

Deep Sentiment Analysis on Tumblr

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Declaration

The work in this thesis is based on research carried out at the Department of Statistics, University of Oxford. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

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Abstract

This thesis proposes a novel approach to sentiment analysis using deep neural networks on both images and text.

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Chapter 1

Introduction

Chapter 2

Tumblr data

2.1 Overview of the data

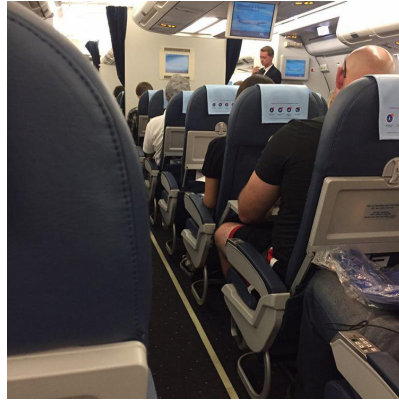
Tumblr's posts were extracted using the official API thanks to their tags that were taken as the ground truth. The tags represent the user's emotion: happy, sad, angry, surprised, scared or disgusted. The data extraction took several weeks due to the API's limitations: 1,000 requests per hour and 5,000 requests per day, with each request containing 20 posts. The final dataset has about one million posts and six different emotions.

Need to talk about preprocessing non-english posts

Here are examples of posts with their associated emotions:



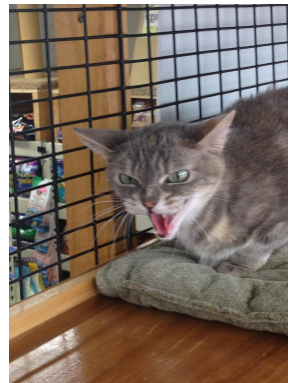
(a) **Happy:** “Just relax with this amazing view #bigsur #california #roadtrip #usa #life #fitness (at McWay Falls)”



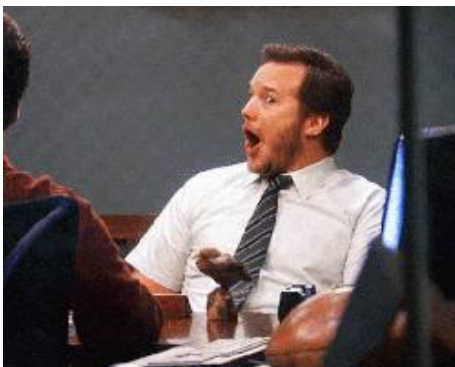
(b) **Scared:** “On a plane guys! We’re about to head out into the sky to Paris, France #Paris #trip #kinda #nervous #fun #vacations”



(c) **Sad:** “It’s okay to be upset. It’s okay to not always be happy. It’s okay to cry. Never hide your emotions in fear of upsetting others or of being a bother If you think no one will listen. Then I will.”



(d) **Angry:** “Tensions were high this Saturday...”



(e) **Surprised:** “Which Tea? Peppermint tea: What is your favorite gif right now?”



(f) **Disgusted:** “Me when I see a couple expressing their affection in physical ways in public”

Figure 2.1: Some examples of Tumblr posts [1]

Chapter 3

Visual recognition

The pictures accompanying the posts usually help a lot in determining the emotion of the user. For instance, happy photos might contain landscapes with the sun or a beach while sad ones might have really dark colors. To analyse the images, we'll use convolutional neural networks, which achieve state-of-the-art performances in many visual recognition tasks. First we'll explain how they work and then we'll dive into the architecture we've used for deep sentiment analysis.

3.1 Convolutional neural networks

A convolutional neural networks, often called ConvNets, can be seen as a simulation of the human visual cortex, that is to say an aggregation of plenty of receptive fields. (some illustrations might be helpful here)

3.1.1 Convolutional layer

Take an image of dimension $(h, w, 3)$ with h the height, w the width and 3 representing the number of channels (red, blue, green). If you simply flatten that image and transform it into a vector of size $h \times w \times 3$ and feed that vector to a neural network, you'll get not-so-good results as you've thrown away all the spatial information. Convolutions extract that spatial information and work the following way:

- Each convolution is described by a filter F of size $(f, f, 3)$, f usually being in the range $[1, 13]$.

