Neural Attention

what it is and
what to do with it

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Tensorflow Meetup

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Milagro cuánto?

Estudiante de doctorado

+ Representation Learning (embeddings)

+ Educational Data Mining

Argument mining

+ INRIA Sophia Antipolis

Sobre qué vamos a charlar hoy?

Disclaimer

Variedad de attention mechanisms

+ Cómo se puede aplicar atención dependiendo el tipo de red

+ Un poco más de detalle sobre sequence labeling

Implementación!

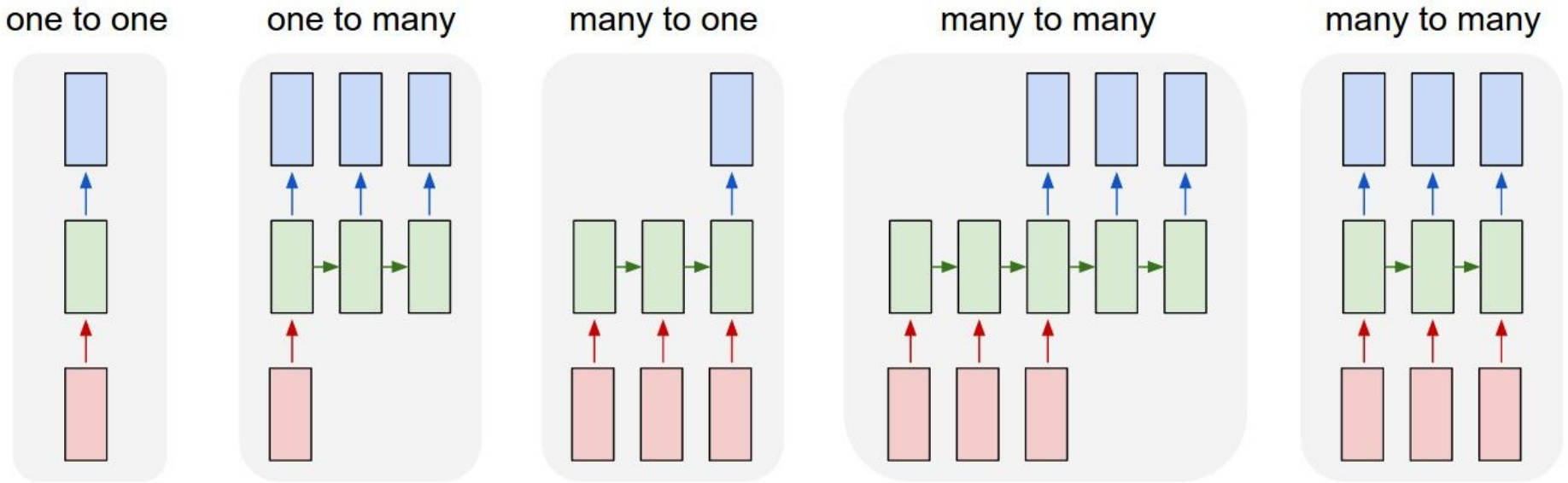
+ Armar un esqueleto de red con atención en Keras

