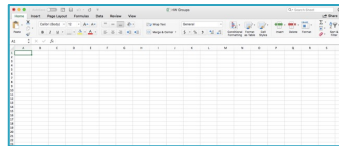
Ingesting Data using Keras

Data Ingestion

Raw Image Data



Raw Tabular Data



How to convert all of these into Tensors so that they can be fed into a DL Network?

Raw Text Data

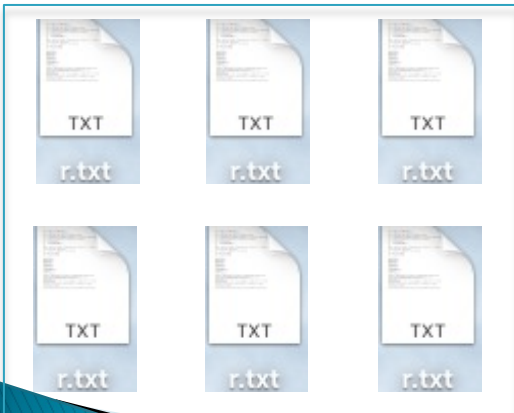
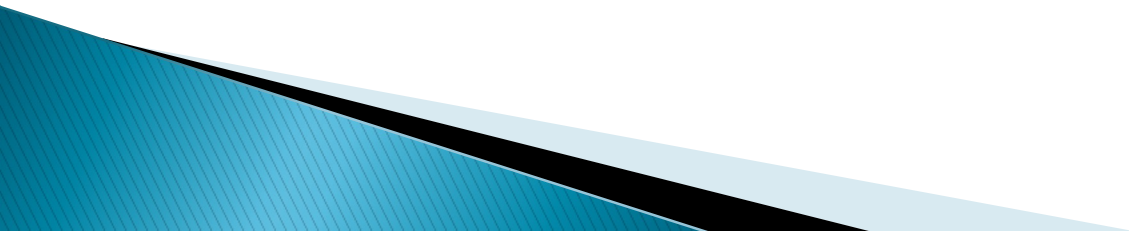


Image Data

(Section 8.2 in Chollet)



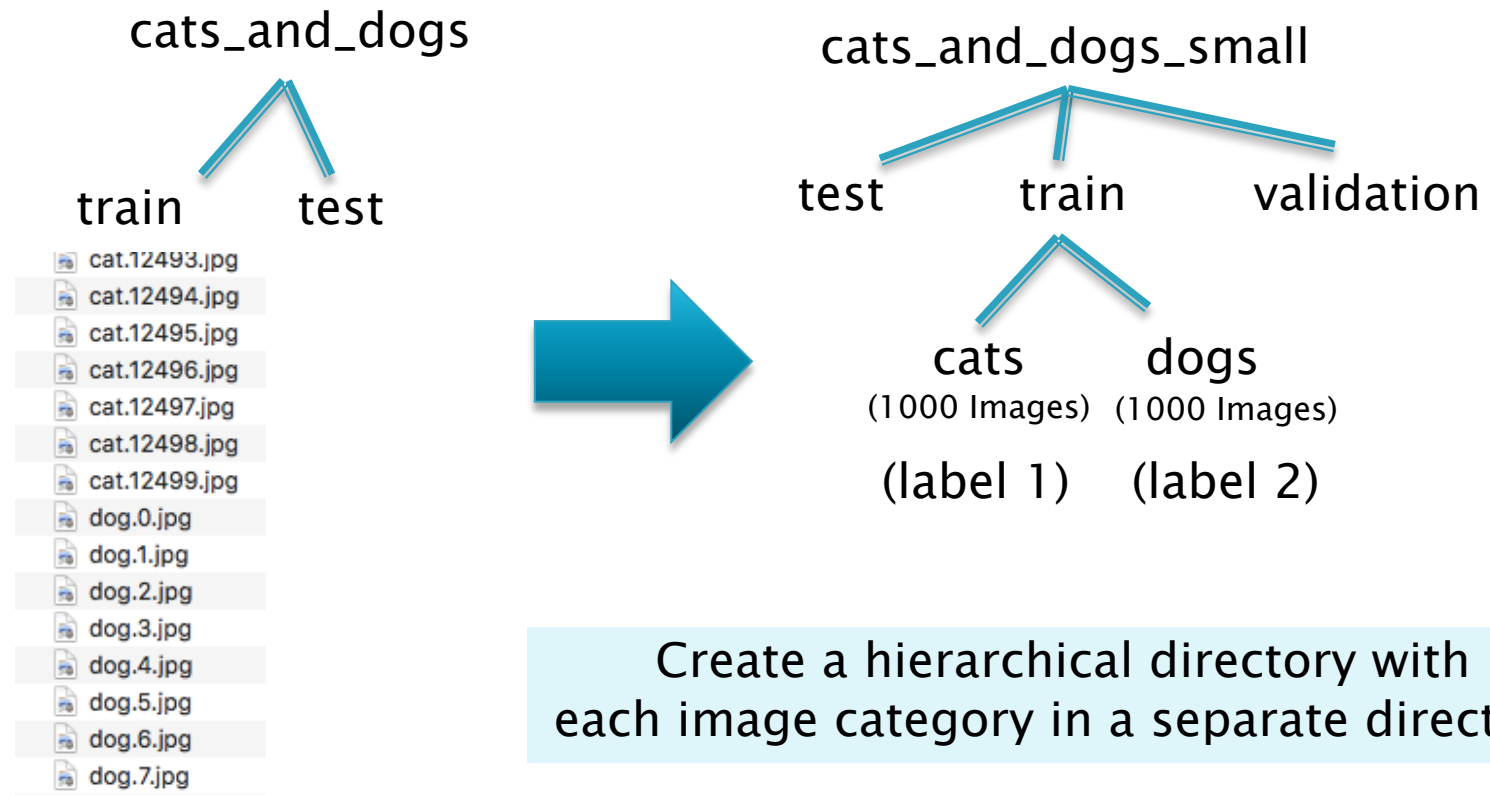
Processing Raw Image Data

- ▶ Read the picture files.
- ▶ Decode the JPEG content to RGB grids of pixels.
- ▶ Convert these into floating point tensors.

- ▶ Keras has utilities to take care of these steps automatically.
 - Keras has a module with image processing helper tools, located at `keras.preprocessing.image`.
- ▶ In particular, it contains the utility `image_dataset_from_directory` that can turn image files on disk into batches of pre-processed tensors.

Cats/Dogs Classification:

