Graphic Lasso: Possible Accuracy for Multi-Layer Model

Jiaxin Hu

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1 Discussion about Identifiability

Suppose we have a dataset with p variables and K categories. In multi-layer model, we assume the rank of decomposition r is known, and the precision matrices are of form

$$\Omega^k = \Theta_0 + \sum_{l=1}^{r} u_{lk}\Theta_l, \quad \text{for} \quad k = 1, ..., K. \tag{1}$$

The identifiability problem for $\{\Theta_0, \Theta_1, ..., \Theta_r, \mathbf{u}_1, ..., \mathbf{u}_r\}$ is actually an identifiability problem for tensor decomposition.

Let $\mathcal{Y} \in \mathbb{R}^{p\times p\times K}$ denote the collection of K networks, where $\mathcal{Y}[,,k] = \Omega^k, k \in [K]$. Let $\mathcal{C} \in \mathbb{R}^{p\times p\times (r+1)}$ denote the collection of "core" networks, where $\mathcal{C}[,,1] = \sqrt{K}\Theta_0$, $\mathcal{C}[,,l] = \Theta_{l-1}, l = 2, ..., (r+1)$. Let $\boldsymbol{U} \in \mathbb{R}^{K\times(r+1)} = (\mathbf{u}_0, \mathbf{u}_1, ..., \mathbf{u}_r)$ denote the factor matrix, where $\mathbf{u}_0 = \mathbf{1}_K/\sqrt{K}$. Rewrite the model (1) in tensor form.

$$\mathcal{Y} = \mathcal{C} \times_3 \boldsymbol{U}. \tag{2}$$

Therefore, the identifiability problem for $\{\Theta_l, \mathbf{u}_l\}$ becomes the identifiability problem for $\{\mathcal{C}, \boldsymbol{U}\}$. Before we discuss the identifiable condition case by case, we first assume $\mathcal{C}$ is full rank on mode 3.

1. **No sparsity constrain on $\boldsymbol{U}$.**

   Proposition 1. *The decomposition $\mathcal{C}$ and $\boldsymbol{U}$ are identifiable if $\boldsymbol{U}$ is an orthonormal matrix, i.e., $\boldsymbol{U}^T\boldsymbol{U} = \boldsymbol{I}_{r+1}$.*

   Proof. Let Unfold$(\cdot)$ denote the unfold representation of a tensor on mode 3. The model (2) is equal to

   $$\text{Unfold}(\mathcal{Y}) = \boldsymbol{U}\text{Unfold}(\mathcal{C}).$$

   By matrix SVD, we have Unfold$(\mathcal{Y}) = \tilde{\boldsymbol{U}}\Sigma\boldsymbol{V}^T$, where $\tilde{\boldsymbol{U}}$ is an orthonormal matrix. The SVD decomposition is unique up to orthogonal rotation (ignore row permutation).

   Note that $\mathbf{u}_0 = \mathbf{1}_K/\sqrt{K}$. There always has a unique orthonormal matrix $\boldsymbol{R}$ such that the first column of $\tilde{\boldsymbol{U}}\boldsymbol{R}$ is equal to $\mathbf{1}_K/\sqrt{K}$. Let $\boldsymbol{U} = \tilde{\boldsymbol{U}}\boldsymbol{R}$ and Unfold$(\mathcal{C}) = \boldsymbol{R}^T\Sigma\boldsymbol{V}$. Then, $\boldsymbol{U}$ and $\mathcal{C}$ are identifiable. □

2. **Membership constrain on $\boldsymbol{U}$. (Without intercept Θ_0)**

   If $\boldsymbol{U}$ is a membership matrix, we are clustering K categories into r groups. Then, the model (1) becomes

   $$\Omega^k = \Theta_{i_k}, \quad \text{for} \quad k = 1, ..., K,$$

where $i_k \in [r]$ is the group for the k-th category. Then, let $\mathcal{C} \in \mathbb{R}^{p\times p\times r}$, where $\mathcal{C}[,,l] = \Theta_l, l = 1, ..., r$, and $\boldsymbol{U} \in \mathbb{R}^{K\times r} = (\mathbf{u}_1, ..., \mathbf{u}_r)$.