PART I

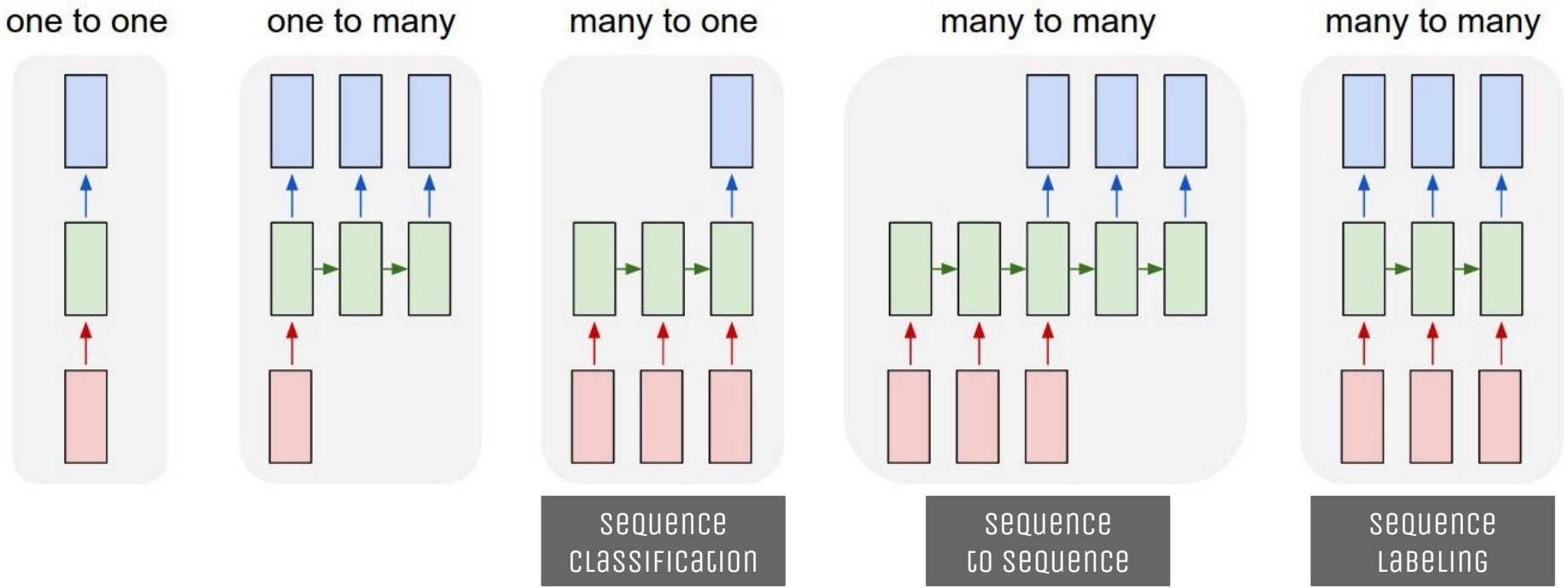
Neural Attention

Weight something with attention scores

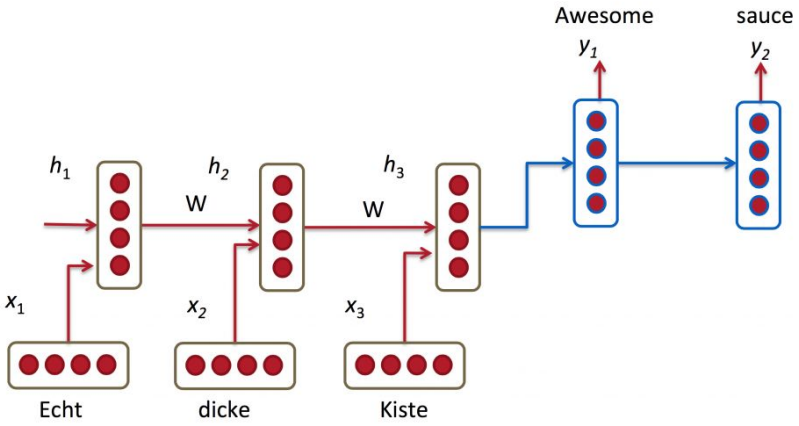
Elegimos el tipo de red

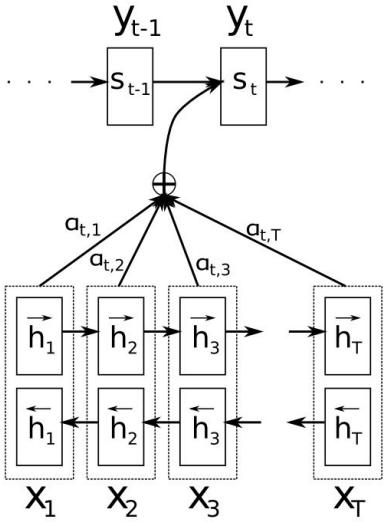


Elegimos el tipo de red



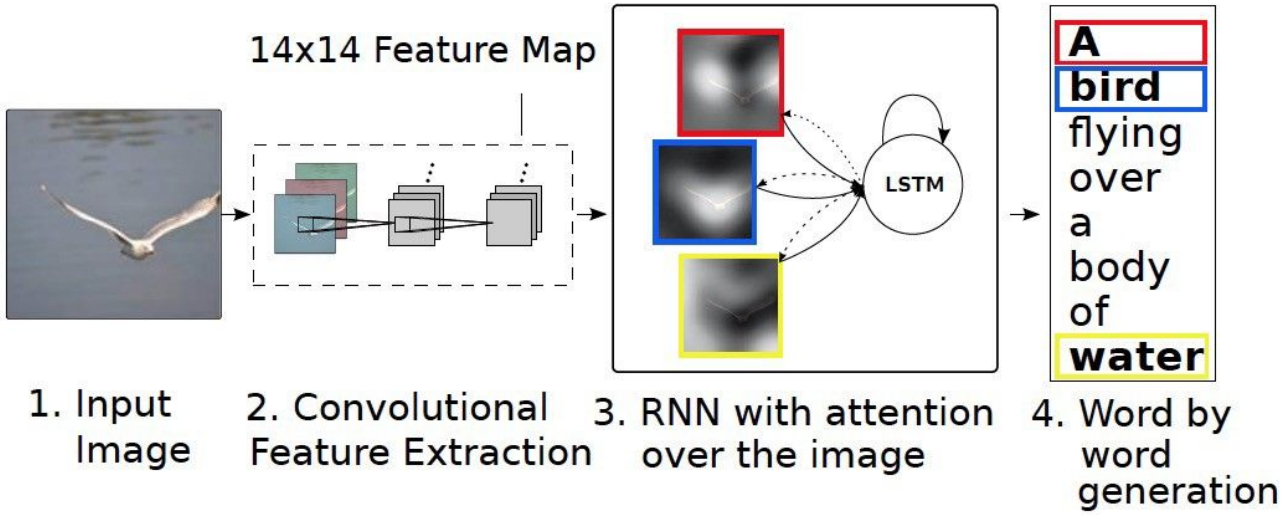
Neural attention for machine translation [2]





