Learning mixtures of spherical Gaussians: moment methods and spectral decompositions

Daniel Hsu and Sham Kakade

Arthur Gretton's notes

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A very basic topic model with k topics. Probability of a topic

$$P(h=j)=w_j, \quad j\in[k],$$

where  $[k] := \{1, \ldots, k\}, h$  is document topic.

A very basic topic model with k topics. Probability of a topic

$$P(h=j)=w_j, \quad j\in [k],$$

where  $[k] := \{1, ..., k\}$ , h is document topic. Documents have length  $\ell$ ,  $t \in [\ell]$ . If word t is the *i*th word, then

$$x_t = e_i$$

where  $e_i$  is the unit vector in dimension *i*. Vocabulary is of size *d*.

Probability vector for topic j is  $\mu_j \in \Delta^{d-1}$ .

Expected *conditional* probability of t th word in a document, given *topic j*:

$$E(x_t|h=j) = \sum_{i=1}^d [\mu_i]_i e_i = \mu_j,$$
$$M := \begin{bmatrix} \mu_1 & \dots & \mu_k \end{bmatrix}.$$

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Moments:

$$M_{2} = E[x_{1} \otimes x_{2}] = \sum_{i=1}^{k} w_{i}\mu_{i} \otimes \mu_{i} = M \operatorname{diag}(w)M^{\top}$$
$$M_{3} = E[x_{1} \otimes x_{2} \otimes x_{3}] = \sum_{i=1}^{k} w_{i}\mu_{i} \otimes \mu_{i} \otimes \mu_{i}$$

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Question: can we learn  $w_i$ ,  $\mu_i$  from empirical moments?

Do we need  $M_3$ ? Recall:

$$M_2 = M \operatorname{diag}(w) M^{\top} = \tilde{M} \operatorname{diag}(\tilde{w}) \tilde{M}^{\top}$$

for some new  $\tilde{M}$ ,  $\tilde{w}$ . Define

$$\tilde{M} = MQ^{-1}$$
  $\tilde{w} = Qw.$ 

What properties must  $Q \in \Re^{k \times k}$  satisfy?

Q should "look like" a matrix of conditional probabilities; i.e., each column should sum to 1:

 $1^{\top}Q = 1^{\top}.$ 

2  $MQ^{-1}$  and Qw should have non-negative entries. So should  $M_2$ ,

$$ilde{\mathcal{M}} ext{diag}( ilde{w}) ilde{\mathcal{M}}^{ op} = \mathcal{M} Q^{-1} ext{diag}(\mathcal{Q}w)\left(Q^{-1}
ight)^{ op} \mathcal{M}^{ op} =: \mathcal{M}_2$$

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So For the proof to work:  $Q \operatorname{diag}(w) Q^{\top}$  should have diagonal entries.

Proof:

$$M$$
diag $(w)M^{\top} = \tilde{M}$ diag $(\tilde{w})\tilde{M}^{\top}$ .

Substituting definitions for  $\tilde{M}$  and  $\tilde{w}$ , we get

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Need to show

$$Q^{-1} \operatorname{diag}(Qw) \left(Q^{-1}\right)^{\top} = \operatorname{diag}(w)$$

under assumptions.

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# Just a moment?

$$egin{aligned} & [ ext{diag}(\mathcal{Q} oldsymbol{w})]_{ii} = \sum_\ell \mathcal{Q}_{i\ell} oldsymbol{w}_\ell \ & = \sum_\ell \underbrace{\left(\sum_{j=1}^k \mathcal{Q}_{j\ell}
ight)}_{=1} \mathcal{Q}_{i\ell} oldsymbol{w}_\ell \end{aligned}$$

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ight)}_{=1} \mathcal{Q}_{i\ell} oldsymbol{w}_\ell \ &= \sum_j \sum_\ell \mathcal{Q}_{j\ell} oldsymbol{w}_\ell \mathcal{Q}_{i\ell} \end{aligned}$$

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# Just a moment?

$$\begin{split} \left[ \operatorname{diag}(\mathcal{Q} w) \right]_{ii} &= \sum_{\ell} \mathcal{Q}_{i\ell} w_{\ell} \\ &= \sum_{\ell} \sum_{\ell} \underbrace{\left( \sum_{j=1}^{k} \mathcal{Q}_{j\ell} \right)}_{=1} \mathcal{Q}_{i\ell} w_{\ell} \\ &= \sum_{j} \sum_{\ell} \mathcal{Q}_{j\ell} w_{\ell} \mathcal{Q}_{i\ell} \\ &= \left( 1^{\top} \mathcal{Q} \operatorname{diag}(w) \mathcal{Q}^{\top} \right)_{i} \\ &= \left( \mathcal{Q} \operatorname{diag}(w) \mathcal{Q}^{\top} \right)_{ii}, \end{split}$$

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