Proposition 2. *The decomposition $\mathcal{C}$ and $\boldsymbol{U}$ are identifiable up to permutation if $\boldsymbol{U}$ is a membership matrix, i.e., in each row of $\boldsymbol{U}$ there is only 1 copy of 1 and massive 0.*

Proof. If $\boldsymbol{U}$ is a membership matrix, the model (2) is a special case of tensor block model. By Proposition 1 in Wang, the matrix $\boldsymbol{U}$ is identifiable if $\mathcal{C}$ is irreducible on mode 3. In our case, we assume $\mathcal{C}$ is full rank on mode 3, and thus $\{\boldsymbol{U}, \mathcal{C}\}$ are identifiable. □

Remark 1. The sparsity of Θ_l won't affect the identifiability in these two cases under the assumption that $\mathcal{C}$ is full rank on mode 3. In no sparsity constrain case, we only need the full rankness of Unfold($\mathcal{C}$), and the sparsity on the first and second mode of $\mathcal{C}$ does not affect the rank of Unfold($\mathcal{C}$). In membership constrain, we only need the mode 3 irreducibility of $\mathcal{C}$.

Remark 2. The two cases above are two extreme cases. Intermediate cases include the fuzzy clustering, where $\sum_{l=1}^r u_{lk} = 1, k \in [K]$, and the sparsity constrain for the column, where $|\mathbf{u}_l|_0 < a, l \in [r]$.

2 A simple extension

Let $Q^k(\Omega) = \operatorname{tr}(S^k\Omega) - \log|\Omega|$. Assume the rank of decomposition r is known. Consider the constrained optimization problem

$$\begin{aligned}
\min_{\mathcal{C}} \quad & \sum_{k=1}^{K} \left[Q^k(\Omega^k)\right] \\
s.t. \quad & \Omega^k = \Theta_0 + \sum_{l=1}^{r} u_{lk}\Theta_l, \quad \text{for} \quad k = 1, ..., K, \\
& \|\Theta_l\|_0 \le b, \quad \text{for} \quad l = 1, ..., r, \\
& \|\Theta_0\|_0 \le b_0, \\
& \text{with more identifiability conditions,}
\end{aligned}$$

where a, b, b_0 are fixed positive constants, $|\cdot|_0$ refers to the vector L_0 norm, and $\|\cdot\|_0$ refers to the matrix L_0 norm. For simplicity, let $\hat{\mathcal{C}} = \{\hat{\Theta}_0, \hat{\Theta}_1, ..., \hat{\Theta}_r, \hat{\mathbf{u}}_1, ..., \hat{\mathbf{u}}_r\}$ denote the estimation, and $\hat{\Omega}^k = \hat{\Theta}_0 + \sum_{l=1}^r \hat{u}_{lk}\hat{\Theta}_l$ for $k = 1, ..., K$.

For true precision matrices Ω^k, let $T^k = \{(j, j')|\omega^k_{j,j'} \neq 0\}$ and $q^k = |T^k|$. Assume $0 < \tau_1 < \phi_{\min}(\Omega^k) \le \phi_{max}(\Omega^k) < \tau_2, k = 1, ..., K$, for some positive constant τ_1, τ_2. This condition can be transferred as some conditions for $\{\Theta_l, \mathbf{u}_l\}$. I will specify the conditions later.

Theorem 2.1. *Suppose two assumptions hold. Let $\{\Omega^k\}$ denote the true precision matrices. For the estimation $\hat{\mathcal{C}}$ such that $\sum_{k=1}^K \left[Q^k(\hat{\Omega}^k)\right] \le \sum_{k=1}^K \left[Q^k(\Omega^k)\right]$ and satisfies the constrains, the following accuracy bound holds with probability tending to 1.*

$$\sum_{k=1}^{K} \left\|\hat{\Omega}^k - \Omega^k\right\|_F \le CK \left(C_1(b_0 + rb) \left(\frac{\log p}{n}\right)^{1/2} + C_2 \left(\frac{p\log p}{n}\right)^{1/2} \right),$$

where n is the sample size for each category, and C, C_1, C_2 are positive constants independent with p, n.

Proof. Let Ω^k denote the true precision matrices for $k = 1, ..., K$. Consider the estimation $\hat{\mathcal{C}}$ such that $\sum_{k=1}^K \left[Q^k(\hat{\Omega}^k)\right] \leq \sum_{k=1}^K \left[Q^k(\Omega^k)\right]$. Let $\Delta^k = \hat{\Omega}^k - \Omega^k$. For a matrix M, let M_T denote the matrix M with all elements outside the index set T replaced by 0, and $\tilde{M} = \text{vec}(M)$ be the vectorization of M. Define the function

$$G(\left\{\Delta^k\right\}) = \sum_{k=1}^K \text{tr}(S(\Omega^k + \Delta^k)) - \text{tr}(\Omega^k) - \log|\Omega^k + \Delta^k| + \log|\Omega^k| = I_1 + I_2, \tag{3}$$

where

$$I_1 = \sum_{k=1}^K \text{tr}((S^k - \Sigma^k)\Delta^k), \quad I_2 = \sum_{k=1}^K (\tilde{\Delta}^k)^T \int_0^1 (1-v)(\Omega^k + v\Delta^k)^{-1} \otimes (\Omega^k + v\Delta^k)^{-1} dv \tilde{\Delta}^k.$$

