

## 1 The Premises

The starting point is to create a simple model of the generation of syntagms in social media. The general idea is the following.

We are "chasing" a specific syntagm  $[w_1 \dots w_n]$  that we have observed being present at the end of the period of observation using the method in [?]. We observe the communication during a period  $T = [1, \dots, n]$ : we assume that at  $t=1$  the syntagm has not been created, and at  $t=n$  has been. We are interested in determining its evolution, in particular, in determining the time  $t$  at which we can assume that the syntagm has been created. Our observations are a sequence of documents  $D_t$ ,  $t=1, \dots, n$ , one for each time step (this will be in general the union of various documents, for example, all the tweets written in a certain group on a given week; for the purpose of our discussion, we merge all the documents into one); the words contained in the documents will form our measurements, as we shall see later on.

Let us place ourselves at a time  $t$  at which the syntagm has not yet emerged. The creation of the syntagm is due to the occurrence of an external event (for example, the syntagm "fake news" was related to the beginning of the 2016 presidential campaign). The event is something that happens at a given point in time and does not necessarily repeat itself. On the other hand, the event creates a *situation*, that is potentially self-supporting in time that is, it may be present after the end of the event. Let us consider two stochastic processes,  $e_t$  and  $s_t$ . The first is the variable that models the occurrence of the event at time  $t$ , the second is the variable that models the existence of a situation conducive to the creation of the syntagm at time  $t$ . Both take values in  $\{0,1\}$  (1 means that the event occurred or the situation is present, 0 means the opposite). The existence of the situation at time  $t$  depends on the existence at time  $t-1$  or the occurrence of the event at time  $t$ . The diagram representing the dependence of the random variables at time  $t$  is the following:



The existence of the situation determines the probability of observing the meaningful syntagm. Let  $w_t$  be the event of the syntagm being formed (again,  $w_t=1$  if the syntagm is present,  $w_t=0$  if not). The presence of the syntagm depends directly only on the existence of the *situation* at time  $t$ . We have therefore the following scheme:



(The square indicates the element that we observe). Here, to use the notation of [?], it is

$$w = [w_1, \dots, w_n] \tag{3}$$

that is  $w$  is the syntagm that we are chasing, composed of  $n$  words.

Note that we are fixating on a single syntagm, which we assume to have identified at the end of the temporal sequence, and we are interested in seeing where it was generated estimating  $e_t$  in such a way to explain the observations. At time  $t$ , we make an observation  $\pi_t$  (we shall see later how this is actually determined). We actually needs two measures, one that determines the information in favor of the hypothesis that at time  $t$  the syntagm was not expressed (call it  $\pi_t^0$ ) and the other expressing the information in favor of the hypothesis that the syntagm was expressed. The direct dependence of  $w$  (we shall omit the index  $t$  when no confusion arises) is on  $s$ , so we can write

$$P(w = i) = \sum_j P(w = i | s = j) P(s = j) \quad (4)$$

or, developing further

$$P(w_t = i) = \sum_j \sum_k \sum_h P[w_t = i | s_t = j] P[s_t = j | s_{t-1} = k, e_t = h] P[s_{t-1} = k] P[e_t = h] \quad (5)$$

The observed variable  $w$  (the syntagm) depends on the latent variables

$$\zeta_t = (s_t, s_{t-1}, e_t) \quad (6)$$

which are the ones whose probability distribution, at each time  $t$ , we have to determine. The problem is solved by minimizing the functional

$$\begin{aligned} \mathcal{L}(\theta) &= \sum_i \pi_t^i \log P(w_t = i | \theta) \\ &= \sum_i \pi_t^i \sum_{j,k,h} P[w_t = i | s_t = j] P[s_t = j | s_{t-1} = k, e_t = h] P[s_{t-1} = k] P[e_t = h] \end{aligned} \quad (7)$$

Here

$$\theta = (P[w_t = i | s_t = j], P[s_t = j | s_{t-1} = k, e_t = h], P[s_{t-1} = k], P[e_t = h]) \quad (8)$$

are the parameters over which we must optimize. Since we have to manipulate these parameters, it is convenient to use a simpler notation. Define

$$\begin{aligned} \alpha_j^i(t) &= P[w_t = i | s_t = j] \\ \beta_{kh}^j(t) &= P[s_t = j | s_{t-1} = k, e_t = h] \\ \nu^k(t) &= P[s_{t-1} = k] \\ \gamma^k(t) &= P[e_t = h] \end{aligned} \quad (9)$$

Note that we put in superscript the value of the conditioned variable and in subscript that of the conditioning variable(s).

