#### **Attention OCR**

 Wojna, Zbigniew, et al. "Attention-based extraction of structured information from street view imagery." 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR). Vol. 1. IEEE, 2017.



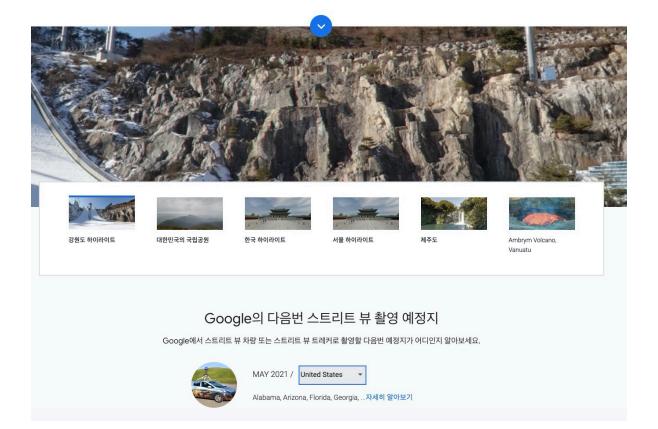
# **Google Street View**

https://www.google.com/streetview/

#### 스트리트 뷰란 무엇인가요?

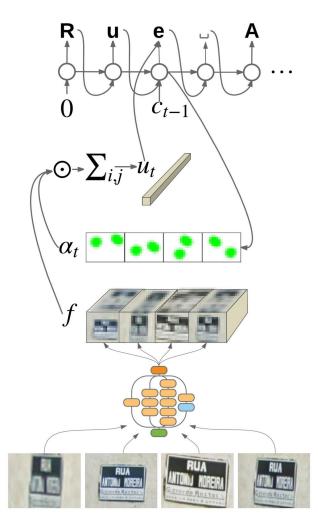


Google 지도의 스트리트 뷰는 우리 주위의 환경을 수백만 개의 파노라마 이미지를 사용하여 Google 지도에 가상으로 표현 한 것입니다. 스트리트 뷰 콘텐츠는 Google과 일반 참여자의 두 가지 출처를 통해 제공됩니다. 이와 같은 공동의 노력을 통 해 전 세계의 사용자들이 가상으로 세계를 탐험할 수 있도록 돕고 있습니다.



# **Methods**

• CNN + Attention + RNN

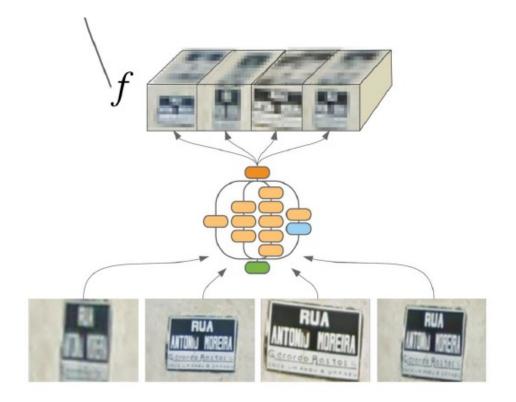


#### **CNN-based feature extraction**

- We consider 3 kinds of CNN: inception-v2 [9], inception-v3 [10] and inception-resnet-v2 [10], which combines inception with resnets [12].
- We will use  $f = \{f_{i,j,c}\}$  to denote the feature map derived by passing the image x through a CNN (here i, j index locations in the feature map, and c indexes channels).

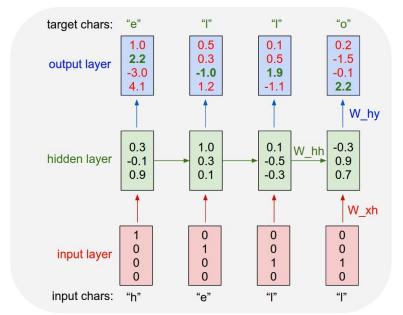
#### **CNN-based feature extraction**

· We pass each of the four views through the same CNN feature extractor, and then concatenate the results into a single large feature map, shown by the cube labeled "f".