With probability tending to 1, we have

$$|I_1| \leq C_1 \left(\frac{\log p}{n}\right)^{1/2} \sum_{k=1}^K \left(|\Delta^k_{T^k}|_1 + |\Delta^k_{T^{k,c}}|_1\right) + C_2 \left(\frac{p\log p}{n}\right)^{1/2} \sum_{k=1}^K \left\|\Delta^k\right\|_F, \quad I_2 \geq \frac{1}{4\tau_2^2} \sum_{k=1}^K \left\|\Delta^k\right\|_F^2.$$

Note that $|\Delta^k_{T^k}|_1 \leq \sqrt{q^k}\left\|\Delta^k\right\|_F$. Then, we only need to deal with $|\Delta^k_{T^{k,c}}|_1$. Rewrite the term, we have

$$|\Delta^k_{T^{k,c}}|_1 = |\hat{\Theta}_{0,T^{k,c}} + \hat{u}_{1k}\hat{\Theta}_{1,T^{k,c}} + \cdots + \hat{u}_{rk}\hat{\Theta}_{r,T^{k,c}}|_1 \leq (b_0 + rb)\left\|\Delta^k\right\|_{\max} \leq (b_0 + rb)\left\|\Delta^k\right\|_F.$$

To let the equation (3) smaller than 0, we have

$$I_2 \leq -I_1 \leq |I_1|. \tag{4}$$

Plugging the upper bound of $|I_1|$ and the lower bound of I_2 into the inequality (4), we have

$$\frac{1}{4\tau_2^2}\sum_{k=1}^K \left\|\Delta^k\right\|_F^2 \leq C_1 \left(\frac{\log p}{n}\right)^{1/2} \sum_{k=1}^K \left(\sqrt{q^k}\left\|\Delta^k\right\|_F + (b_0 + rb)\left\|\Delta^k\right\|_F\right) + C_2 \left(\frac{p\log p}{n}\right)^{1/2} \sum_{k=1}^K \left\|\Delta^k\right\|_F.$$

By Cauchy Schwartz inequality, we know that $\sum_{k=1}^K \left\|\Delta^k\right\|_F^2 \geq \frac{1}{K}(\sum_{k=1}^K \left\|\Delta^k\right\|_F)^2$. Also, note that $q^k \leq (b_0 + rb), k = 1, ...K$. Dividing by $\sum_{k=1}^K \left\|\Delta^k\right\|_F$ on both sides of the inequality, we obtain the accuracy rate

$$\sum_{k=1}^K \left\|\Delta^k\right\|_F = \sum_{k=1}^K \left\|\hat{\Omega}^k - \Omega^k\right\|_F \leq 4\tau_2^2 K \left(C_1(b_0 + rb)\left(\frac{\log p}{n}\right)^{1/2} + C_2\left(\frac{p\log p}{n}\right)^{1/2}\right). \tag{5}$$

□

Remark 3. The accuracy (5) holds when q^k are fixed. Otherwise, the accuracy is of order $\mathcal{O}_p\left[q\left\{\frac{\log p}{n}\right\}^{1/2}\right]$.

Remark 4. This proof does not utilize the special structure of Ω^k. We can go through the proof with the constrain $|\Omega^k| < s$.

Remark 5. Both accuracy results of our constrained estimator and penalized estimator are of order $F(p, q)\left(\frac{\log p}{n}\right)^{1/2}$, where $F(p, q) = (p+q)^{1/2}$ for penalized estimator and $F(p, q) = (p+q^2)^{1/2}$ with $q = b_0 + rb$ in our estimator. In case of growing (p, n) and fixed q, the two estimators share the same accuracy rate.

3 Others

Can the factor K be improved?