## 2 The method

We use the general method of the EM (Expectation Maximization) algorithm [?]. I will skip over it a bit; if necessary I will put more details in a following draft. The function  $\mathcal{L}$  is bounded from below by

$$g(\theta, \theta') = \sum_i \pi^i \mathbb{E}_{\zeta | w=i, \theta'} [\log P(w = i, \zeta = (j, k, h) | \theta)] + \sum_i \pi^i H[P(\zeta | \theta')] \quad (10)$$

Here, during the iteration,  $\theta'$  is the set of parameters determined at the previous step, and  $\theta$  the set we solve for. the second term is independent of  $\theta$ , so we can optimize

$$\begin{aligned}
Q &= \sum_i \pi^i \mathbb{E}_{\zeta|w=i, \theta'} [\log P(w=i, \zeta=(j, k, h)|\theta)] \\
&= \sum_i \pi^i \sum_{j, k, h} P(\zeta=(j, k, h)|w=i, \theta') \log P(w=i, \zeta=(j, k, h)|\theta) \\
&= \sum_i \pi^i \sum_{j, k, h} P(\zeta=(j, k, h)|w=i, \theta') \log P[w_t=i|s_t=j] P[s_t=j|s_{t-1}=k, e_t=h] P[s_{t-1}=k] P[e_t=h] \\
&= \sum_{i, j, k, h} \pi^i \tau_i^{jkh} \log \alpha_j^i \beta_{kh}^j \nu^k \gamma^h
\end{aligned} \tag{11}$$

where we have set

$$\tau_i^{jkh} = P(s_t=j, s_{t-1}=k, e_t=h|w=i) \tag{12}$$

In the **E** step, we determine  $Q$ , that is, in practice, we determine  $\tau_i^{jkh}$ , which is given by

$$\tau_i^{jkh} = \frac{\alpha_j^i \beta_{kh}^j \nu^k \gamma^h}{\sum_{jkh} \alpha_j^i \beta_{kh}^j \nu^k \gamma^h} \tag{13}$$

For the **M** step we maximize  $Q$  subject to the constraints

$$\sum_i \alpha_j^i = 1 \quad \sum_j \beta_{kh}^j = 1 \quad \sum_h \gamma^h = 1 \tag{14}$$

We apply the Lagrange multipliers and minimize

$$\mathcal{F} = \sum_{i, j, k, h} \pi^i \tau_i^{jkh} \log \alpha_j^i \beta_{kh}^j \nu^k \gamma^h - \sum_j \lambda_j \left( \sum_i \alpha_j^i - 1 \right) - \sum_{k, h} \mu_{kh} \left( \sum_j \beta_{kh}^j - 1 \right) - \epsilon \left( \sum_h \gamma^h - 1 \right) \tag{15}$$

We determine the parameters by setting to zero the derivatives of  $\mathcal{F}$

$$\begin{aligned}
\frac{\partial \mathcal{F}}{\partial \alpha_j^i} &= \sum_{hk} \tau_i^{jkh} \pi^i \frac{1}{\alpha_j^i} - \lambda_j = 0 & \alpha_j^i &= \frac{\pi^i}{\lambda_j} \sum_{k, h} \tau_i^{jkh} \\
\frac{\partial \mathcal{F}}{\partial \beta_{kh}^j} &= \sum_i \tau_i^{jkh} \pi^i \frac{1}{\beta_{kh}^j} - \mu_{kh} = 0 & \beta_{kh}^j &= \frac{1}{\mu_{kh}} \sum_i \tau_i^{jkh} \pi^i \\
\frac{\partial \mathcal{F}}{\partial \gamma^h} &= \sum_{ijk} \tau_i^{jkh} \pi^i \frac{1}{\gamma^h} - \epsilon = 0 & \gamma^h &= \frac{1}{\epsilon} \sum_{ijk} \tau_i^{jkh} \pi^i
\end{aligned}$$

The Lagrange multipliers are determined by normalization

$$\begin{aligned}
\alpha_j^i &= \frac{\pi^i \sum_{kh} \tau_i^{jkh}}{\sum_i \pi^i \sum_{kh} \tau_i^{jkh}} \\
\beta_{kh}^j &= \frac{\sum_i \pi^i \tau_i^{jkh}}{\sum_{i,j} \pi^i \tau_i^{jkh}} \\
\gamma^h &= \frac{\sum_{ijk} \pi^i \tau_i^{jkh}}{\sum_{i,j,k,h} \pi^i \tau_i^{jkh}}
\end{aligned} \tag{16}$$

With the new vales of the parameters we calculate  $\tau_i^{jkh}$  using (13), then new values of the parameters, etc. until convergence. This gives, among other things, the value  $\gamma^1 = P(e_t = 1)$ , which gives us the probability that the event that caused the syntagm to be created happened at time  $t$ .

The calculation depends on the value  $\nu^k$ , which is equal to  $P(s_{t-1} = h)$ . In order to run the approximation over a span of time, it is necessary to compute  $P(s_t = h)$ . From

$$P(s_t = j) = \sum_{k,h} P[s_t = j | s_{t-1} = k, e_t = h] P[s_{t-1} = k] P[e_t = h] \tag{17}$$

we derive

$$\nu^j(t) = \sum_{k,h} \beta_{kh}^j \nu^k(t-1) \gamma^h \tag{18}$$

### 3 The algorithm

We consider a time span  $\Delta = [1, \dots, T]$  over which we want to determine the emergence of the syntagm. At each time  $t$  we have a set of document, which we use to determine the measurements  $\pi^i(t)$  ( $i \in \{0, 1\}$ ) that determine the information supporting the hypothesis that the syntagm is not present ( $\pi^0(t)$ ) and that is present ( $\pi^1(t)$ ). We shall consider how to determine  $\pi^i(t)$  in the next section. For the moment, let us consider that a sequence  $[\pi^i(1), \dots, \pi^i(t)]$  is available.

