



问题与实验

实验目的



尝试利用fold-in绕开LatLRR的训练实现快速测试



比较不同特征 (raw data、XZ、LX) 的性状表现，期望LX较好

2018.6.7



$$\min_{Z,L} \|Z\|_* + \|L\|_* + \|E\|_1 \quad s.t. X = XZ + LX + E \xrightarrow{\text{Yale Face}} 2016 \times 160 \quad 17 \sim 20 \text{ minutes}$$

$$\min_{Z,L} \|Z\|_* + \|L\|_* \quad s.t. X = XZ + LX \xrightarrow{\text{complete solutions}} Z^* = V_X(I - S)V_X^T \text{ and } L^* = U_X S U_X^T$$

$SVD(X) = U_X \Sigma_X V_X^T$ S is any block-diagonal matrix that satisfies two constraints:

ECML 2013

- 1) its blocks are compatible with Σ_X , i.e., if $(\Sigma_X)_{ii} \neq (\Sigma_X)_{jj}$, then $S_{ij} = 0$
- 2) both S and $I - S$ are positive semidefinite.

V_X 是通过对AL已经选出的点进行SVD分解所得,提前计算 V_X 、 S , 新加入一个测试点利用SVD快速计算出新的 V_{X_new} , 再利用 $Z^* = V_X(I - S)V_X^T$ 直接获得新的关联度矩阵 Z_{new}^*

Using Linear Algebra Intelligent Information Retrieval

1995 SIAM



$$A_k = \begin{matrix} A_k \\ \vdots \\ k \end{matrix} = \begin{matrix} U \\ \vdots \\ k \end{matrix} \Sigma \begin{matrix} V^T \\ \vdots \\ k \end{matrix}$$

Document
Vectors

$m \times n$ $m \times k$ $k \times k$ $k \times n$

The diagram illustrates the Singular Value Decomposition (SVD) of a matrix A_k . The matrix A_k is shown as a tall rectangle. It is equal to the product of three matrices: U , Σ , and V^T . Matrix U is $m \times k$, Σ is $k \times k$ (diagonal), and V^T is $k \times n$. The label "Document Vectors" is placed next to the V^T matrix.



$$\begin{array}{c|c|c|c} \boxed{\begin{matrix} A_k \\ m \times n \end{matrix}} & = & \boxed{\begin{matrix} U_k \\ m \times k \end{matrix}} & \boxed{\begin{matrix} \Sigma_k \\ k \times k \end{matrix}} \\ & & & \\ & q & q & \\ & & & \\ \hline (m+q) \times n & & (m+q) \times k & \\ & & & \\ & & & \\ & & & k \times k & k \times n \end{array}$$

$$\hat{t} = t^T V_k \Sigma_k^{-1} \quad (q \times k) = (q \times n) \ (n \times k) \ (k \times k)$$



$$\begin{matrix} A_k \\ m \times n \end{matrix} = \begin{matrix} U_k \\ m \times k \end{matrix}$$