First, consider the case $r = 0, K > 1$. Then, we have $\Theta_0 = \Omega^k, k = 1, ..., K$. Let $\hat{\Theta}_0$ be the estimator of $\Omega^k, k = 1, ..., K$, and thus $\Delta^k = \hat{\Omega}^k - \Omega^k = \Delta, k = 1, ..., K$. Define the function

$$G(\Delta) = \frac{1}{K}\sum_{k=1}^{K} \mathrm{tr}(S^k(\Theta_0 + \Delta)) - \mathrm{tr}(S^k\Theta_0) - \log|\Theta_0 + \Delta| + \log|\Theta_0| = I_1 + I_2,$$

where

$$I_1 = \mathrm{tr}((\frac{1}{K}\sum_{k=1}^{K} S^k - \Sigma)\Delta), \quad I_2 = (\tilde{\Delta})^T \int_0^1 (1-v)(\Theta_0 + v\Delta)^{-1} \otimes (\Theta_0 + v\Delta)^{-1} dv \tilde{\Delta}.$$

Note that $\frac{1}{K}\sum_{k=1}^{K} S^k$ can be considered as the sample covariance matrix with sample size nK. Then, the upper bound for $|I_1|$ is

$$|I_1| \le C_1 \left(\frac{\log p}{nK}\right)^{1/2} (|\Delta|_1) + C_2 \left(\frac{p \log p}{nK}\right)^{1/2} \|\Delta\|_F .$$

proof in Lemma 2

Since $I_2 \ge \frac{1}{4\tau_2^2}\|\Delta\|_F^2$, $|\Delta|_1 \le \sqrt{q}\|\Delta\|_F + (b_0 + rb)\|\Delta\|_F$, and we need $I_2 \le |I_1|$, we obtain the error bound

$$\|\Delta\|_F^2 \le \frac{4\tau_2^2}{K^{1/2}} F(p, q, n) \|\Delta\|_F ,$$

and thus $\|\Delta\|_F = \left\|\hat{\Theta}_0 - \Theta_0\right\|_F$ decreases in K of order $\mathcal{O}(K^{-1/2})$.

This result agrees with the intuition. As K growing, the sample size for estimating the Θ_0 becomes larger. Then, the error for the estimation goes smaller.

My thoughts.(Jan 11)

Consider the problem for scalar. Let $Y_{ij} \sim_{i.i.d.} N(\mu, \sigma^2), i = 1, ..., n, j = 1, ..., K$. Then, we have

$$\sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - \bar{Y})^2 = \sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - Y_{\cdot j})^2 + \sum_{j=1}^{K} n(Y_{\cdot j} - \bar{Y})^2,$$

where $\bar{Y} = \frac{1}{nK}\sum_{i,j} Y_{ij}$ and $Y_{\cdot j} = \frac{1}{n}\sum_i Y_{ij}$. Note that $Y_{\cdot j} \sim_{i.i.d.} N(\mu, \frac{\sigma^2}{n})$. We have

$$\frac{1}{K}\sum_{j=1}^{K}(Y_{\cdot j} - \bar{Y})^2 \to_{a.s.} \frac{\sigma^2}{n},$$

as $K \to \infty$. For all $\epsilon > 0$, we have n, K large enough such that

$$\frac{1}{nK}\sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - \bar{Y})^2 = \frac{1}{nK}\sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - Y_{\cdot j})^2 + \epsilon.$$

The term $\frac{1}{nK}\sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - \bar{Y})^2$ is the sample variance with sample size nK, and $\frac{1}{nK}\sum_{j=1}^{K}\sum_{i=1}^{n}(Y_{ij} - Y_{\cdot j})^2$ is the average of the sample variance for each group.

In multi-layer model, let S denote the sample covariance matrix with sample size nK and S^k be the sample covariance matrix for each group. Similarly as the scalar example, we may have S and $\frac{1}{K}\sum_k S^k$ close enough when n, K are large, and then we can go through the above proof.

For the log-determinant term,

$$\sum_{k=1}^{K} \log|\Omega^k| - \log|\Omega^k + \Delta^k| \quad \text{is replaced by} \quad K\log|\Theta_0| - K\log|\Theta_0 + \Delta|.$$

Consider the function $f(t) = \log|\Omega' + t\Delta'|$. By Taylor expansion for $t = 1$ around $t = 0$, we have

$$f(1) - f(0) = \log|\Omega'| - \log|\Omega' + \Delta'| = \mathrm{tr}(\Sigma'\Delta') + (\tilde{\Delta}')^T \int_0^1 (1-v)(\Omega' + v\Delta')^{-1} \otimes (\Omega' + v\Delta')^{-1} dv \tilde{\Delta}'.$$

The Taylor expansion takes derivatives of t. It seems impossible to let $K\log|\Theta_0| - K\log|\Theta_0 + \Delta|$ unrelated with K?