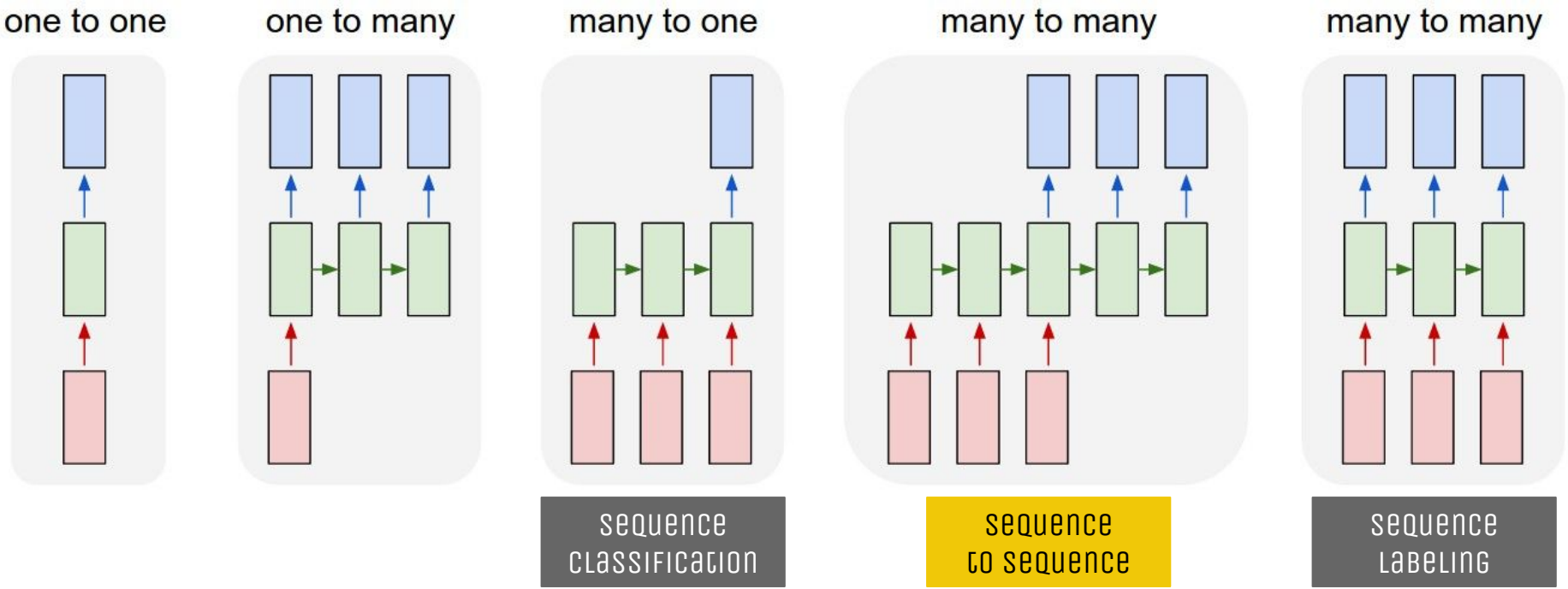
Para generar cada palabra en el idioma target, pesamos todos los **recurrent output** de la red.

NA for image captioning



Para generar cada palabra, la red pesa los feature descriptors **(input)** de la imagen para identificar qué posiciones son importantes.

Elegimos el tipo de red



PART II

Mini Prototipo

Resources

Dataset: CoNLL NER task from Kaggle

Código: Github repo

+ Notebook con las distintas redes

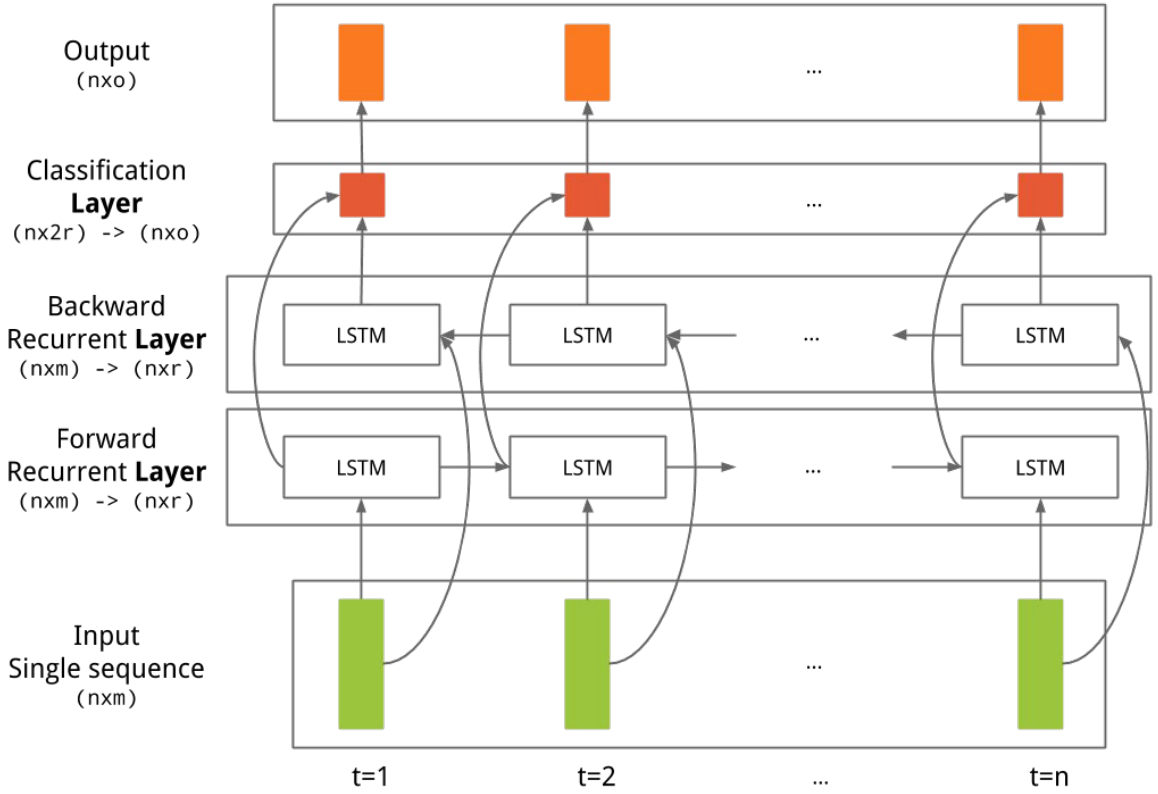
+ Visualización en JavaScript

Modelos entrenados

Named Entity Recognition and Classification

Thousands of demonstrators have marched through London to protest the war in Iraq and demand the withdrawal of British troops from that country . Families of soldiers killed in the conflict joined the protesters who carried banners with such slogans as "Bush Number One Terrorist" and "Stop the Bombings".