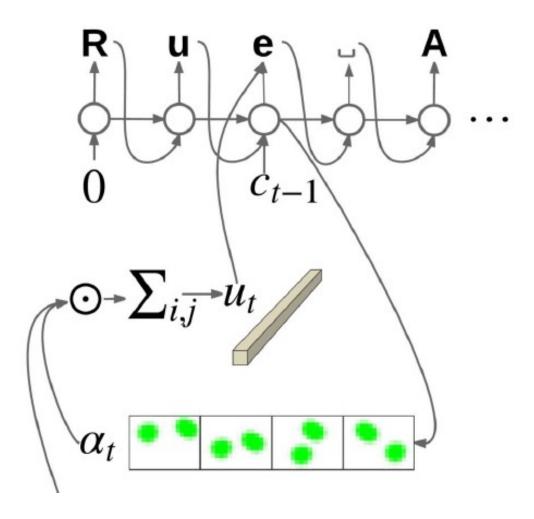


# RNNs을 이용한 Character-level Language Modeling (Char-RNN)

- Training :인풋 데이터(input data-x-)에서 글자(Character)를 하나 뒤로 민 타겟 데이터(target data-y-)로 RNNs을 학 습한다.
- Input Data : 전체 문장 중 일정 길이의 글자들의 배열 (e.g. hell(전체 문장 중 일정 길이의 글자들의 배열))
- Target Data : 전체 데이터중 Input Data를 한글자 뒤로 민 배열 (e.g. ello(전체 데이터중 Input Data를 한글자 뒤로 민 배열)



# **RNN & Spatial Attention**



#### RNN

- this acts as a character level language model, which takes inputs from the image, as we explain below.
- we compute a weighted combination of the features (the context) as follows:

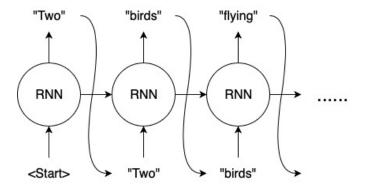
$$u_{t,c} = \sum_{i,j} \alpha_{t,i,j} f_{i,j,c}$$

The total input to the RNN at time t is defined as

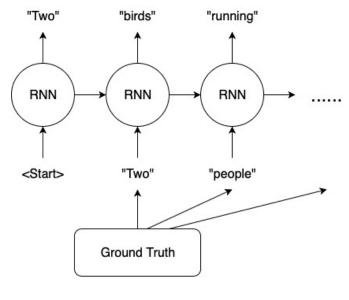
$$\hat{x}_t = W_c c_{t-1}^{OneHot} + W_{u_1} u_{t-1}$$

• where  $c_{t-1}$  is the index of the previous letter (ground truth during training, predicted during test time).

# **Teacher Forcing**



Without Teacher Forcing



With Teacher Forcing

#### RNN

We then compute the output and next state of the RNN as follows:

$$(o_t, s_t) = \text{RNNstep}(\hat{x}_t, s_{t-1})$$

The final predicted distribution over letters at time t is given by

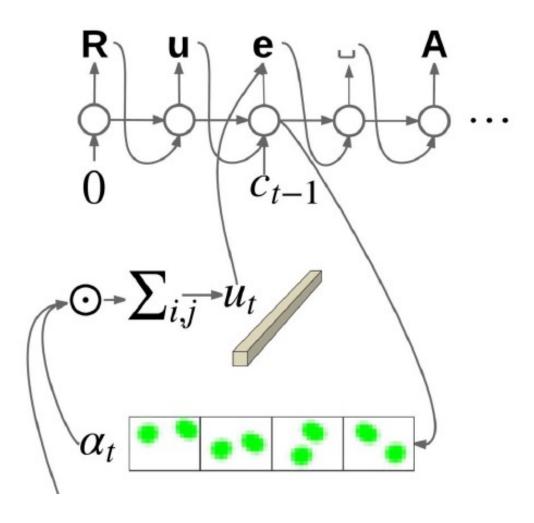
$$\hat{o}_t = \operatorname{softmax}(W_o o_t + W_{u_2} u_t)$$

This combines information from the RNN,  $o_t$ , with information from the attentional feature vector,  $u_t$ . Finally, we compute the most likely letter:

$$c_t = \arg\max_{c} \hat{o}_t(c)$$

This is called greedy decoding.