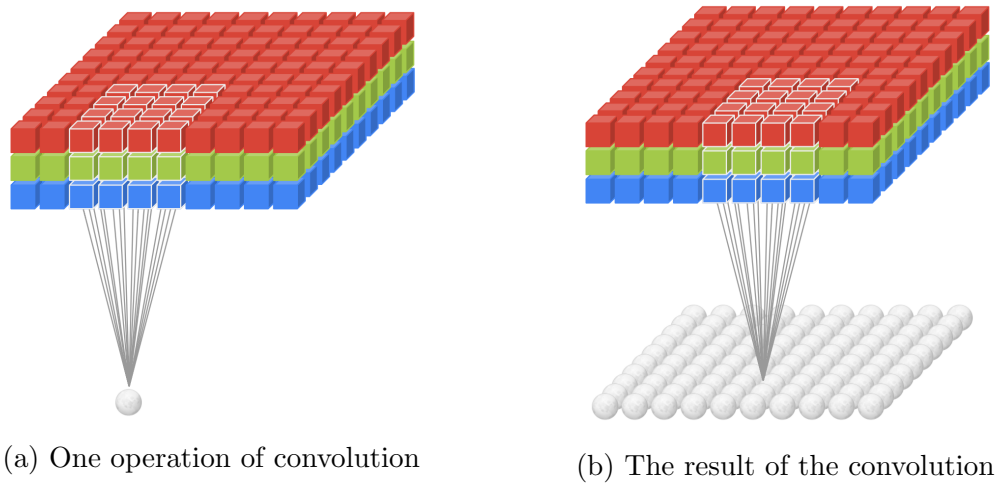


Figure 3.1: A convolution, each neuron been a ‘receptive field’ [2]

- Position the filter on the upper left of the image and element-wise multiply with the filter, then sum those numbers to obtain a raw number.
- Slide across the image, one pixel at a time horizontally and vertically, and repeat the previous operation.

By sliding through the image, you would get a new matrix of dimension $(h_{new}, w_{new}, 1)$, with $h_{new} = h - f + 1$ and $w_{new} = w - f + 1$. However, we usually don’t want to reduce the size of our input image that fast, as we usually have several convolutions. To ensure that the image has the same size, zero-padding is used: we add p zeros to the borders of the input image to preserve the spatial size of the input. With zero-padding, h_{new} becomes: $h_{new} = h + 2p - f + 1$, and we want that h_{new} equals h :

$$h + 2p - f + 1 = h$$

Therefore, $p = \frac{f-1}{2}$.

A convolution extract information about the image such as edges or blotches of some color (Figure 3.2). The grayscale and edges filters were hardcoded but in a ConvNet setting, the weights of the filter F are learned through optimising a loss function – in our case, a metric measuring how accurate our predictions of the emotions are. The network will learn weights that will detect features that will be most relevant to our specific task. Most of the time, more than a single convolution are used: just repeat that operation d (the depth) times, to create a new tensor

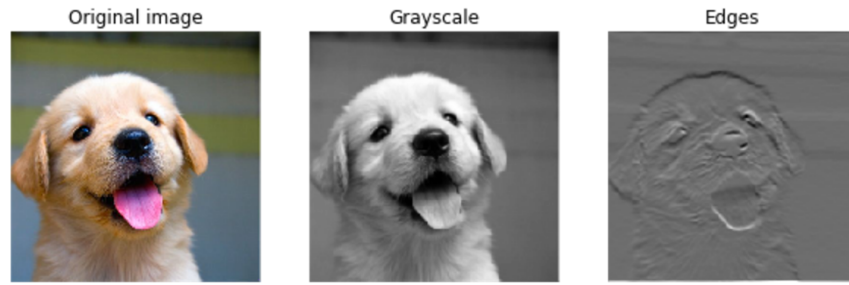


Figure 3.2: Examples of convolution

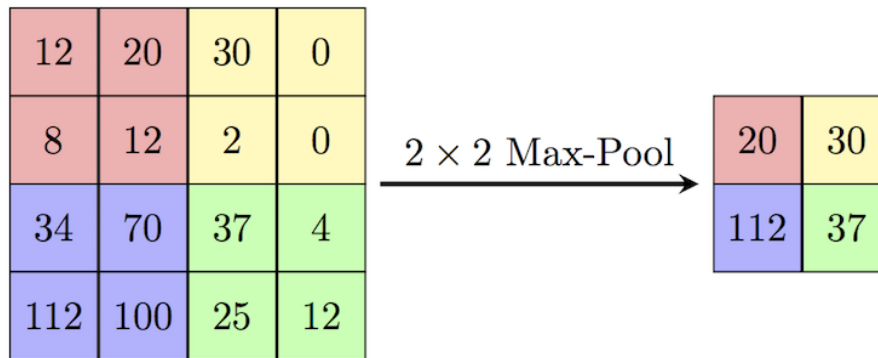


Figure 3.3: Max pooling [3]

of dimension (h, w, d) . We can then apply convolutions on that new image. First layers will recognise simple features such as edges or aggregation of colors, and deeper layers might activate on faces, wheels and so on.

3.1.2 Pooling layer

After a few iterations of convolutions, inserting pooling layers in-between convolutional layers might be a good idea to control the spatial complexity of the network. More concretely, what is most used in practice is the 2×2 max-pooling:

- Pick a channel among the d ones.
- Position yourself on the top-left 2×2 square of the image and take the max.
- Repeat by sliding through the image vertically and horizontally with a stride (step) of 2.

After applying max pooling to each channel, the resulting image's dimension is $(\frac{h}{2}, \frac{w}{2}, d)$ and we have discarded 75% of the neurons (as in each max-pool operation,

we only keep the maximum neuron among the fours), effectively reducing the number of parameters and controlling overfitting.