geo gpe per



General

RNN for

NERC

```
def add_embedding_layer(self, layers):
    layers = Embedding(
        input_dim=self.vocabulary_size,
        output_dim=self.max_sentence_length,
        input_length=self.max_sentence_length)(layers)
    return Dropout(0.1)(layers)

def add_recurrent_layer(self, layers):
    return Bidirectional(
        LSTM(units=100, return_sequences=True,
             recurrent_dropout=0.1))(layers)

def add_output_layer(self, layers):
    return TimeDistributed(
        Dense(self.n_labels, activation="softmax"))(layers)

def build(self):
    input = Input(shape=(max_sentence_length,))
    layers = self.add_embedding_layer(input)
    layers = self.add_recurrent_layer(layers)
    layers = self.add_output_layer(layers)

    self.model = Model(input, layers)
    self.model.compile(
        optimizer="adam", loss="categorical_crossentropy",
        metrics=["accuracy"])
```

Vanilla

LSTM

```
model.evaluate(X_test, y_test)
```

	precision	recall	f1-score	support
O	1.00	1.00	1.00	995317
geo	0.84	0.85	0.85	9014
gpe	0.95	0.93	0.94	3177
per	0.88	0.85	0.86	6882
org	0.81	0.71	0.76	7301
tim	0.85	0.89	0.87	5196
art	0.39	0.18	0.25	144
nat	0.51	0.40	0.45	45
eve	0.42	0.47	0.45	104
avg / total	0.99	0.99	0.99	1027180

Vanilla

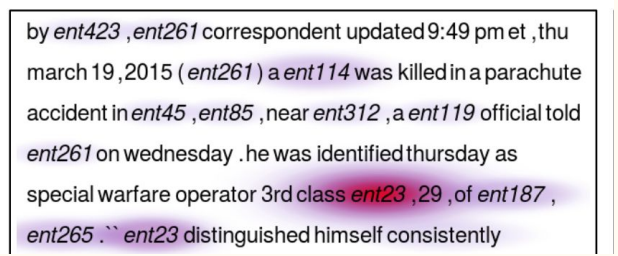
LSTM

Agreguemos atención

What and where to weight?

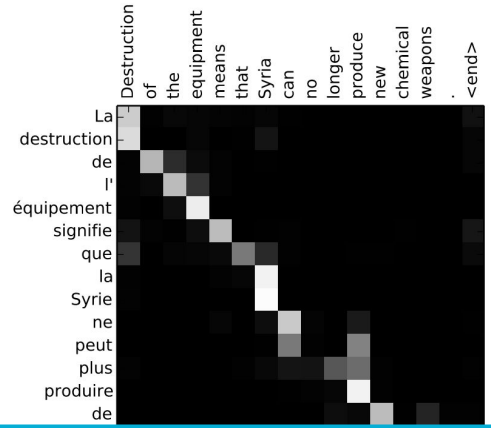
Before Recurrence

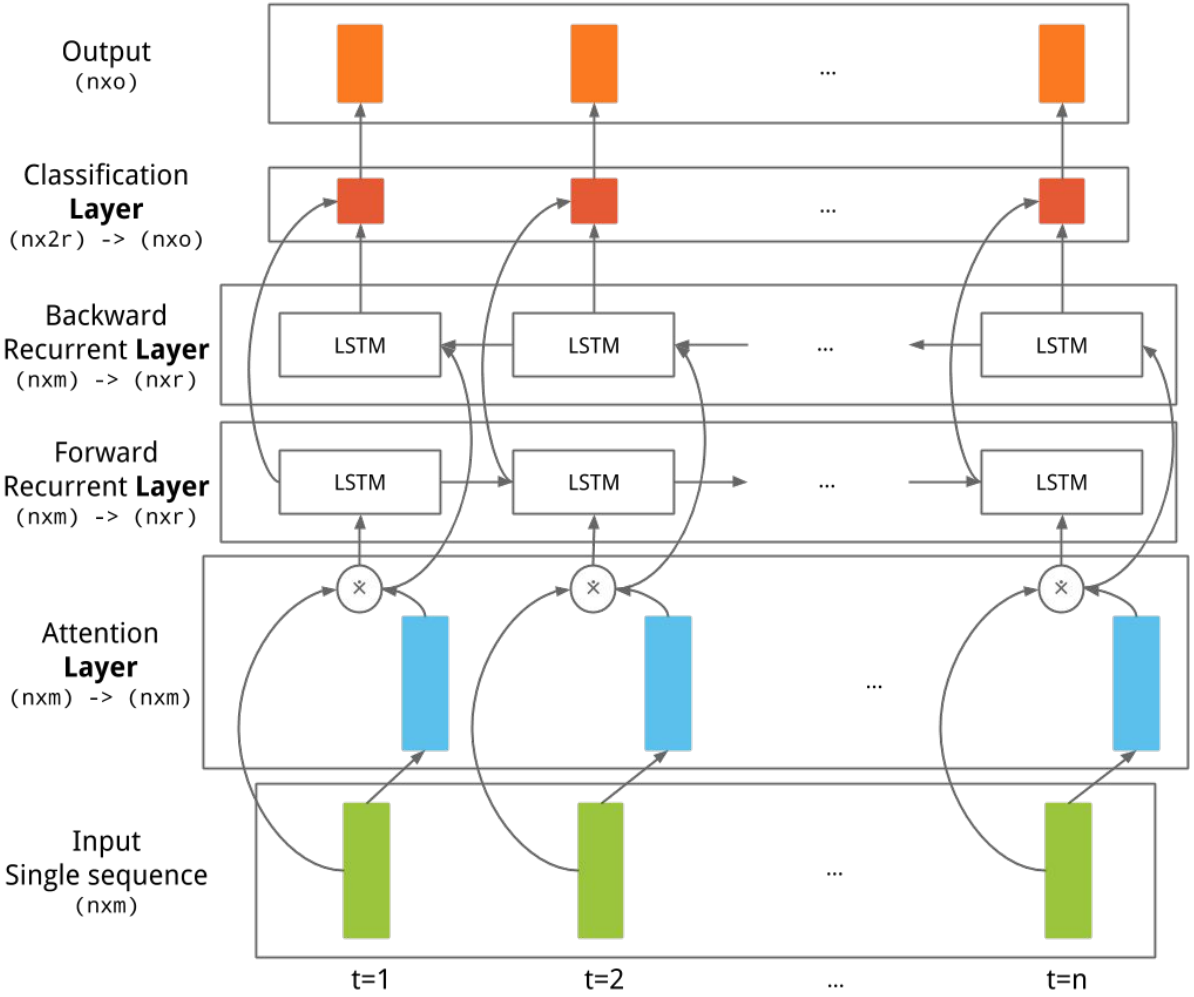
Podemos interpretar mejor cómo impacta el input en la clasificación. En general entendemos el espacio del input.