We run the estimation time-wise, from  $t = 1$  to  $t = T$ , using at each time the values  $\nu^j(t)$  in order to run the computation at  $t + 1$ . In order to do this, we must initialize  $\nu^h(0)$ . We can assume that the situation is not present at time 0 and set  $\nu^0(0) = 1$ ,  $\nu^1(0) = 0$ , or use a small probability  $p$  for the existence of the situation. The algorithm is in Figure 1:

Convergence is determined by the stabilization of the parameters, any number of criteria that measure the change in the parameters between iterations can be used. The list  $\Psi$  contains, for each time  $t$ , the probability that the event that caused the syntagm to be generated happened at time  $t$ .

## 4 The measure

The final piece of the puzzle that has to be put into place is the measurement  $\pi^i(t)$ . We have defined it informally as the information that supports the hypothesis that the syntagm has been created (resp., has not been created). This is quite a fuzzy definition, and probably can be satisfied in many different ways. This is one possibility.

We are "chasing" a syntagm  $[w_1 \cdots w_n]$  and, as evidence, we have, at each time  $t$ , a document  $D_t$ . The data that we extract are essentially:

- i) the number of observations of the individual words  $n(w_1), \dots, n(w_n)$ ;
- ii) the number of observations of the whole sequence of words that composes the syntagm  $n(w_1, \dots, w_n)$ ;
- iii) the "quality" of the syntagm,  $q([w_1 \cdots w_n])$ , determined as in [?].

The general idea is that if we see many occurrences of the whole syntagm ( $n(w_1, \dots, w_n)$  high) and the syntagm is significant ( $q([w_1 \cdots w_n])$  high), then there is evidence of its presence ( $\pi^1(t)$  high,  $\pi^0(t)$  low). Vice versa, if the words are observed individually but not as a whole ( $n(w_1), \dots, n(w_n)$  high,  $n(w_1, \dots, w_n)$  low) or the whole is not a viable syntagm ( $q([w_1 \cdots w_n])$  low), then the evidence supports the absence of the syntagm ( $\pi^0(t)$  high,  $\pi^1(t)$  low).

So, OK, without further ado, one possibility is

$$\pi^1 = \begin{cases} q([w_1 \cdots w_n]) \frac{n(w_1, \dots, w_n)}{\max(n(w_1), \dots, n(w_n))} & \text{if } \max(n(w_1), \dots, n(w_n)) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

$$\pi^0 = 1 - \pi^1$$

Note that if  $\max(n(w_1), \dots, n(w_n)) = 0$  (no words of the syntagm are observed), we consider that there is sure evidence of the absence of the syntagm. This might not be the best choice: one can consider this case neutral ( $\pi^1 = 1/2$ ) or even discard the information at that time. There things should be tried out.

Quite honestly, this is the part I feel less sure about. The general idea of the information  $\pi^i(t)$  is quite clear, as are the general characteristics that these coefficients should have vis-à-vis the observations, but the specific form that these function should have is still something to be worked out.

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1.   $\Psi \leftarrow []$ 
2.  for  $t \leftarrow 1$  to  $T$  do
3.    initialize  $\alpha_j^i, \beta_{kh}^j, \gamma^h, \tau_i^{jkh}$ 
4.    while not convergence do
5.       $\tau_i^{jkh} \leftarrow \frac{\alpha_j^i \beta_{kh}^j \nu^k(t-1) \gamma^h}{\sum_{jkh} \alpha_j^i \beta_{kh}^j \nu^k(t-1) \gamma^h} \quad (i, j, k, h \in \{0, 1\})$ 
6.       $\alpha_j^i \leftarrow \frac{kh}{\sum_i \pi^i(t) \sum_{kh} \tau_i^{jkh}} \quad (i, j \in \{0, 1\})$ 
7.       $\beta_{kh}^j \leftarrow \frac{i}{\sum_{i,j} \pi^i(t) \tau_i^{jkh}} \quad (j, k, h \in \{0, 1\})$ 
8.       $\gamma^h \leftarrow \frac{ijk}{\sum_{i,j,k,h} \pi^i(t) \tau_i^{jkh}} \quad (h \in \{0, 1\})$ 
9.    od
10.    $\nu^j(t) = \sum_{k,h} \beta_{kh}^j \nu^k(t-1) \gamma^h \quad (j \in \{0, 1\})$ 
11.    $\Psi \leftarrow \Psi + [\gamma^1]$ 
12. od

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Figure 1: The algorithm for the determination of the probability of having the syntagm-creating event.

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