50,000 images evenly divided between cats and dogs



Creating Training and Validation Datasets

```
from tensorflow.keras.utils import image_dataset_from_directory

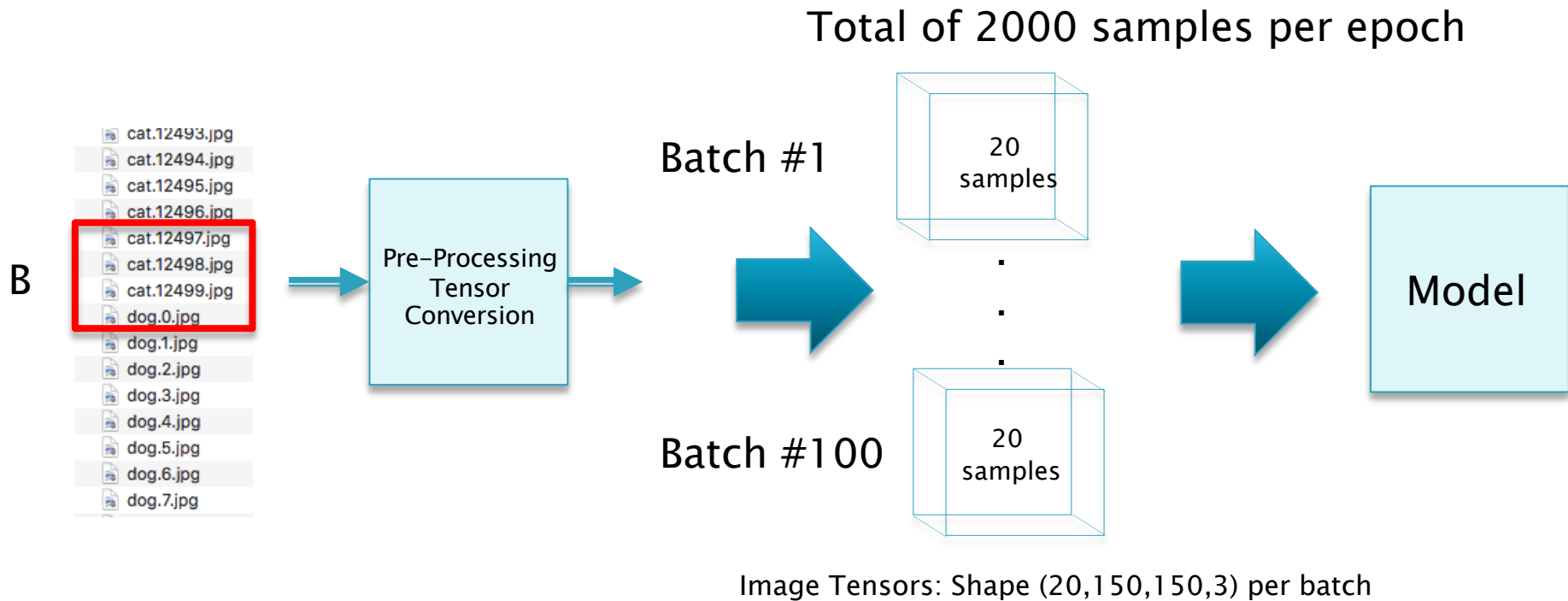
train_dataset = image_dataset_from_directory(
    new_base_dir / "train",
    image_size=(150, 150),
    batch_size=20)
validation_dataset = image_dataset_from_directory(
    new_base_dir / "validation",
    image_size=(150, 150),
    batch_size=20)
```

Found 2000 files belonging to 2 classes.

Found 1000 files belonging to 2 classes.

- Converts the jpg images to the RGB format, and stores them as tensors of shape (150,150,3)
- Converts these into floating point tensors
- Crops the images so that they all have a size of (150,150) pixels
- Creates batches of image data (of size 20 in this case) and stores them in tensors of shape (20,150,150,3), which are then fed into the model during execution.
- Creates Labels for each image. This is done by assigning a different one-hot label to images belonging to different directories.

Training



Model

```
from keras.layers import Embedding, Flatten, Dense
from tensorflow.keras import optimizers

from keras import Model
from keras import layers
from keras import Input

input_tensor = Input(shape=(150,150,3,))
a = layers.Flatten()(input_tensor)
a = layers.Rescaling(1./255)(a)
layer_1 = layers.Dense(64, activation='relu')(a)
layer_2 = layers.Dense(64, activation='relu')(layer_1)
layer_3 = layers.Dense(64, activation='relu')(layer_2)
layer_4 = layers.Dense(64, activation='relu')(layer_3)
output_tensor = layers.Dense(1, activation='sigmoid')(layer_4)

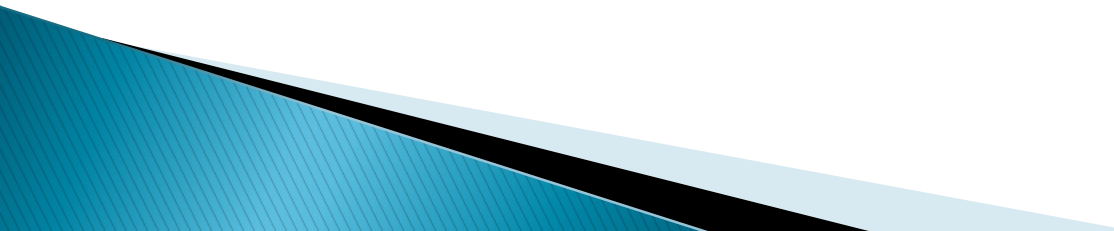
model = Model(input_tensor, output_tensor)

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(learning_rate=1e-4),
              metrics=['acc'])

model.summary()
```

Text Data

(Section 11.3.3 in Chollet)

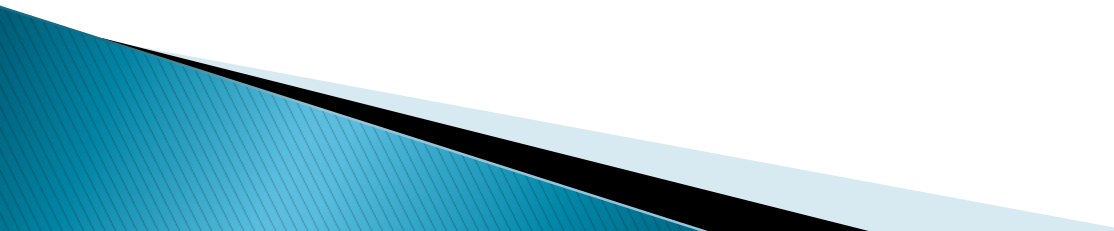


Feeding Text into the Neural Network

- ▶ Map 10,000 most frequently occurring words to integers → Each review becomes a vector (of variable length)
- ▶ Pad out the vectors with 0s so that they are of the same length
- ▶ Create Tensors of shape (samples, word_indices)
- ▶ Map each word_index to an embedding vector, so now the input Tensor has shape (samples, word_indices, embedding)

Keras contains the utility [text_dataset_from_directory](#) that can turn image files on disk into batches of pre-processed tensors.

IMDB: Movie Review Database

- ▶ 50,000 Reviews
 - ▶ 25,000 Reviews for Training, 25,000 for Test
 - ▶ 50% negative, 50% positive reviews
- 

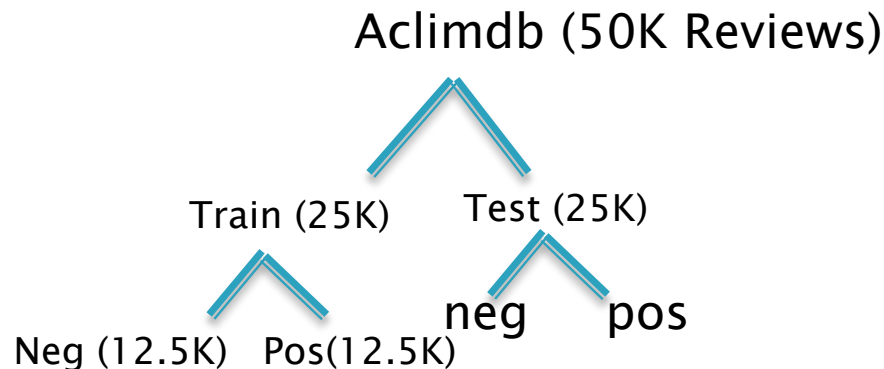
Raw Text Data

```
import os

#imdb_dir = '/home/ubuntu/data/aclImdb'
imdb_dir = '/Users/subirvarma/handson-ml/datasets/aclImdb'
train_dir = os.path.join(imdb_dir, 'train')

labels = []
texts = []

for label_type in ['neg', 'pos']:
    dir_name = os.path.join(train_dir, label_type)
    for fname in os.listdir(dir_name):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname))
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)
```



- 0_3.txt
- 1_1.txt
- 2_1.txt
- 3_4.txt
- 4_4.txt
- 5_3.txt
- 6_1.txt
- 7_3.txt
- 8_4.txt
- 9_1.txt
- 10_2.txt
- 11_3.txt
- 12_1.txt
- 13_2.txt
- 14_2.txt
- 15_1.txt
- 16_3.txt
- 17_3.txt
- 18_3.txt
- 19_4.txt

12,500 Positive Reviews
12,500 Negative Reviews

Create a Batched Dataset

```
from tensorflow import keras
batch_size = 32

train_ds = keras.utils.text_dataset_from_directory(
    "aclImdb/train", batch_size=batch_size
)
val_ds = keras.utils.text_dataset_from_directory(
    "aclImdb/val", batch_size=batch_size
)
test_ds = keras.utils.text_dataset_from_directory(
    "aclImdb/test", batch_size=batch_size
)
```