After Recurrence

Podemos interpretar mejor qué información procesada es relevante para el cálculo del output





RNN + Att

para NERC

```python
class AttBiLSTM(BiLSTM):

    def add_attention_block(self, layers):
        """Apply an attention block to a partial model layers."""
        return layers

    def add_embedding_layer(self, layers):
        layers = super(AttBiLSTM, self).add_embedding_layer(layers)
        return self.add_attention_block(layers)
```

Definimos una nueva clase AttBiLSTM

y sobreescribimos la capa de

embeddings agregando un

post-proceso de atención

Soon to be

attention

LSTM

How to calculate the attention score?

Inspiración: Philippe Remy

Para el problema de sequence labeling, el repositorio Keras Attention Mechanism de Philippe Remy implementa una solución muy básica

Soft attention

Vector de pesos es **real**

La función es **derivable**

No funciona tan bien con secuencias largas [1]

Hard attention

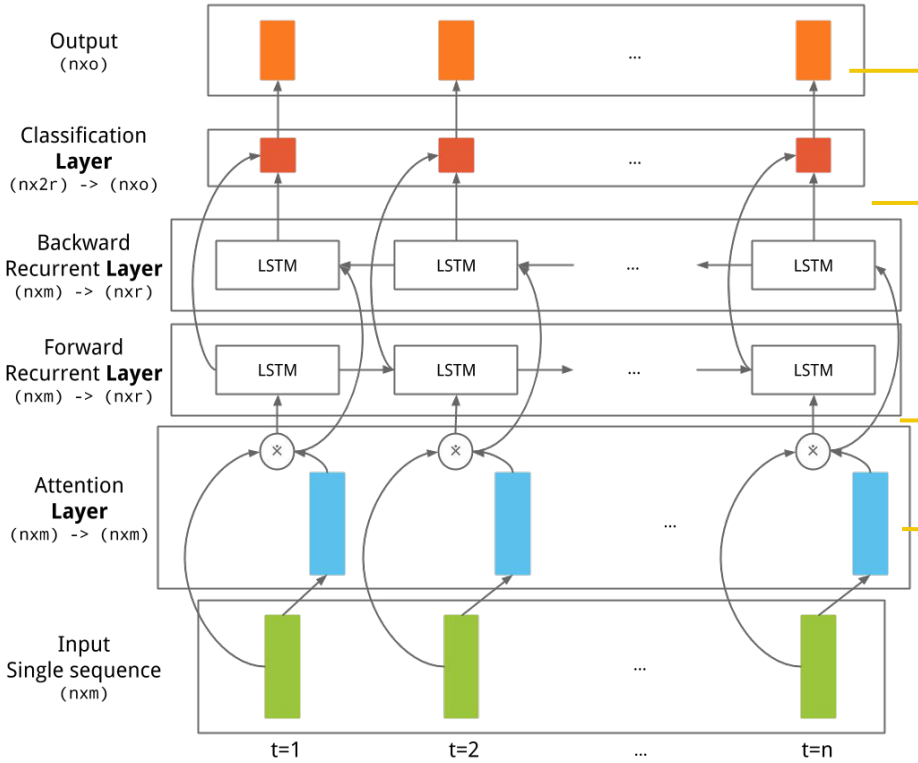
Vector de pesos es **binario**

La función **no es derivable**

Costoso de optimizar

Útil para secuencias largas

Formal definition



$$y_t = softmax(W_o r_t)$$

$$r_t = bilstm(\hat{x}_t, \hat{x}_{t-1})$$

$$\hat{x}_t = x_t \otimes a_t$$

pointwise multiplication

$$a_t = softmax(xW_a)_t$$

```python
class AttBiLSTM(BiLSTM):

    def add_attention_block(self, layers):
        """Apply an attention block to a partial model layers."""
        feature_vector_size = K.int_shape(layers)[-1]
        att_layer = Dense(feature_vector_size, activation='softmax',
            name='attention_matrix_score')(layers)
        layers = merge([att_layer, layers],  mode='mul')
        return layers

    def add_embedding_layer(self, layers):
        layers = super(AttBiLSTM, self).add_embedding_layer(layers)
        return self.add_attention_block(layers)
```

First attempt

attention

LSTM

¡La atención es sólo una capa densa!