# **RNN & Spatial Attention**



## **Spatial Attention**

 Most prior works that use spatial attention for OCR (e.g., [1], [16]–[20]) predict the mask based on the current RNN state, as follows:

$$a_{t,i,j} = V_a^T \tanh(W_s s_t + W_f f_{i,j,:})$$

$$\alpha_t = \operatorname{softmax}_{i,j}(a_t)$$

• where V<sub>a</sub> is a vector and tanh is applied elementwise to its vector argument. This combines content from the image, via  $W_f$ f, with a time-varying offset, via  $W_s$ s<sub>t</sub>, to determine where to look.

## **Spatial Attention**

- To make the model "location aware", we concatenate  $f_{i,j}$ : with a one-hot encoding of the spatial coordinates (i, j), as shown in Figure 2.
- More precisely, we replace the argument to the tanh function with the following:

$$W_s s_t + W_{f_1} f_{i,j,:} + W_{f_2} e_i + W_{f_3} e_j$$

• where  $e_i$  is a one-hot encoding of coordinate  $f_{i,j}$ , and similarly for  $e_i$ . This is equivalent to adding a spatially varying matrix of bias terms.

# **Spatial Attention**

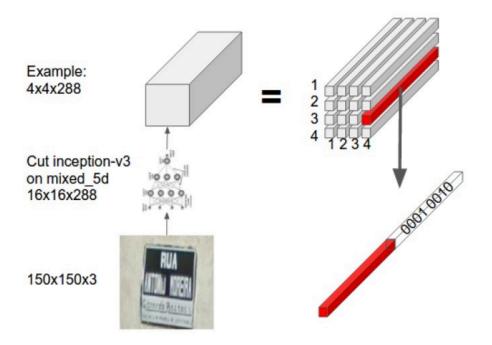


Fig. 2: Adding pixel coordinates to image features.

## **Handling Multiple View**

- In the FSNS dataset, we have four views for each input sign, each of size 150x150.
- We process each of these independently, through the same CNN-based feature extractor (parameters are shared), to compute four feature maps.
- We then concatenate these horizontally to create a single input feature map. For example, suppose the feature map for each of the four views is 16 x 16 x 320; then after concatenation, the feature map  $f_{i,i,c}$  will be 64 x 16 x 320.



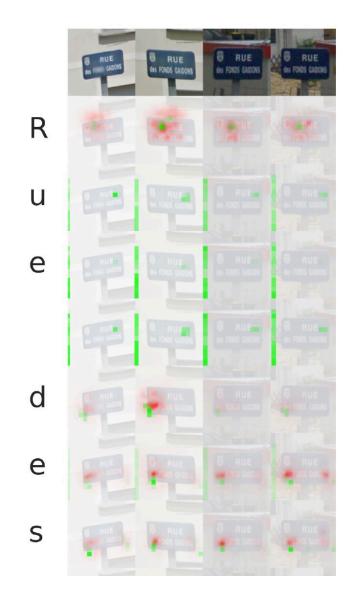
## **Handling Multiple View**

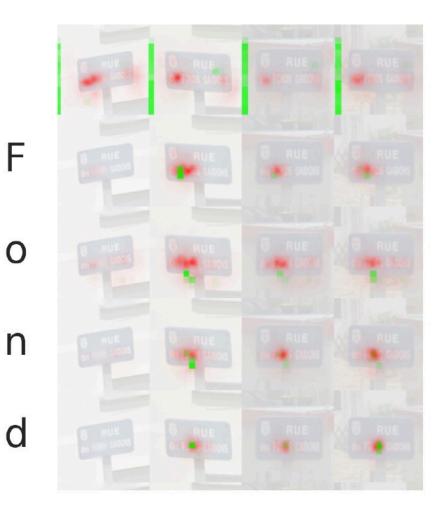
- The FSNS dataset [7] contains 965,917 training images, 38,633 validation images and 42,839 test images.
- Each image has up to 4 tiles, intended to be a different view of the same physical street sign from Street View imagery from France. The size of every tile is 150x150 pixels.
- All the transcriptions of the street name are up to 37 characters long. (Our model takes advantage of this fact and always runs 37 steps, with an optional out-of-alphabet padded symbol.)
- There are 134 possible characters to choose from at each location, but most of the street names consist only of Latin letters.