Result →

(Review 1, Label 1)

-
-
-

(Review 32, Label 32)

But Data still in
Text strings

Each Review is paired up with the corresponding Label

Text Vectorization: Text to Integers

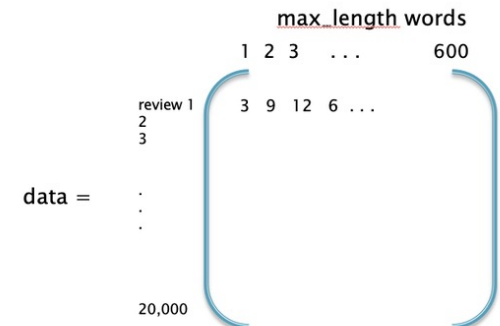
```
from tensorflow.keras import layers

max_length = 600
max_tokens = 20000
text_vectorization = layers.TextVectorization(
    max_tokens=max_tokens,
    output_mode="int",
    output_sequence_length=max_length,
)
text_vectorization.adapt(text_only_train_ds)

int_train_ds = train_ds.map(lambda x, y: (text_vectorization(x), y))
int_val_ds = val_ds.map(lambda x, y: (text_vectorization(x), y))
int_test_ds = test_ds.map(lambda x, y: (text_vectorization(x), y))
```

Takes each review and converts it from text to integers.

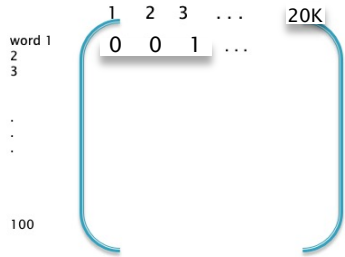
- It does so by cutting of the number of words in the reviews to the top 20,000 most frequently occurring words (specified by the parameter *max_tokens*), and then mapping each word to a unique integer in the range 0 to 20,000 (after removing all punctuation).
- It furthermore truncates each review to a maximum of *max_length* = 600 words, and pads the reviews with less than 600 words with zeroes.



Feeding Data into the Model (Trained Embedding)

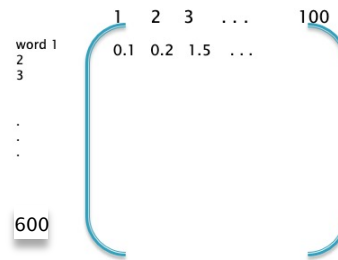
Review

(3,7,21,...,5) →



Embedded Representation with 1-Hot Encoding

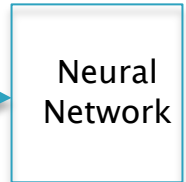
Embedding Layer



A better Embedded Representation



Flattened Vector (60,000 D)

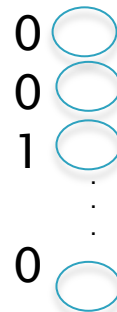


```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	(None, 100, 100)	1000000
flatten_2 (Flatten)	(None, 10000)	0
dense_2 (Dense)	(None, 32)	320032
dense_3 (Dense)	(None, 1)	33
Total params: 1,320,065		
Trainable params: 1,320,065		
Non-trainable params: 0		

Vector of size 20K

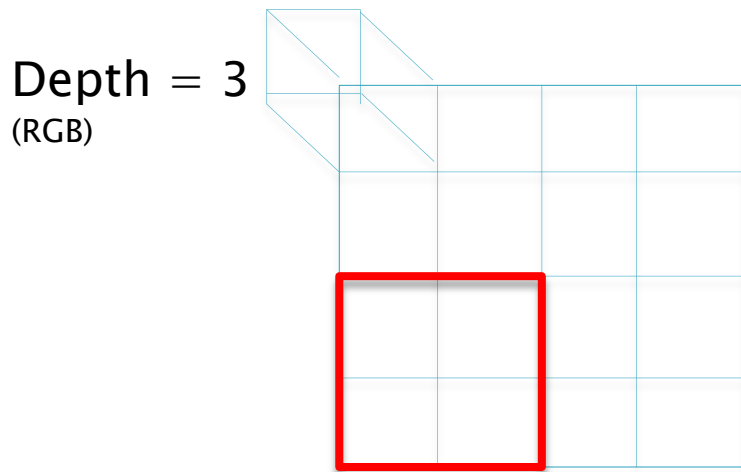


Vector of size 100



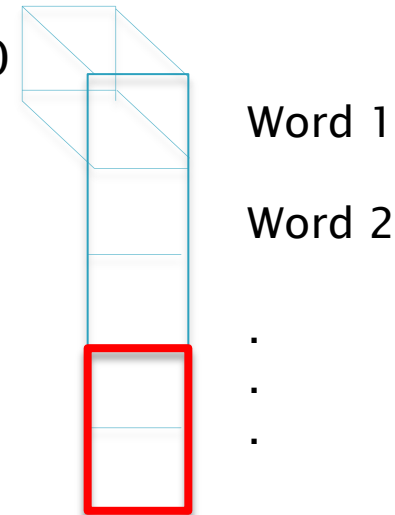
E = Embedding Matrix

Comparing Image and Text Representations



3D Tensor

Depth = 100
(Embedding)



2D Tensor

Top Level: Image
2nd Level : Pixels
3rd Level: RGB

Sentence
Words
Embedding

Tabular Data

Keras Utilities for Tabular Data

▶ Structured Data Example:

https://keras.io/examples/structured_data/structured_data_classification_from_scratch/

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	1	145	233	1	2	150	0	2.3	3	0	fixed	0
1	67	1	4	160	286	0	2	108	1	1.5	2	3	normal	1
2	67	1	4	120	229	0	2	129	1	2.6	2	2	reversible	0
3	37	1	3	130	250	0	0	187	0	3.5	3	0	normal	0
4	41	0	2	130	204	0	2	172	0	1.4	1	0	normal	0

Number Category

Cleveland Clinic Foundation Heart Disease Data

Predict this column

Tabular Data

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	1	145	233	1	2	150	0	2.3	3	0	fixed	0
1	67	1	4	160	286	0	2	108	1	1.5	2	3	normal	1
2	67	1	4	120	229	0	2	129	1	2.6	2	2	reversible	0
3	37	1	3	130	250	0	0	187	0	3.5	3	0	normal	0
4	41	0	2	130	204	0	2	172	0	1.4	1	0	normal	0

Column	Description	Feature Type
Age	Age in years	Numerical
Sex	(1 = male; 0 = female)	Categorical
CP	Chest pain type (0, 1, 2, 3, 4)	Categorical
Trestbpd	Resting blood pressure (in mm Hg on admission)	Numerical
Chol	Serum cholesterol in mg/dl	Numerical
FBS	fasting blood sugar in 120 mg/dl (1 = true; 0 = false)	Categorical
RestECG	Resting electrocardiogram results (0, 1, 2)	Categorical
Thalach	Maximum heart rate achieved	Numerical
Exang	Exercise induced angina (1 = yes; 0 = no)	Categorical
Oldpeak	ST depression induced by exercise relative to rest	Numerical
Slope	Slope of the peak exercise ST segment	Numerical
CA	Number of major vessels (0-3) colored by fluoroscopy	Both numerical & categorical
Thal	3 = normal; 6 = fixed defect; 7 = reversible defect	Categorical
Target	Diagnosis of heart disease (1 = true; 0 = false)	Target

Creating the Dataset

We start by downloading the data and storing it in a Pandas dataframe.