Calculamos un peso para cada **feature**

en cada **timestep**

```python
class AttBiLSTM(BiLSTM):

    def add_attention_block(self, layers):
        """Apply an attention block to a partial model layers."""
        feature_vector_size = K.int_shape(layers)[-1]
        att_layer = Dense(feature_vector_size, activation='softmax',
            name='attention_matrix_score')(layers)
        # Calculate a single score for each timestep
        att_layer = Lambda(lambda x: K.mean(x, axis=2),
                           name='attention_vector_score')(att_layer)
        # Reshape to obtain the same shape as input
        att_layer = Permute((2, 1))(
            RepeatVector(feature_vector_size)(att_layer))
        layers = merge([att_layer, layers],  mode='mul')
        return layers

    def add_embedding_layer(self, layers):
        layers = super(AttBiLSTM, self).add_embedding_layer(layers)
        return self.add_attention_block(layers)
```

Calculamos un peso para cada **timestep**,

tomando el promedio de los pesos.

Finally

attention

LSTM

	precision	recall	f1-score	support
O	1.00	1.00	1.00	994779
geo	0.82	0.86	0.84	9071
gpe	0.96	0.89	0.92	3350
per	0.90	0.79	0.84	7014
org	0.81	0.69	0.75	7410
tim	0.87	0.86	0.87	5236
art	0.00	0.00	0.00	134
nat	0.00	0.00	0.00	55
eve	0.24	0.03	0.05	130
prev-prev-lemma	0.00	0.00	0.00	1
avg / total	0.99	0.99	0.99	1027180

Finally

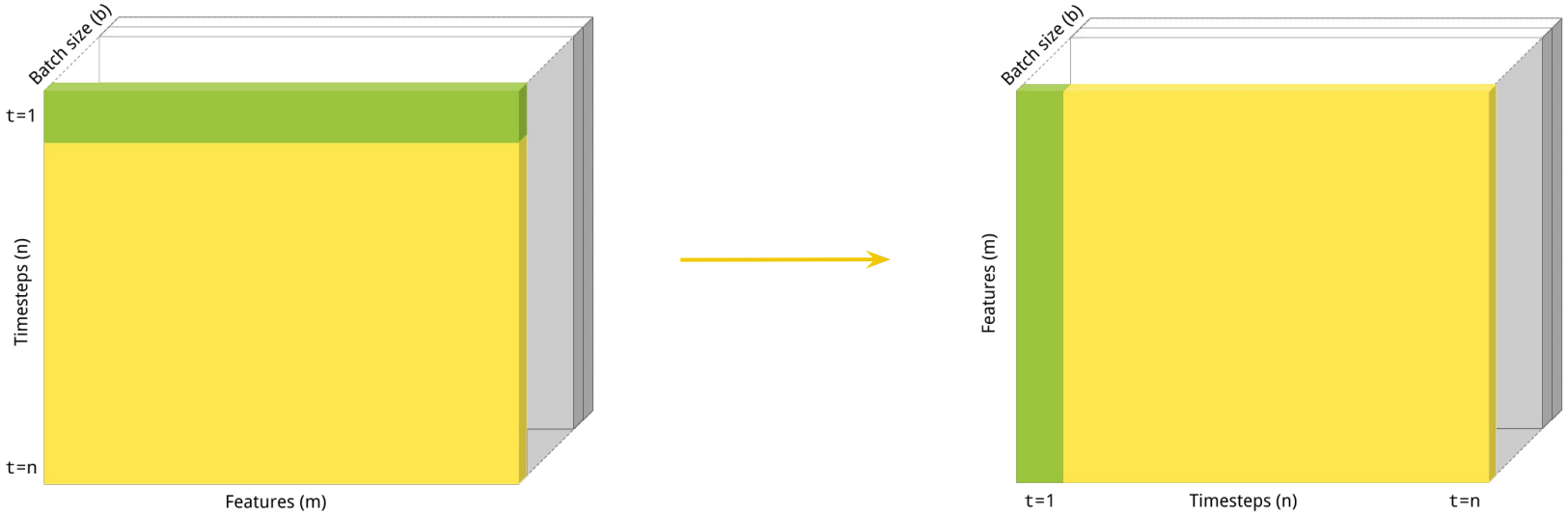
attention

LSTM

Cuando aplicamos la capa densa, cada attention score se calcula usando los valores de los **otros features** en el **mismo timestep**.

Another solution

El repositorio [Keras Attention Mechanism] de Philippe Remy también implementa una solución muy básica, permutando las últimas dimensiones del input



```python
class AttBiLSTM2(BiLSTM):

    def add_attention_block(self, layers):
        """Apply an attention block to a partial model layers."""
        timesteps = K.int_shape(layers)[-2]
        att_layer = Permute((2, 1))(att_layer)
        att_layer = TimeDistributed(
            Dense(timesteps, activation='softmax'),
            name='attention_matrix_score')(att_layer)
        # Calculate a single score for each timestep
        att_layer = Lambda(lambda x: K.mean(x, axis=2),
                           name='attention_vector_score')(att_layer)
        # Reshape to obtain the same shape as input
        att_layer = Permute((2, 1))(
            RepeatVector(feature_vector_size)(att_layer))
        layers = merge([att_layer, layers],  mode='mul')
        return layers

    def add_embedding_layer(self, layers):
        layers = super(AttBiLSTM, self).add_embedding_layer(layers)
        return self.add_attention_block(layers)
```

Calculamos un peso para cada **timestep**,

tomando el promedio de los pesos.