Thoughts (Jan 12)

Lemma 1. *Let $Z_i \sim_{i.i.d.} \mathcal{N}(0, \Sigma)$ and $\phi_{max}(\Sigma) \le \tau < \infty$. Let $\Sigma = [\![\Sigma_{ij}]\!]$, then*

$$P\left(\left|\sum_{i=1}^{n} Z_{ij}Z_{ik} - \Sigma_{jk}\right| \ge n\nu\right) \le c_1 e^{-c_2 n\nu^2}, \quad \textit{for} \quad |\nu| \le \delta,$$

where c_1, c_2, δ depends on τ only.

Proof. See Lemma 1 of Rothman et.al. □

Lemma 2. *With the probability tending to 1, we have the upper bound*

$$|I_1| = |tr((\frac{1}{K}\sum_{k=1}^{K} S^k - \Sigma)\Delta)| \le C_1\left(\frac{\log p}{nK}\right)^{1/2}(|\Delta^-|_1) + C_2\left(\frac{p\log p}{nK}\right)^{1/2}\left\|\Delta^+\right\|_F.$$

Proof. Let $\bar{S} = \frac{1}{K}\sum_{k=1}^{K} S^k$. Let $X_1^k, ..., X_n^k \sim_{i.i.d.} \mathcal{N}_p(0, \Sigma)$ denote the sample for k-th category. Consider the entry of $\bar{S}$.

$$\begin{aligned}\bar{S}_{jk} &= \frac{1}{K}\sum_{m=1}^{K}\frac{1}{n}\sum_{i=1}^{n}(X_{ij}^m - X_{.j}^m)(X_{ik}^m - X_{.k}^m)\\ &= \frac{1}{nK}\sum_{i=1}^{n}\sum_{m=1}^{K}\left(X_{ij}^m X_{ik}^m - X_{.j}^m X_{.k}^m\right),\end{aligned}$$

where $X_{.j}^m = \frac{1}{n}\sum_i X_{ij}^m$. By Lemma (1), we have

$$\left|\frac{1}{nK}\sum_{i=1}^{n}\sum_{m=1}^{K} X_{ij}^m X_{ik}^m - \Sigma_{jk}\right| \le C\sqrt{\frac{\log p}{nK}},$$

by letting $n = nK$ and $\nu = \sqrt{\frac{\log p}{nK}}$, with probability tending to 1 as $p \to \infty$. Also, by SLLN, $X_{.j}^m \to_{a.s.} 0$ as $n \to \infty$ for $j = 1, ..., p, m = 1, ..., K$. Then, we have

$$\max_{jk}|\bar{S}_{jk} - \Sigma_{jk}| \le C_1\sqrt{\frac{\log p}{nK}},$$

with probability tending to 1 for some constant C_1.

Back to $|I_1|$. We obtain the upper bound

$$
\begin{aligned}
|I_1| &\le |\sum_{i\neq j}(\bar{S}_{ij}-\Sigma_{ij})\Delta_{ij}| + |\sum_{i=1}^{p}(\bar{S}_{ii}-\Sigma_{ii})\Delta_{ii}| \\
&\le C_1\sqrt{\frac{\log p}{nK}}|\Delta^-|_1 + \left[\sum_{i=1}^{p}(\bar{S}_{ii}-\Sigma_{ii})^2\right]^{1/2}\left\|\Delta^+\right\|_F \\
&\le C_1\sqrt{\frac{\log p}{nK}}|\Delta^-|_1 + C_2\sqrt{\frac{p\log p}{nK}}\left\|\Delta^+\right\|_F
\end{aligned}
$$

$\square$

Comparison Table.