```
file_url = "http://storage.googleapis.com/download.tensorflow.org/data/heart.csv"
dataframe = pd.read_csv(file_url)
dataframe.shape
```

```
(303, 14)
```

The data is randomly split in validation and training sets

```
val_dataframe = dataframe.sample(frac=0.2, random_state=1337)
train_dataframe = dataframe.drop(val_dataframe.index)

print(
    "Using %d samples for training and %d for validation"
    % (len(train_dataframe), len(val_dataframe))
)
```

```
Using 242 samples for training and 61 for validation
```

The following procedure invokes the [Dataset.from_tensor_slices](#) procedure in order to create labels for each input and pair it with the rest of the data in each row.

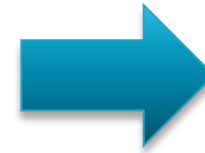
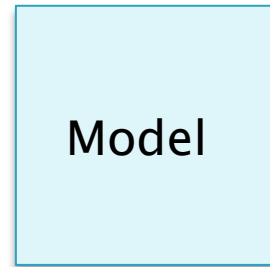
This results in the formation of the training and validation datasets.

```
def dataframe_to_dataset(dataframe):
    dataframe = dataframe.copy()
    labels = dataframe.pop("target")
    ds = tf.data.Dataset.from_tensor_slices((dict(dataframe), labels))
    ds = ds.shuffle(buffer_size=len(dataframe))
    return ds

train_ds = dataframe_to_dataset(train_dataframe)
val_ds = dataframe_to_dataset(val_dataframe)
```

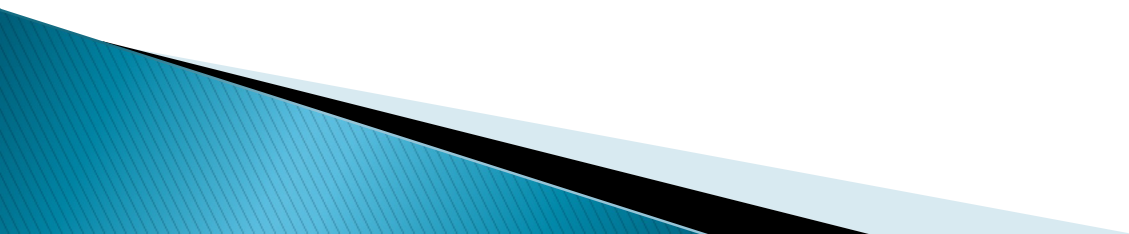
Training

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	1	145	233	1	2	150	0	2.3	3	0	fixed	0
1	67	1	4	160	286	0	2	108	1	1.5	2	3	normal	1
2	67	1	4	120	229	0	2	129	1	2.6	2	2	reversible	0
3	37	1	3	130	250	0	0	187	0	3.5	3	0	normal	0
4	41	0	2	130	204	0	2	172	0	1.4	1	0	normal	0



Target

Time Series Analysis



Time Series Analysis

Input 2D Tensor of shape (9,14)

1	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol)	rho (g/m ³)	wv (m/s)	max. wv (m/wd (deg)	
2	01.01.2009 00:10:00	996.52	-8.02	265.4	-8.9	93.3	3.33	3.11	0.22	1.94	3.12	1307.75	1.03	1.75	152.3
3	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	3.03	1309.8	0.72	1.5	136.1
4	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31	93.9	3.21	3.01	0.2	1.88	3.02	1310.24	0.19	0.63	171.6
5	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	3.08	1309.19	0.34	0.5	198
6	01.01.2009 00:50:00	996.51	-8.27	265.15	-9.04	94.1	3.27	3.08	0.19	1.92	3.09	1309	0.32	0.63	214.3
7	01.01.2009 01:00:00	996.5	-8.05	265.38	-8.78	94.4	3.33	3.14	0.19	1.96	3.15	1307.86	0.21	0.63	192.7
8	01.01.2009 01:10:00	996.5	-7.62	265.81	-8.3	94.8	3.44	3.26	0.18	2.04	3.27	1305.68	0.18	0.63	166.5
9	01.01.2009 01:20:00	996.5	-7.62	265.81	-8.36	94.4	3.44	3.25	0.19	2.03	3.26	1305.69	0.19	0.5	118.6
10	01.01.2009 01:30:00	996.5	-7.91	265.52	-8.73	93.8	3.36	3.15	0.21	1.97	3.16	1307.17	0.28	0.75	188.5
11	01.01.2009 01:40:00	996.53	-8.43	264.99	-9.34	93.1	3.23	3	0.22	1.88	3.02	1309.85	0.59	0.88	185
12	01.01.2009 01:50:00	996.62	-8.76	264.66	-9.66	93.1	3.14	2.93	0.22	1.83	2.94	1311.64	0.45	0.88	183.2
13	01.01.2009 02:00:00	996.62	-8.88	264.54	-9.77	93.2	3.12	2.9	0.21	1.81	2.91	1312.25	0.25	0.63	190.3
14	-----	-----	-8.85	264.57	-9.7	93.5	3.12	2.92	0.2	1.82	2.93	1312.11	0.16	0.5	158.3
15	-----	-----	-8.83	264.58	-9.68	93.5	3.13	2.92	0.2	1.83	2.93	1312.15	0.36	0.63	184.8
16	-----	-----	-8.66	264.74	-9.46	93.9	3.17	2.98	0.19	1.86	2.99	1311.37	0.33	0.75	155.9
17	01.01.2009 02:40:00	996.81	-8.66	264.74	-9.5	93.6	3.17	2.97	0.2	1.85	2.98	1311.38	0.07	0.5	272.4
18	01.01.2009 02:50:00	996.86	-8.7	264.7	-9.55	93.5	3.16	2.95	0.21	1.85	2.96	1311.64	0.32	0.63	219.2
19	01.01.2009 03:00:00	996.84	-8.81	264.59	-9.66	93.5	3.13	2.93	0.2	1.83	2.94	1312.18	0.18	0.63	167.2
20	01.01.2009 03:10:00	996.87	-8.84	264.56	-9.69	93.5	3.13	2.92	0.2	1.83	2.93	1312.37	0.07	0.25	129.3
21	01.01.2009 03:20:00	996.97	-8.94	264.45	-9.82	93.3	3.1	2.89	0.21	1.81	2.9	1313.01	0.1	0.63	115.3
22	01.01.2009 03:30:00	997.08	-8.94	264.44	-9.8	93.4	3.1	2.9	0.2	1.81	2.9	1313.15	0.3	0.75	149.3
23	01.01.2009 03:40:00	997.1	-8.86	264.52	-9.76	93.1	3.12	2.9	0.22	1.81	2.91	1312.78	0.29	0.75	149.7
24	01.01.2009 03:50:00	997.06	-8.99	264.39	-9.99	92.4	3.09	2.85	0.23	1.78	2.86	1313.39	0.12	0.63	231.7
25	01.01.2009 04:00:00	996.99	-9.05	264.34	-10.02	92.6	3.07	2.85	0.23	1.78	2.85	1313.61	0.1	0.38	240
26	01.01.2009 04:10:00	997.05	-9.23	264.15	-10.25	92.2	3.03	2.79	0.24	1.74	2.8	1314.62	0.1	0.38	203.9
27	01.01.2009 04:20:00	997.11	-9.49	263.89	-10.54	92	2.97	2.73	0.24	1.71	2.74	1316.02	0.34	0.75	159.7
28	01.01.2009 04:30:00	997.19	-9.5	263.87	-10.51	92.3	2.97	2.74	0.23	1.71	2.75	1316.16	0.43	0.88	66.16
29	01.01.2009 04:40:00	997.24	-9.35	264.02	-10.29	92.8	3	2.79	0.22	1.74	2.79	1315.47	0.4	0.88	105