Philippe Remy

attention

LSTM

```
model.evaluate(X_test, y_test)
```

	precision	recall	f1-score	support
O	1.00	1.00	1.00	994779
geo	0.82	0.87	0.85	9071
gpe	0.96	0.89	0.92	3350
per	0.91	0.79	0.85	7014
org	0.84	0.68	0.75	7410
tim	0.91	0.85	0.88	5236
art	0.00	0.00	0.00	134
nat	0.00	0.00	0.00	55
eve	0.50	0.01	0.02	130
prev-prev-lemma	0.00	0.00	0.00	1
avg / total	0.99	0.99	0.99	1027180

Philippe Remy

attention

LSTM

Cuando aplicamos la capa densa, cada attention score se calcula usando en valor del **mismo feature** en **otros timesteps**.

Time-wise

$$a_t = softmax(xW_a)_t$$

La atención se basa solamente en la información de la instancia

Funciona con cualquier input

Feature-wise

$$a_t = softmax(x^T W_a)_t$$

La atención se basa en el promedio de la atención por feature

Necesitamos saber el tamaño de las secuencias de antemano

Si aplicamos una función de softmax a los attention scores, los transformamos en una distribución de probabilidad en (0, 1)

Suavizamos el valor de muchas neuronas

Without softmax - Model 1

```
model.evaluate(X_test, y_test)
```

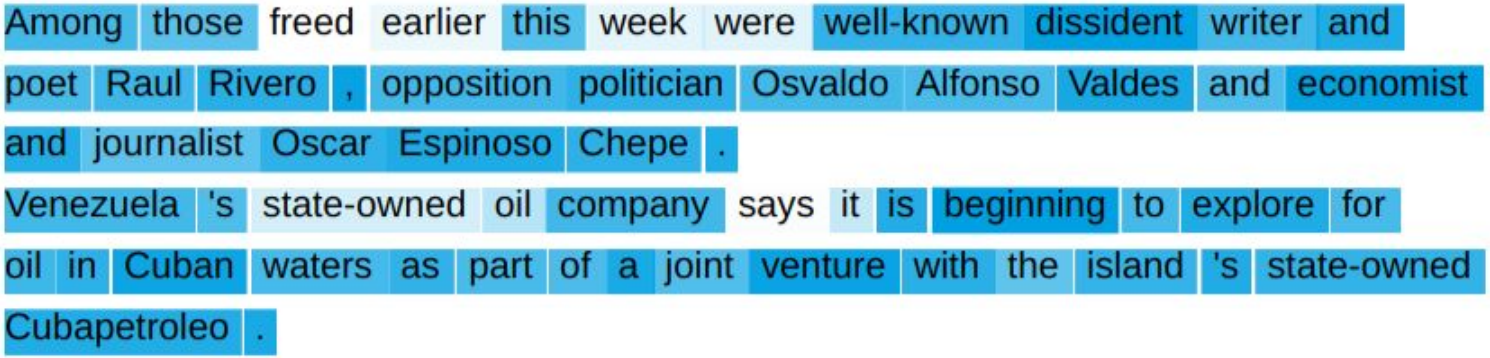
	precision	recall	f1-score	support
O	1.00	1.00	1.00	994779
geo	0.85	0.83	0.84	9071
gpe	0.96	0.91	0.93	3350
per	0.90	0.83	0.86	7014
org	0.73	0.75	0.74	7410
tim	0.90	0.86	0.88	5236
art	0.39	0.21	0.27	134
nat	0.47	0.47	0.47	55
eve	0.59	0.44	0.50	130
prev-prev-lemma	0.00	0.00	0.00	1
avg / total	0.99	0.99	0.99	1027180

Without softmax - Model 2

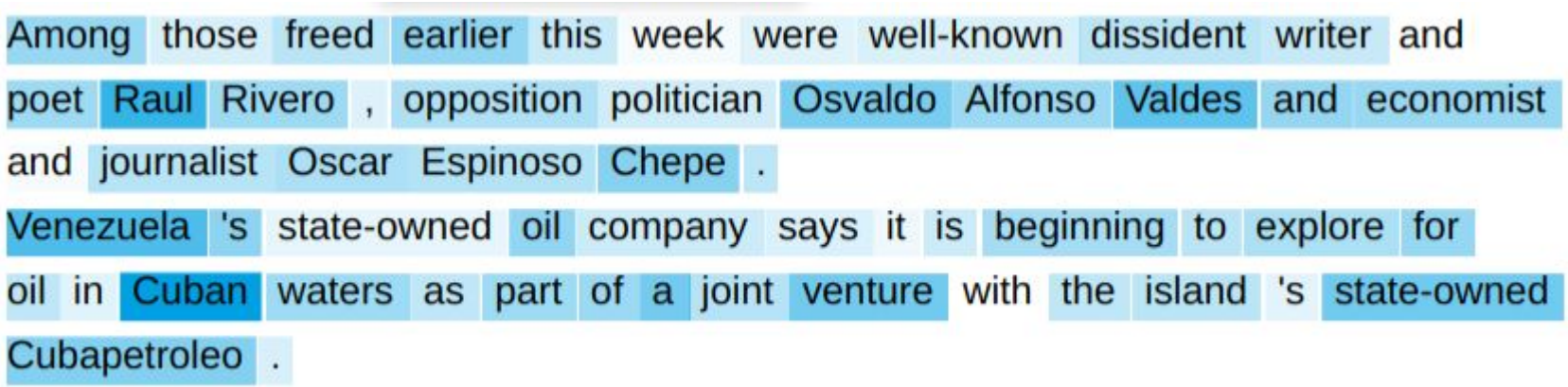
	precision	recall	f1-score	support
O	1.00	1.00	1.00	994779
geo	0.85	0.83	0.84	9071
gpe	0.96	0.91	0.93	3350
per	0.90	0.83	0.86	7014
org	0.73	0.75	0.74	7410
tim	0.90	0.86	0.88	5236
art	0.39	0.21	0.27	134
nat	0.47	0.47	0.47	55
eve	0.59	0.44	0.50	130
prev-prev-lemma	0.00	0.00	0.00	1
avg / total	0.99	0.99	0.99	1027180