	Penalized	
	L_0	L_1
Ground Truth	For $k \in [K]$, $$\lvert\Omega^k\rvert_0 < s$$, where $\lvert\cdot\rvert_0$ denote the number of nonzero elements in the matrix, and $s > 1$ is a positive constant.	For $k \in [K]$, $$\lvert\Omega^k\rvert_1 < c,$$ where norm $\lvert\Omega\rvert_1 = \sum_{(i,j)} \lvert\omega_{ij}\rvert$.
Fitting techniques	The estimator is the solution to the optimization problem $$\min_{\{\Omega^k\}} Q^k(\Omega^k) + \lambda\sum_{k=1}^{K}\lvert\Omega^k\rvert_0.$$	The estimator is the solution to the optimization problem $$\min_{\{\Omega^k\}} Q^k(\Omega^k) + \lambda\sum_{k=1}^{K}\lvert\Omega^k\rvert_1.$$
Accuracy	For $\lambda \ge 0$, $$\sum_k \lVert\Delta_k\rVert_F^2 \le 4\tau_2^2\left(F(p,q,n)\sum_k\left\lVert\Delta^k\right\rVert_F + K\lambda q\right)$$ where $F(p,q,n) = C_1 p\left(\frac{\log p}{n}\right)^{1/2} + C_2\left(\frac{p\log p}{n}\right)^{1/2}$. Then, the error sqrt(q) $$\sum_k \lVert\Delta_k\rVert_F = \mathcal{O}(\frac{K\sqrt{\lambda}}{n^{1/4}}).$$ If $\lambda \ge \Lambda_1\left(\frac{\log p}{n}\right)^{1/2}$, the error becomes of order $\mathcal{O}(K/n^{1/2})$.	For $\lambda \ge \Lambda_1\left(\frac{\log p}{n}\right)^{1/2}$, we have $$\sum_k \lVert\Delta_k\rVert_F^2 \le 4\tau_2^2\left(\lambda\sqrt{q} + F(p,q,n)\right)\sum_k\left\lVert\Delta^k\right\rVert_F,$$ where $F(p,q,n) = C_1\left(\frac{q\log p}{n}\right)^{1/2} + C_2\left(\frac{p\log p}{n}\right)^{1/2}$. Then, we have $$\sum_k\left\lVert\Delta^k\right\rVert_F \le 4\tau_2^2 K\left(\lambda\sqrt{q} + F(p,q,n)\right).$$

I3 - I12 = \lambda |Delta_Tc|_0 - (\log p/n)^{1/2} |Delta_Tc|_1 > 0 when lambda is very large

	Constrained	
	L_0	L_1
Ground Truth	For $k \in [K]$, $$\lvert\Omega^k\rvert_0 < s$$, where $\lvert\cdot\rvert_0$ denote the number of nonzero elements in the matrix, and $s > 1$ is a positive constant.	For $k \in [K]$, $$\lvert\Omega^k\rvert_1 < c,$$ where norm $\lvert\Omega\rvert_1 = \sum_{(i,j)} \lvert\omega_{ij}\rvert$.
Fitting techniques	The estimator is the solution to the optimization problem $$\min_{\{\Omega^k\}} Q^k(\Omega^k)$$ $$s.t. \quad \lvert\Omega^k\rvert_0 < s, \quad k \in [K]$$	The estimator is the solution to the optimization problem $$\min_{\{\Omega^k\}} Q^k(\Omega^k)$$ $$s.t. \quad \lvert\Omega^k\rvert_1 < c, \quad k \in [K]$$
Accuracy	We have $$\sum_k \lVert\Delta_k\rVert_F^2 \leq 4\tau_2^2 F(p,s,n) \sum_k \left\lVert\Delta^k\right\rVert_F,$$ where $F(p,s,n) = C_1 s \left(\frac{\log p}{n}\right)^{1/2} + C_2 \left(\frac{p\log p}{n}\right)^{1/2}$. Then sqrt(s) $$\sum_k \lVert\Delta_k\rVert_F \leq 4\tau_2^2 K F(p,s,n).$$	We have $$\sum_k \lVert\Delta_k\rVert_F^2 \leq 4\tau_2^2 F(p,q,n) \sum_k \left\lVert\Delta^k\right\rVert_F,$$ where $F(p,q,n) = C_1 p \left(\frac{\log p}{n}\right)^{1/2} + C_2 \left(\frac{p\log p}{n}\right)^{1/2}$. Then, $$\sum_k \lVert\Delta_k\rVert_F \leq 4\tau_2^2 K F(p,q,n).$$ This one does not use the constrain \lvert\Omega\rvert<c

|Delta_Tc|_1 \leq \sqrt(s) ||Delta||_F

If C = |\Omega_T|_1,
|\Omega_T+ \Delta_T|_1 + |Delta_Tc|_1 \leq |\Omega_T|_1
|\Omega_T| - |\Delta_T|_1 + |\Delta_Tc|_1 \leq |\Omega_T|_1

4 Next

|x|-|y| \leq |x +y|

- > |\Delta_Tc|_1 \leq |\Delta_T|_1 \leq \sqrt{q} |\Delta|_F

- Think about the identifiability of the intermediate cases (spare matrix factorization).
- Think about the proof which utilizes the special structure of the Ω^k.