#### **Street View Business Names Dataset**

- This is an internal dataset which contains ~ 1M single view images of business storefronts extracted from Google Street View imagery. See Figure 5 for some examples.
- The size of every image is 352x352. All transcriptions contain up to 33 symbols, with 128 characters in the vocabulary.

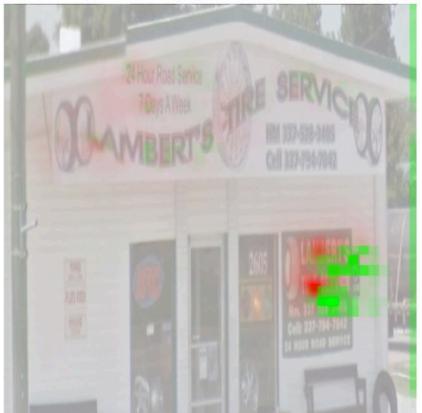
### Visualization of saliency maps (in red) and attention masks (in green) on an FSNS image.





Visualization of the time-averaged saliency maps (in red) and attention masks (in green).





## **Accuracy**

TABLE I: Accuracy on FSNS test set.

CNN _	Attention	Accuracy
Smith et al. [7]	NA	72.46%
Inception-v2	Standard	80.7%
Inception-v2	Location	81.8%
Inception-v3	Standard	83.1%
Inception-v3	Location	84.0%
Inception-resnet-v2	Standard	83.3%
Inception-resnet-v2	Location	84.2%

# **Error Analysis**

TABLE V: Breakdown of error types on FSNS.

Error type	Percent
Wrong ground truth	48
Wrong / Added / Missing accent over e	17
Wrong single letter inside the word	9
Wrong single letter at the	8
beginning / end of word	//Y
Added / Missing hyphen (-)	7
Wrong full word	6
Read from the wrong view	3
Wrong / Added / Missing accent	2
over different letter than e	

## **Error Analysis**





(a) Confused by font. Pred = 'Avenue Georges Frere', GT = 'Avenue General (b) Read text from the wrong view. Pred='Boulevard des Talus', Frere'. GT='Boulevard Charles'.

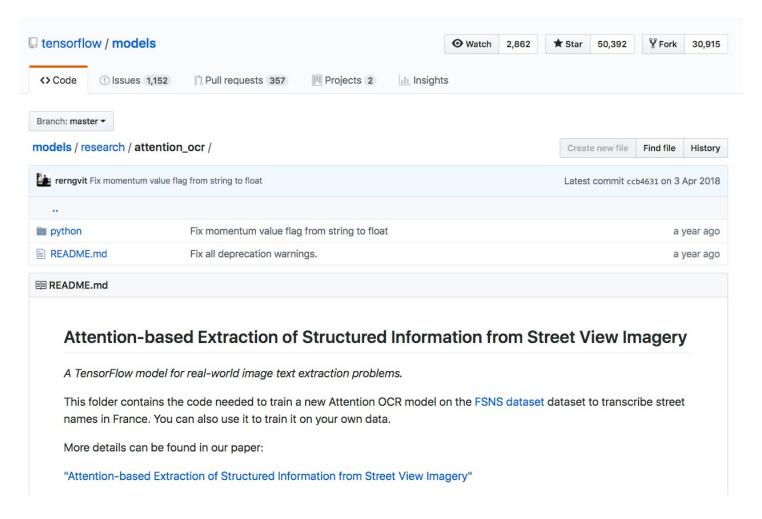




(c) Confusion due to scratched letter, which looks like 'J', but model uses (d) The model has better language prior than the human annotator. Pred='Avenue des Erables', Wrong GT='Avenue des Enadles'. its prior to produce 'O'. Pred='Impasse des Jorfèvres', GT='Impasse des Orfévres'.

## **Attention OCR Implementation**

https://github.com/tensorflow/models/tree/master/research/attention\_ocr



# Thank you!