Chapter 4

Natural Language Processing

Text analysis

4.1 Section 1

Chapter 5

Recurrent Neural Networks for text generation

5.1 Section 1

Chapter 6

Useful maths in LaTeX

6.1 Equations related

$$\frac{\partial u_1}{\partial t} = \Delta w_1 \quad \text{in } \Omega, t > 0, \quad (6.1)$$

$$\frac{\partial u_2}{\partial t} = \Delta w_2 \quad \text{in } \Omega, t > 0, \quad (6.2)$$

where

$$w_1 = \frac{\delta F(u_1, u_2)}{\delta u_1}, \quad (6.3)$$

$$w_2 = \frac{\delta F(u_1, u_2)}{\delta u_2}, \quad (6.4)$$

$$\begin{aligned} F(u_1, u_2) = & b_1 u_1^4 - a_1 u_1^2 + c_1 |\nabla u_1|^2 \\ & + b_2 u_2^4 - a_2 u_2^2 + c_2 |\nabla u_2|^2 \\ & + D \left(u_1 + \sqrt{\frac{a_1}{2b_1}} \right)^2 \left(u_2 + \sqrt{\frac{a_2}{2b_2}} \right)^2. \end{aligned} \quad (6.5)$$

$$U_1^n = \sum_{i=1}^J U_{1,i}^n \eta_i, \quad W_1^n = \sum_{i=1}^J W_{1,i}^n \eta_i, \quad (6.6)$$

$$U_2^n = \sum_{i=1}^J U_{2,i}^n \eta_i, \quad W_2^n = \sum_{i=1}^J W_{2,i}^n \eta_i, \quad (6.7)$$

We also use the following notation, for $1 \leq q < \infty$,

$$L^q(0, T; W^{m,p}(\Omega)) := \left\{ \eta(x, t) : \eta(\cdot, t) \in W^{m,p}(\Omega), \int_0^T \|\eta(\cdot, t)\|_{m,p}^q dt < \infty \right\},$$

$$L^\infty(0, T; W^{m,p}(\Omega)) := \left\{ \eta(x, t) : \eta(\cdot, t) \in W^{m,p}(\Omega), \operatorname{ess\,sup}_{t \in (0, T)} \|\eta(\cdot, t)\|_{m,p} < \infty \right\},$$

Cases

$$|v|_{0,r} \leq C |v|_{0,p}^{1-\mu} \|v\|_{m,p}^\mu, \quad \text{holds for } r \in \begin{cases} [p, \infty] & \text{if } m - \frac{d}{p} > 0, \\ [p, \infty) & \text{if } m - \frac{d}{p} = 0, \\ [p, -\frac{d}{m-d/p}] & \text{if } m - \frac{d}{p} < 0. \end{cases} \quad (6.8)$$

6.2 Writing

Lemma 6.2.1 Let $u, v, \eta \in H^1(\Omega)$, $f = u - v$, $g = u^m v^{n-m}$, $m, n = 0, 1, 2$, and $n - m \geq 0$. Then for $d = 1, 2, 3$,

$$\left| \int_{\Omega} f g \eta dx \right| \leq C |u - v|_0 \|u\|_1^m \|v\|_1^{n-m} \|\eta\|_1. \quad (6.9)$$

Proof: Note that using the Cauchy-Schwarz inequality we have

$$|(u)^m v^{n-m}|_{0,p} \leq \begin{cases} |u|_{0,2mp}^m |v|_{0,2(n-m)p}^{(n-m)} & \text{for } n - m \neq 0, \text{ and } m \neq 0, \\ |u|_{0,mp}^m \text{ or } |v|_{0,(n-m)p}^{(n-m)} & \text{for } m = 0, \text{ or } n - m = 0 \text{ respectively.} \end{cases}$$

Noting the generalise Hölder inequality and the result above we have

$$\begin{aligned} \left| \int_{\Omega} f g \eta dx \right| &\leq |u - v|_0 |u^m v^{n-m}|_{0,3} \|\eta\|_{0,6}, \\ &\leq |u - v|_0 \|\eta\|_{0,6} \begin{cases} |u|_{0,6}^2 & \text{for } m = 2, \\ |u|_{0,6} |v|_{0,6} & \text{for } m = 1, \\ |v|_{0,6}^2 & \text{for } m = 0, \end{cases} \\ &\leq C |u - v|_0 \|u\|_1^m \|v\|_1^{n-m} \|\eta\|_1, \end{aligned}$$

where we have noted (6.8) to obtain the last inequality. This ends the proof. \square

We consider the problem:

(P) Find $\{u_i, w_i\}$ such that $u_i \in H^1(0, T; (H^1(\Omega))') \cap L^\infty(0, T; H^1(\Omega))$ for *a.e.*
 $t \in (0, T)$, $w_i \in L^2(0, T; H^1(\Omega))$

$$\left\langle \frac{\partial u_1}{\partial t}, \eta \right\rangle$$

Chapter 7

Conclusions

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Appendix A

Basic and Auxiliary Results

A.1 Basic Results