Visualizing attention

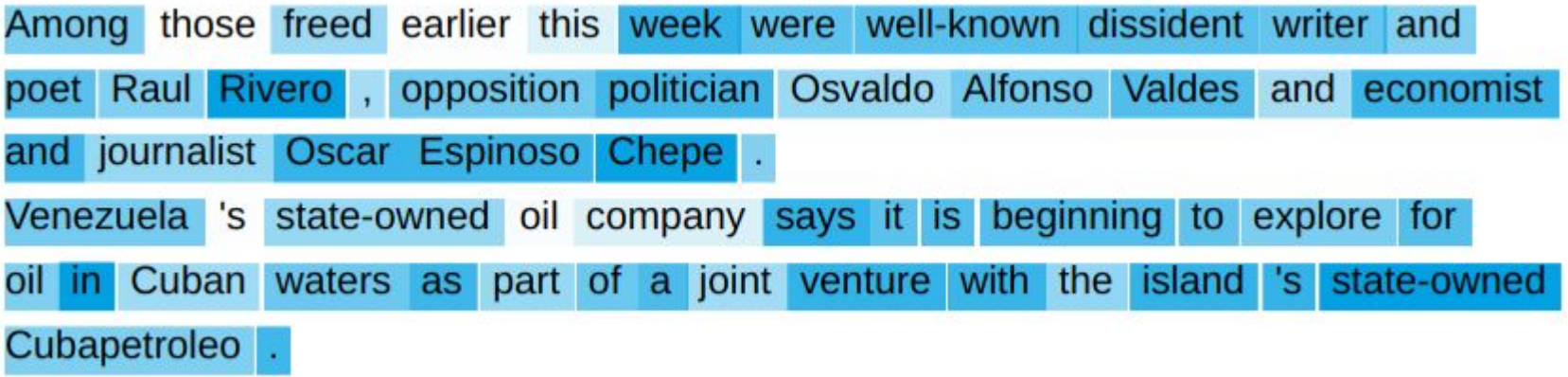
Attention 1 visualization: softmax



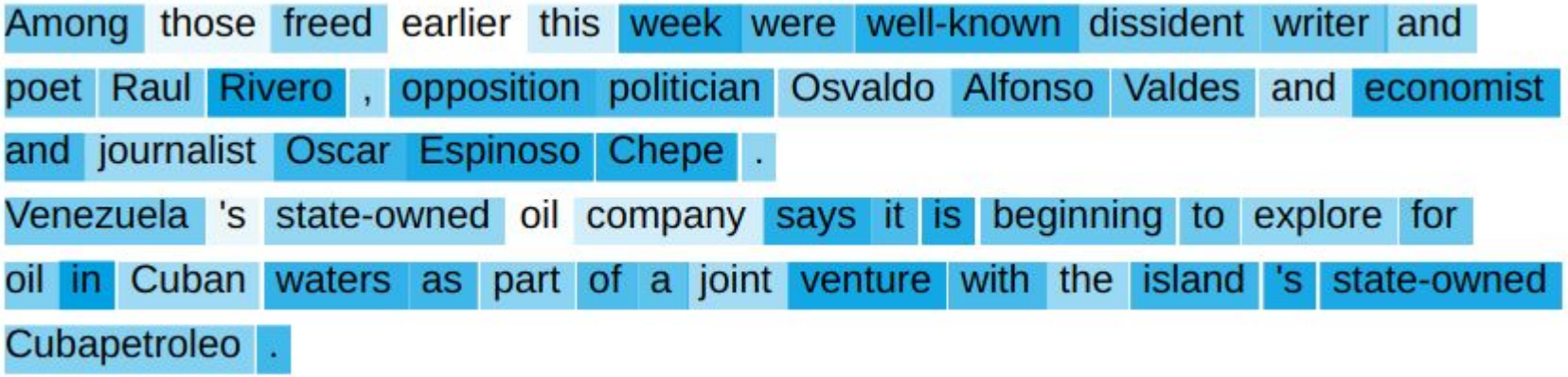
Attention 2 visualization: softmax



Attention 1 visualization: linear



Attention 2 visualization: linear



Take-home questions

¿Interpretabilidad o performance?

¿Time-wise o feature-wise?

¿Aplicamos softmax o no?

Preguntas

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github.com/
mit0110

linkedin.com/in/
milagro-teruel/

Referencias

[1] Reinforced Self-Attention Network: a Hybrid of Hard and Soft Attention for Sequence Modeling

[2] Attention and memory in deep learning and nlp. Wildml

[3] Show, Attend and Tell: Neural Image Caption Generation with Visual Attention