30	01.01.2009 04:50:00	997.37	-9.47	263.89	-10.46	92.4	2.97	2.75	0.23	1.72	2.75	1316.25	0.37	0.75	125.8
31	01.01.2009 05:00:00	997.46	-9.63	263.72	-10.65	92.2	2.94	2.71	0.23	1.69	2.71	1317.19	0.4	0.88	157
32	01.01.2009 05:10:00	997.43	-9.67	263.68	-10.63	92.6	2.93	2.71	0.22	1.69	2.72	1317.35	0.36	0.75	132.5
33	01.01.2009 05:20:00	997.42	-9.68	263.67	-10.73	92	2.92	2.69	0.23	1.68	2.7	1317.4	0.09	0.5	143.2
34	01.01.2009 05:30:00	997.53	-9.9	263.45	-10.98	91.7	2.87	2.64	0.24	1.64	2.64	1318.68	0.29	1	72.5
35	01.01.2009 05:40:00	997.6	-9.91	263.43	-10.9	92.4	2.87	2.65	0.22	1.66	2.66	1318.81	0.5	1	60.72

Output Label

14 quantities recorded every 10 minutes from 2009-2016

Time Series Analysis

Input Batch: 3D Tensor of shape (2,9,14)

1	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol)	rho (g/m ³)	wv (m/s)	max. wv (m/wd (deg)	
2	01.01.2009 00:10:00	996.52	-8.02	265.4	-8.9	93.3	3.33	3.11	0.22	1.94	3.12	1307.75	1.03	1.75	152.3
3	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	3.03	1309.8	0.72	1.5	136.1
4	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31	93.9	3.21	3.01	0.2	1.88	3.02	1310.24	0.19	0.63	171.6
5	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	3.08	1309.19	0.34	0.5	198
6	01.01.2009 00:50:00	996.51	-8.27	265.15	-9.04	94.1	3.27	3.08	0.19	1.92	3.09	1309	0.32	0.63	214.3
7	01.01.2009 01:00:00	996.5	-8.05	265.38	-8.78	94.4	3.33	3.14	0.19	1.96	3.15	1307.86	0.21	0.63	192.7
8	01.01.2009 01:10:00	996.5	-7.62	265.81	-8.3	94.8	3.44	3.26	0.18	2.04	3.27	1305.68	0.18	0.63	166.5
9	01.01.2009 01:20:00	996.5	-7.62	265.81	-8.36	94.4	3.44	3.25	0.19	2.03	3.26	1305.69	0.19	0.5	118.6
10	01.01.2009 01:30:00	996.5	-7.91	265.52	-8.73	93.8	3.36	3.15	0.21	1.97	3.16	1307.17	0.28	0.75	188.9
11	01.01.2009 01:40:00	996.53	-8.43	264.99	-9.34	93.1	3.23	3	0.22	1.88	3.02	1309.85	0.59	0.88	185
12	01.01.2009 01:50:00	996.62	-8.76	264.66	-9.66	93.1	3.14	2.93	0.22	1.83	2.94	1311.64	0.45	0.88	183.2
13	01.01.2009 02:00:00	996.62	-8.88	264.54	-9.77	93.2	3.12	2.9	0.21	1.81	2.91	1312.25	0.25	0.63	190.3
14	01.01.2009 02:10:00	996.63	-8.85	264.57	-9.7	93.5	3.12	2.92	0.2	1.82	2.93	1312.11	0.16	0.5	158.3
15	01.01.2009 02:20:00	996.74	-8.83	264.58	-9.68	93.5	3.13	2.92	0.2	1.83	2.93	1312.15	0.36	0.63	184.8
16	01.01.2009 02:30:00	996.81	-8.66	264.74	-9.46	93.9	3.17	2.98	0.19	1.86	2.99	1311.37	0.33	0.75	155.9
17	01.01.2009 02:40:00	996.81	-8.66	264.74	-9.5	93.6	3.17	2.97	0.2	1.85	2.98	1311.38	0.07	0.5	272.4
18	01.01.2009 02:50:00	996.86	-8.7	264.7	-9.55	93.5	3.16	2.95	0.21	1.85	2.96	1311.64	0.32	0.63	219.2
19	01.01.2009 03:00:00	996.84	-8.81	264.59	-9.66	93.5	3.13	2.93	0.2	1.83	2.94	1312.18	0.18	0.63	167.2
20	01.01.2009 03:10:00	996.87	-8.84	264.56	-9.69	93.5	3.13	2.92	0.2	1.83	2.93	1312.37	0.07	0.25	129.3
21	01.01.2009 03:20:00	996.97	-8.94	264.45	-9.82	93.3	3.1	2.89	0.21	1.81	2.9	1313.01	0.1	0.63	115.3
22	01.01.2009 03:30:00	997.08	-8.94	264.44	-9.8	93.4	3.1	2.9	0.2	1.81	2.9	1313.15	0.3	0.75	149.3
23	01.01.2009 03:40:00	997.1	-8.86	264.52	-9.76	93.1	3.12	2.9	0.22	1.81	2.91	1312.78	0.29	0.75	149.7
24	01.01.2009 03:50:00	997.06	-8.99	264.39	-9.99	92.4	3.09	2.85	0.23	1.78	2.86	1313.39	0.12	0.63	231.7
25	01.01.2009 04:00:00	996.99	-9.05	264.34	-10.02	92.6	3.07	2.85	0.23	1.78	2.85	1313.61	0.1	0.38	240
26	01.01.2009 04:10:00	997.05	-9.23	264.15	-10.25	92.2	3.03	2.79	0.24	1.74	2.8	1314.62	0.1	0.38	203.9
27	01.01.2009 04:20:00	997.11	-9.49	263.89	-10.54	92	2.97	2.73	0.24	1.71	2.74	1316.02	0.34	0.75	159.7
28	01.01.2009 04:30:00	997.19	-9.5	263.87	-10.51	92.3	2.97	2.74	0.23	1.71	2.75	1316.16	0.43	0.88	66.16
29	01.01.2009 04:40:00	997.24	-9.35	264.02	-10.29	92.8	3	2.79	0.22	1.74	2.79	1315.47	0.4	0.88	105
30	01.01.2009 04:50:00	997.37	-9.47	263.89	-10.46	92.4	2.97	2.75	0.23	1.72	2.75	1316.25	0.37	0.75	125.8
31	01.01.2009 05:00:00	997.46	-9.63	263.72	-10.65	92.2	2.94	2.71	0.23	1.69	2.71	1317.19	0.4	0.88	157
32	01.01.2009 05:10:00	997.43	-9.67	263.68	-10.63	92.6	2.93	2.71	0.22	1.69	2.72	1317.35	0.36	0.75	132.5
33	01.01.2009 05:20:00	997.42	-9.68	263.67	-10.73	92	2.92	2.69	0.23	1.68	2.7	1317.4	0.09	0.5	143.2
34	01.01.2009 05:30:00	997.53	-9.9	263.45	-10.98	91.7	2.87	2.64	0.24	1.64	2.64	1318.68	0.29	1	72.5
35	01.01.2009 05:40:00	997.6	-9.91	263.43	-10.9	92.4	2.87	2.65	0.22	1.66	2.66	1318.81	0.5	1	60.72

jena_climate_2009_2016

14 quantities recorded every 10 minutes from 2009-2016

Raw Tabular Data

Inspecting the data

