

What if there is noise?

### Abstract Topic Model

① Unknown topic matrix  $A$ , distribution  $M$  on simplex in  $\mathbb{R}^r$

② For each document  $i$

a) Sample  $W_i$  from  $M$

b) Generate  $L$  words i.i.d. from  $AW_i$

Can we recover  $A$ ? Notice that

$$\mathbb{E}[\tilde{M}|W] = M = AW$$

↑  
empirical term-by-document

but  $\tilde{M}$  and  $M$  are far apart. Why? sparsity

This is a rich model, containing

supp on corners    dirichlet    lognormal    hierarchical

pure, LDA, CTM, Pachinko

as special cases

Thm [Anora, Ge, Mitra] there is a polynomial time algorithm for learning  $A$  when it is separable, under nondegeneracy conditions

It's not obvious how to use NMF

def: The Gram matrix  $G$  is

$$G_{j,j'} \triangleq P \left[ \begin{array}{l} \text{in random document,} \\ \begin{array}{l} \text{1st word = } j \\ \text{2nd word = } j' \end{array} \end{array} \right]$$

def: The topic co-occurrence  $R$  is

$$R_{i,i'} \triangleq P \left[ \begin{array}{l} \text{in random document,} \\ \begin{array}{l} \text{1st word was sampled from topic } i \\ \text{2nd word " " topic } i' \end{array} \end{array} \right]$$

By law of total expectation

$$G_{j,j'} = \sum_{i,i'} R_{i,i'} A_{ji} A_{j'i'} \quad \text{what conditional independence is implicit here?}$$

$$\Rightarrow G = A R A^T$$

Can we apply separable NMF to  $G$ ?

Yes, but much better probabilistic approach  
that uses non-anchors too!

Let  $w_i = 1^{st}$  word of random document,  $t_i$ , the topic it came from

Fact:  $j$  is an anchor word iff

$$P[t_i | w_i=j] \text{ is a point mass}$$

Furthermore we can expand

$$P[w_1=j | w_2=j'] =$$

$$\sum_{i'} P[w_1=j | w_2=j', t_2=i'] P[t_2=i' | w_2=j]$$

By conditional independence

$$(*) = \sum_{i'} P[w_1=j | t_2=i'] P[t_2=i' | w_2=j']$$

Claim:  $P[w_1=j | t_2=i'] = P[w_1=j | w_2=\pi(i')]$

This implies

$$(*) = \sum_{i'} P[w_1=j | w_2=\pi(i')] P[t_2=i' | w_2=j'] \quad \underbrace{\qquad}_{\text{unknowns}}$$

This linear system has unique soln if R is full rank

Note: It uses all words, not just anchor words

Finally, by Bayes rule

$$(2) P[w_2=j' | t_2=i'] = \frac{P[t_2=i' | w_2=j'] P[w_2=j']}{P[t_2=i']}$$

and moreover

$$IP[t_2=i'] = \sum_j IP[t_2=i' | w_2=j] IP[w_2=j]$$

Thus our algorithm is

Anchor-Bayes

Compute Gram matrix G

Compute the anchorwords (via separable NMF)

Solve (1) for  $IP[t_2=i' | w_2=j']$

Solve (2) to compute  $IP[w_2=j' | t_2=i']$

$$= A_{j'i'}$$

Proof of Claim let's expand

$$IP[w_1=j | w_2=\Pi(i')] =$$

$$\sum_{i''} IP[w_1=j | w_2=\Pi(i'), t_2=i'']$$

$$IP[t_2=i'' | w_2=\Pi(i'')]$$

does this use  
uniqueness of  
anchor words?  
no

$$= \begin{cases} 1 & \text{if } i'' = j \\ 0 & \text{else} \end{cases}$$

$$= P[w_1=j \mid w_2=\pi(i'), t_2=i']$$

by conditional independence

$$= P[w_1=j \mid t_2=i'] \quad \text{B}$$

Are natural topic models separable?

UCI Dataset  $\rightsquigarrow$  MALLET  $\rightsquigarrow \hat{A}$   
300k NYT articles

Findings: with  $r=200$ , about 0.9 fraction  
of topics had a near anchor word  
(posterior  $\geq 0.9$ )

How do algorithms based on separability  
perform?

$\hat{A} \rightsquigarrow$  synthetic documents  $\rightsquigarrow$  MALLET  
 $\rightsquigarrow$  Anchor Bayes

Findings: More accurate, and a hundred  
times faster

What do we find on real data?

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