```
import os

#data_dir = '/home/ubuntu/data/'
data_dir = '/Users/subirvarma/handson-ml/datasets/'
fname = os.path.join(data_dir, 'jena_climate_2009_2016.csv')

f = open(fname)
data = f.read()
f.close()

lines = data.split('\n')
header = lines[0].split(',')
lines = lines[1:]

print(header)
print(len(lines))

['Date Time', 'p (mbar)', 'T (degC)', 'Tpot (K)', 'Tdew (degC)', 'rh (%)', 'VPmax (mbar)', 'VPact (mbar)', 'VPdef (mbar)', 'sh (g/kg)', 'H2OC (mmol/mol)', 'rho (g/m**3)', 'wv (m/s)', 'max. wv (m/s)', 'wd (deg)']
420551
```

Outputs a count of 420,551 lines of data

Raw Tabular Data

Let's convert all of these 420,551 lines of data into a Numpy array:

```
: import numpy as np

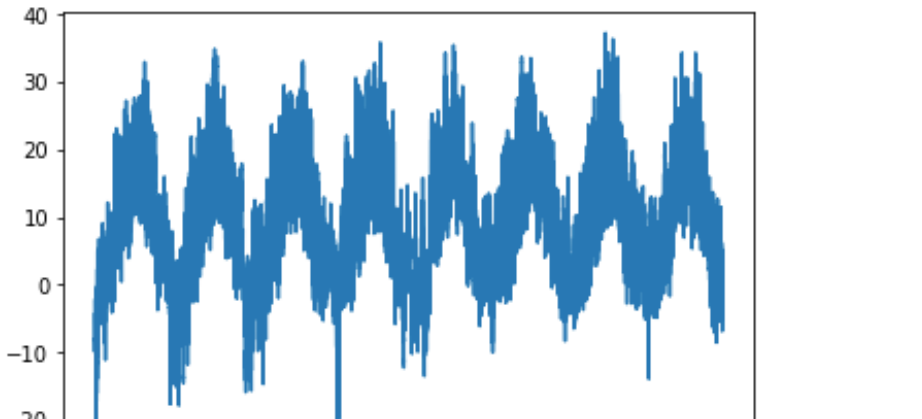
float_data = np.zeros((len(lines), len(header) - 1))
for i, line in enumerate(lines):
    values = [float(x) for x in line.split(',')[1:]]
    float_data[i, :] = values
```

Leave out the first row
and the first column

For instance, here is the plot of temperature (in degrees Celsius) over time

```
: from matplotlib import pyplot as plt

temp = float_data[:, 1] # temperature (in degrees Cel
plt.plot(range(len(temp)), temp)
plt.show()
```



Raw Tabular Data: Normalize the Data

Split samples into training validation and test

```
num_train_samples = int(0.5 * len(raw_data))
num_val_samples = int(0.25 * len(raw_data))
num_test_samples = len(raw_data) - num_train_samples - num_val_samples
print("num_train_samples:", num_train_samples)
print("num_val_samples:", num_val_samples)
print("num_test_samples:", num_test_samples)
```

```
num_train_samples: 210275
num_val_samples: 105137
num_test_samples: 105139
```

Data Normalization

```
mean = float_data[:200000].mean(axis=0)
float_data -= mean
std = float_data[:200000].std(axis=0)
float_data /= std
```


Dataset for Time Series Analysis

Sample once every hour

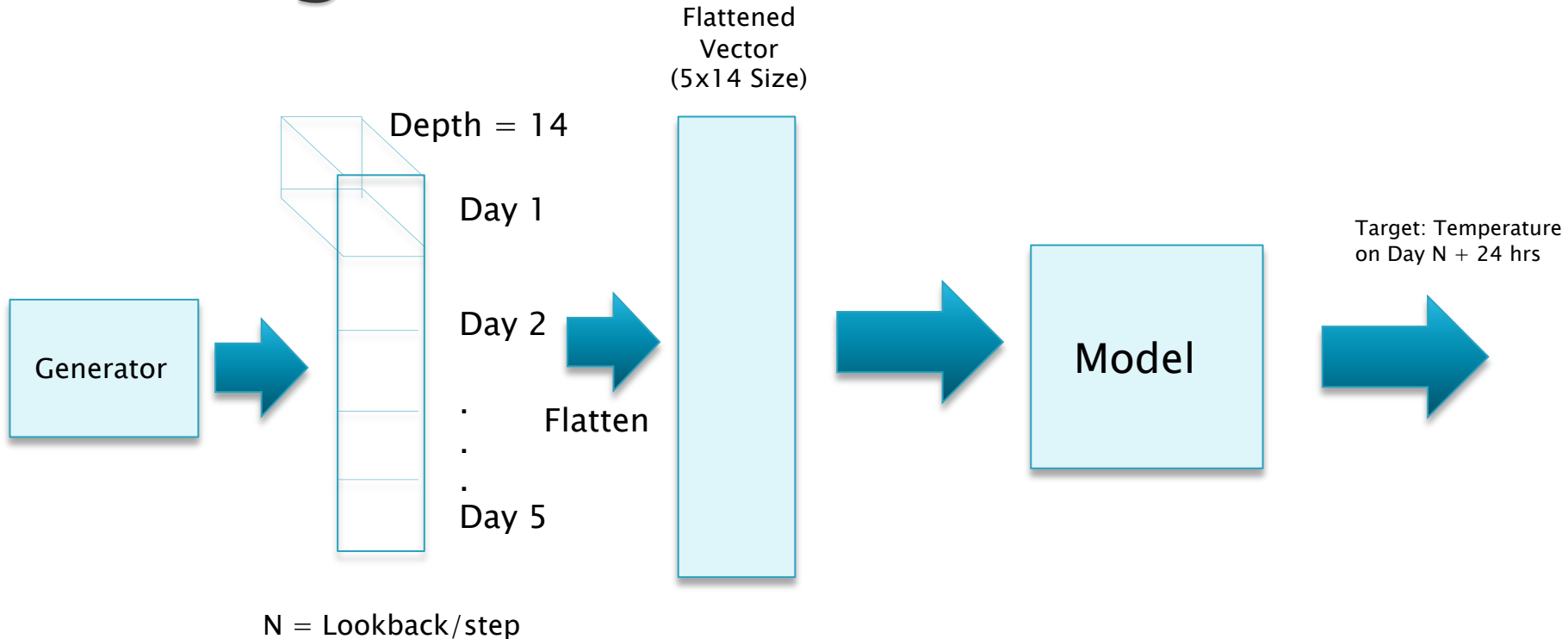
```
sampling_rate = 6 ← Equivalent to 5 days of measurements  
sequence_length = 120  
delay = sampling_rate * (sequence_length + 24 - 1) ← Try to predict temperature 1 day into the future  
batch_size = 256
```

```
train_dataset = tensorflow.keras.utils.timeseries_dataset_from_array(  
    raw_data[:-delay],  
    targets=temperature[delay:],  
    sampling_rate=sampling_rate,  
    sequence_length=sequence_length,  
    shuffle=True,  
    batch_size=batch_size,  
    start_index=0,  
    end_index=num_train_samples)
```

```
val_dataset = tensorflow.keras.utils.timeseries_dataset_from_array(  
    raw_data[:-delay],  
    targets=temperature[delay:],  
    sampling_rate=sampling_rate,  
    sequence_length=sequence_length,  
    shuffle=True,  
    batch_size=batch_size,  
    start_index=num_train_samples,  
    end_index=num_train_samples + num_val_samples)
```

```
test_dataset = tensorflow.keras.utils.timeseries_dataset_from_array(  
    raw_data[:-delay],  
    targets=temperature[delay:],  
    sampling_rate=sampling_rate,  
    sequence_length=sequence_length,  
    shuffle=True,  
    batch_size=batch_size,  
    start_index=num_train_samples + num_val_samples)
```

Training



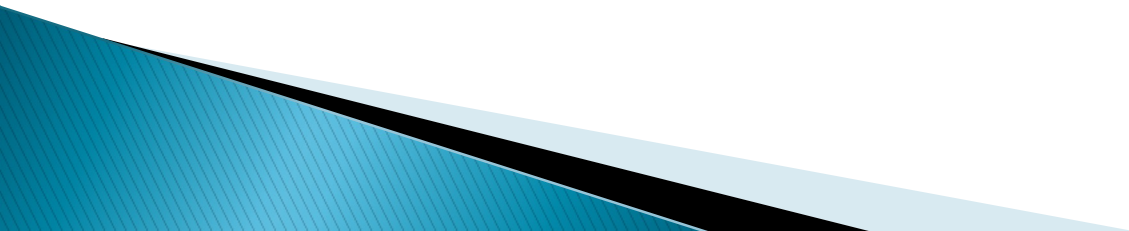
```
from keras.models import Sequential
from keras import layers
from tensorflow.keras.optimizers import RMSprop

from tensorflow import keras
from tensorflow.keras import layers

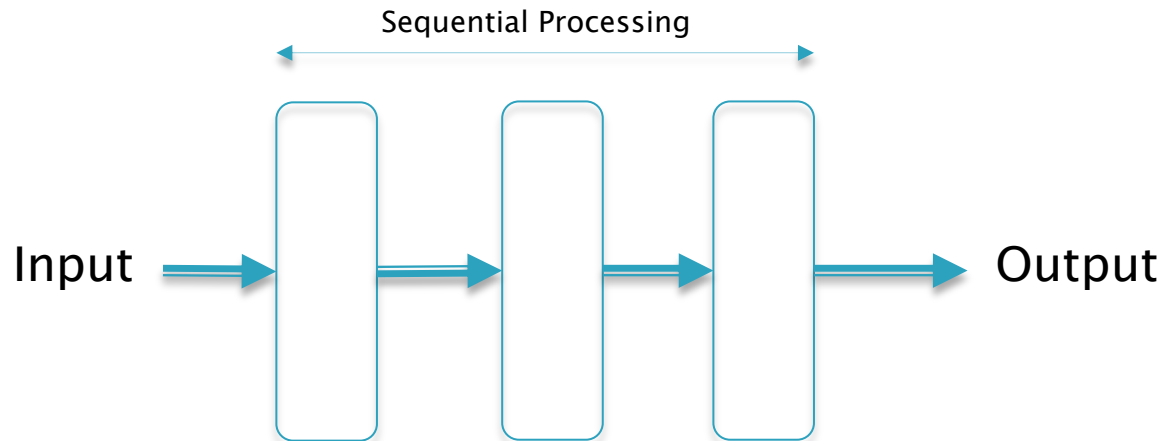
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Flatten()(inputs)
x = layers.Dense(16, activation="relu")(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset)
```

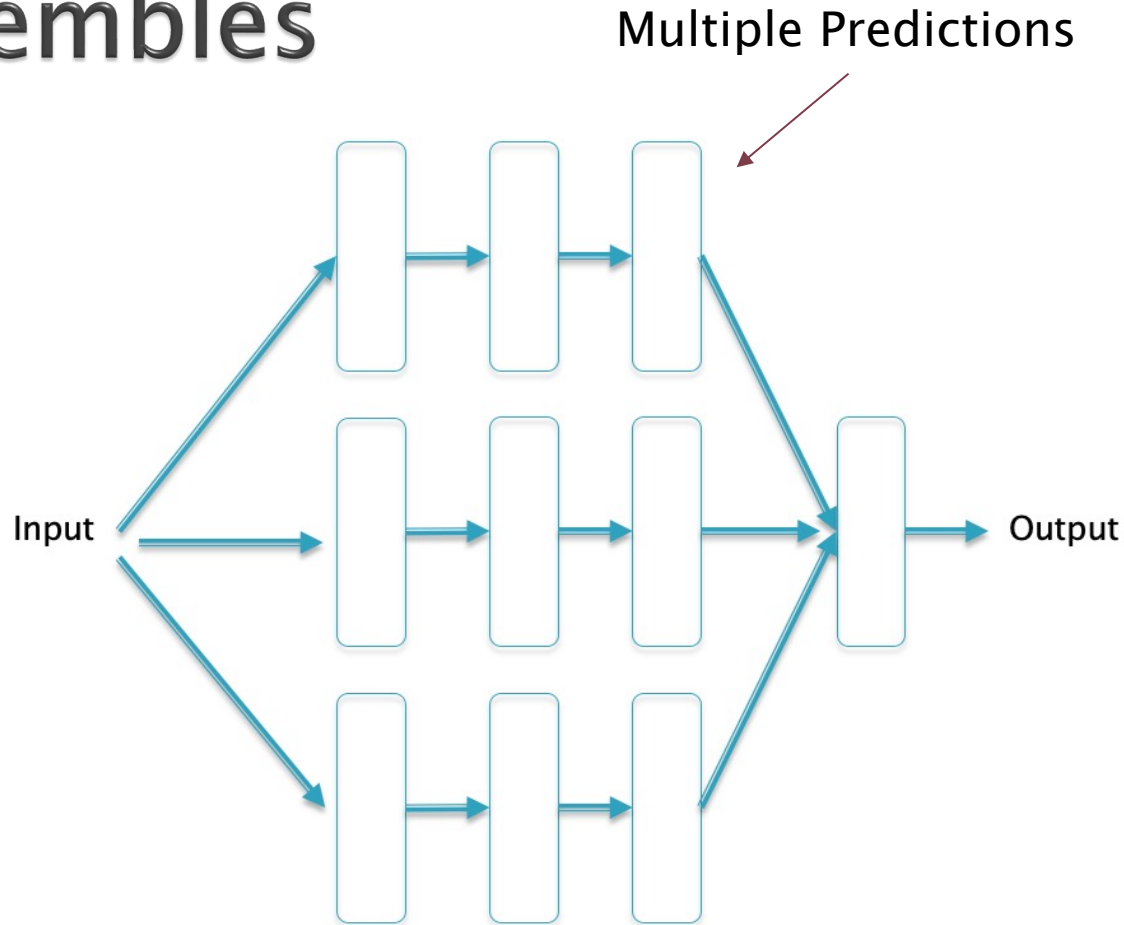
Network Topologies for Deep Networks



Sequential Processing



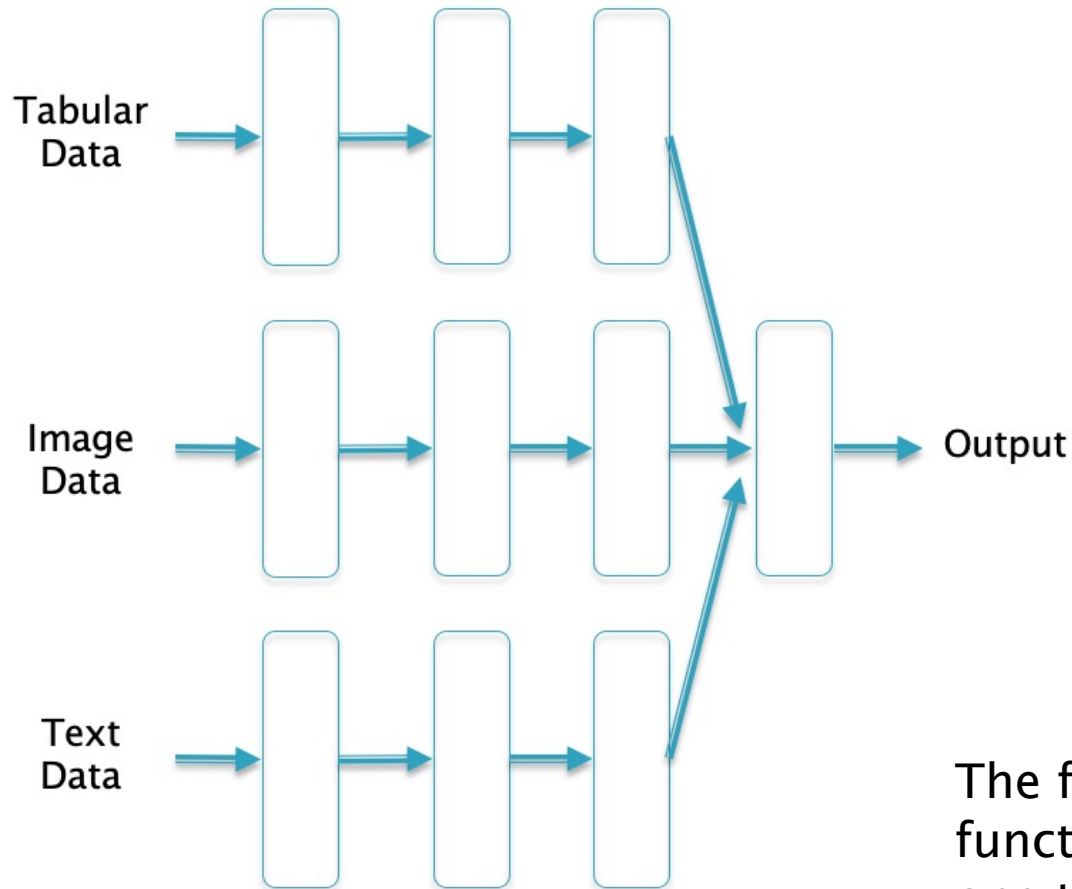
Parallel Processing: Model Ensembles



Example: Majority Vote models

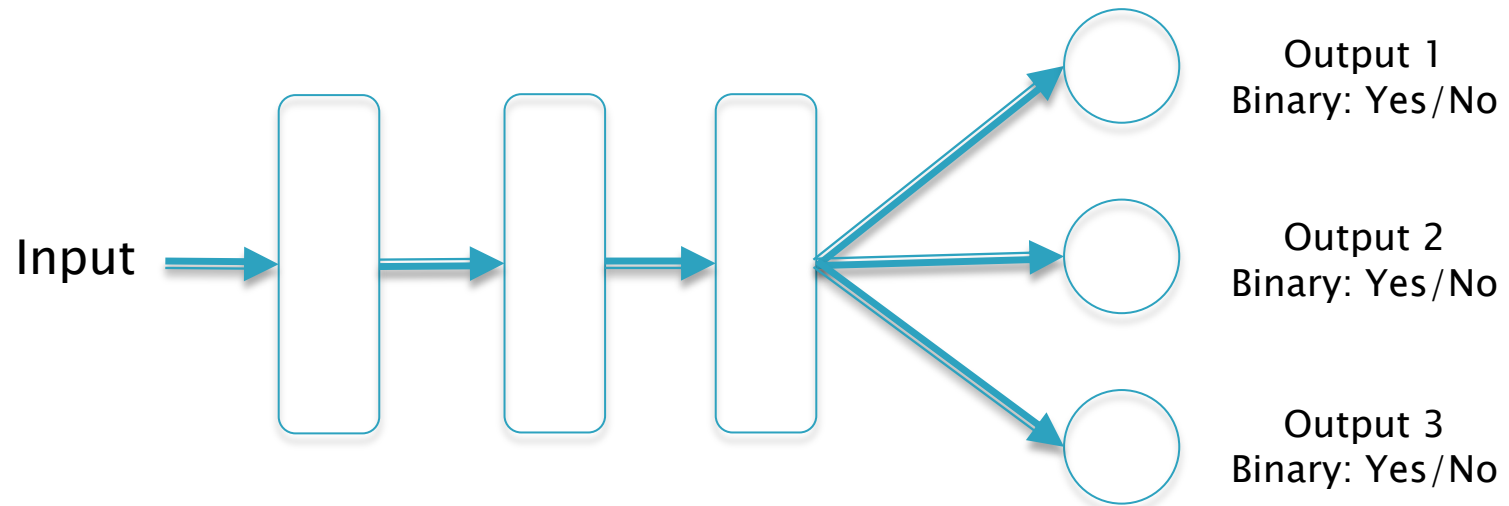
Increases prediction accuracy

Multi-Input Models



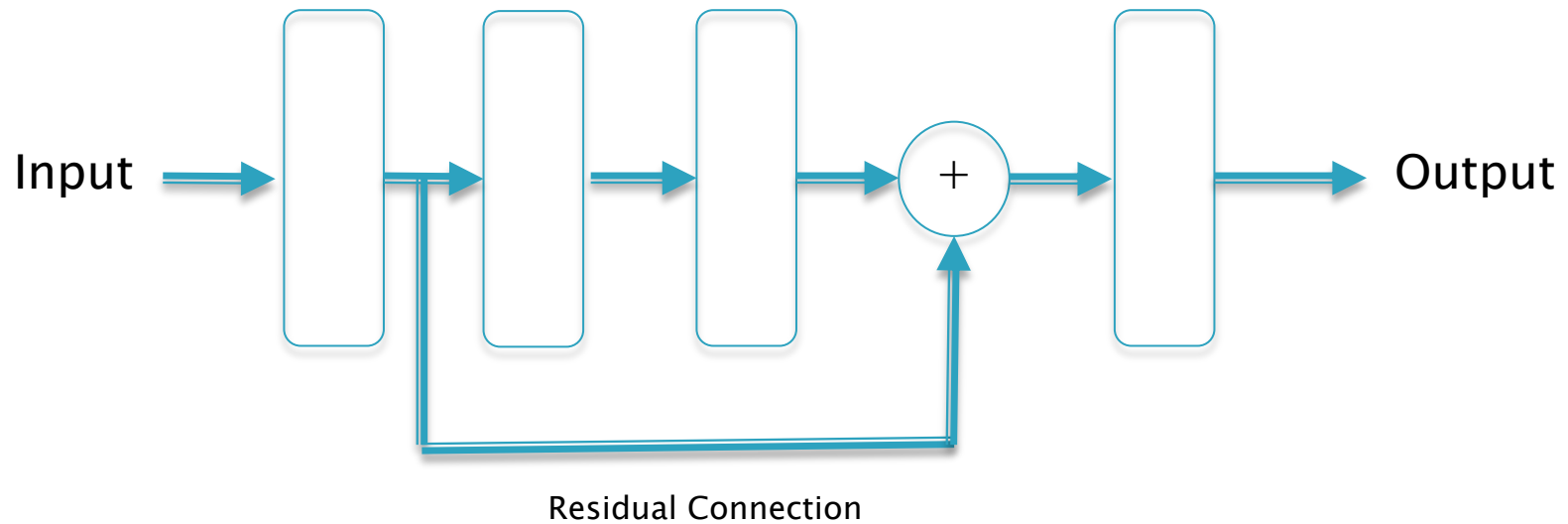
The final decision is a function of more than one type of input data

Multi-Label Classification



For classifying more than one object per input

Residual Connections



Enables the training of models with hundreds of hidden layers

Keras Sequential vs Functional API

All these different topologies can be easily coded using the Keras Functional API

```
import keras
keras.__version__
from keras import Sequential, Model
from keras import layers
from keras import Input

from keras.datasets import cifar10

(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

train_images = train_images.reshape((50000, 32 * 32 * 3))
train_images = train_images.astype('float32') / 255

test_images = test_images.reshape((10000, 32 * 32 * 3))
test_images = test_images.astype('float32') / 255

from tensorflow.keras.utils import to_categorical

train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

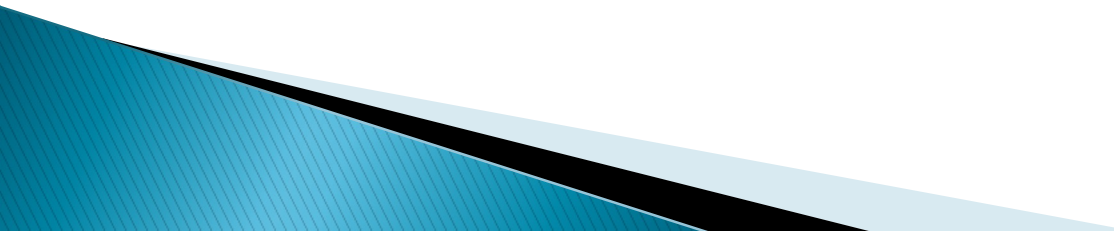
input_tensor = Input(shape=(32 * 32 * 3,))
x = layers.Dense(20, activation='relu')(input_tensor)
y = layers.Dense(15, activation='relu')(x)
output_tensor = layers.Dense(10, activation='softmax')(y)

model = Model(input_tensor, output_tensor)

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

history = model.fit(train_images, train_labels, epochs=10, batch_size=128, validation_split=0.2)
```

Keras Callbacks

- ▶ **Model Checkpointing**: Saving the current state of the model at different points during training
 - ▶ **Early Stopping**: Interrupting Training when the Validation Loss is no longer improving (and saving the best model)
 - ▶ **Dynamically adjusting hyper parameter values**:
Example Learning Rate
 - ▶ **Logging Training and Validation Metrics**
- 

Further Reading

- ▶ Das and Varma: Chapter 6 – NNDeepLearning
- ▶ Keras Code Examples: <https://keras.io/examples/>
- ▶ Neural Network Playground
<https://playground.tensorflow.org>