$$\begin{matrix} \Sigma_k \\ k \times k \end{matrix}$$

$$\begin{matrix} V_k^T \\ k \times n \end{matrix}$$

p

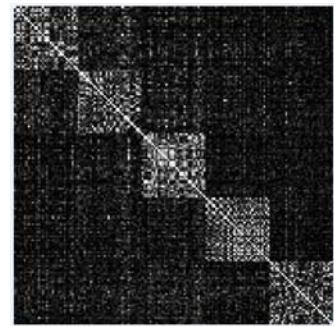
$k \times k$

$k \times (n + p)$

$m \times (n + p)$

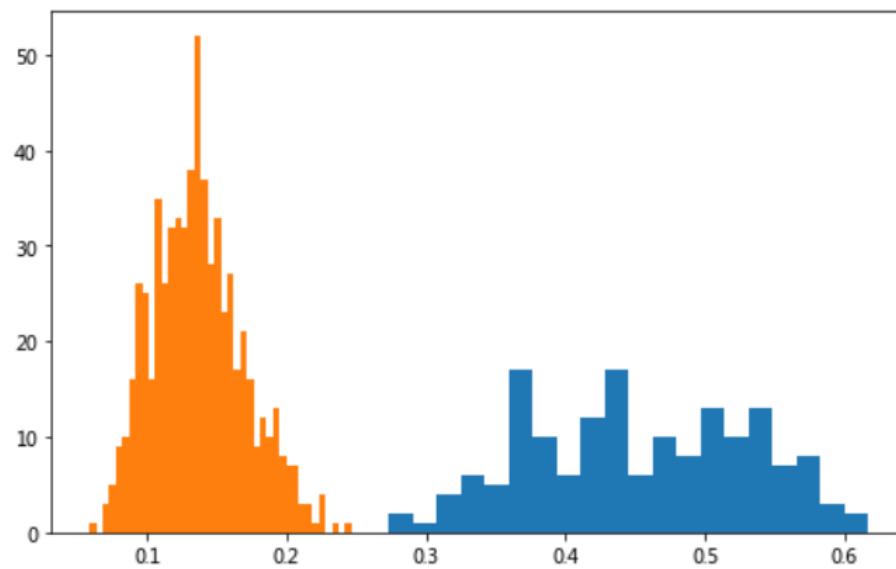
$m \times k$

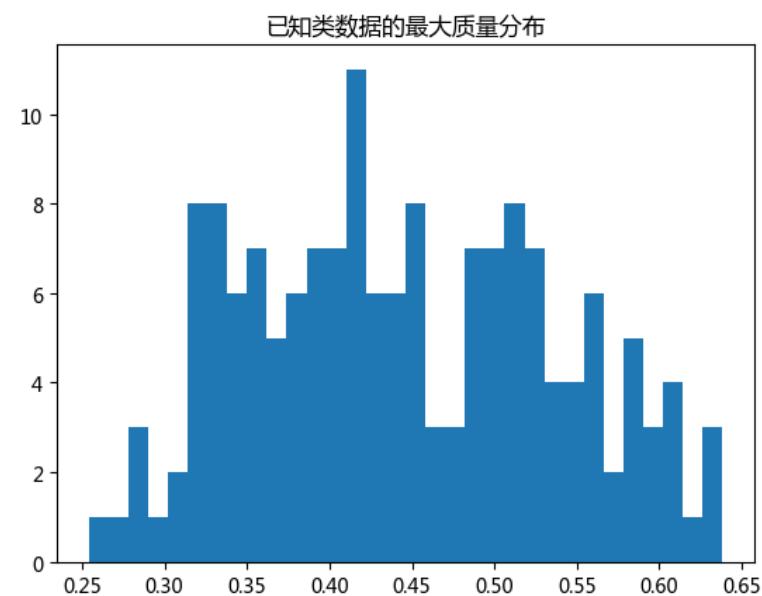
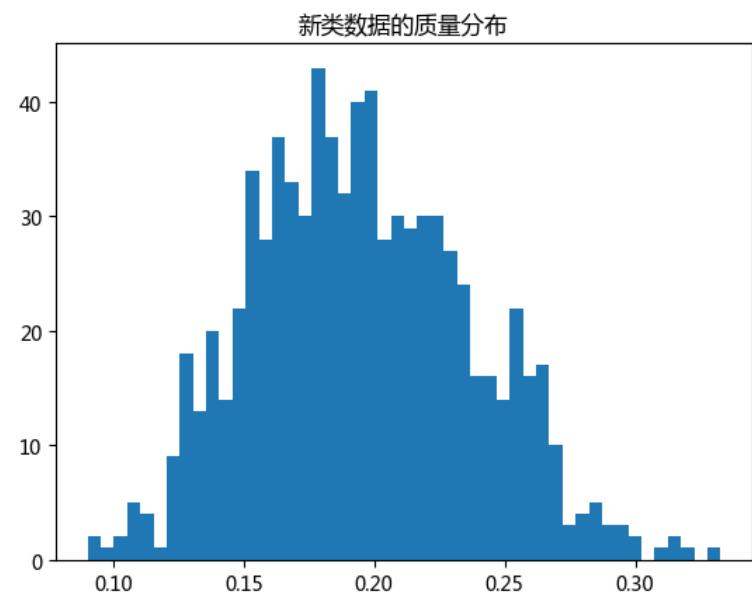
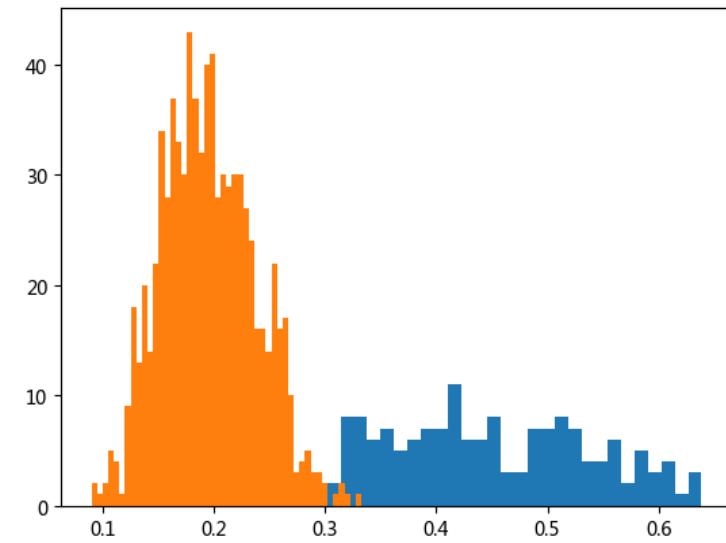
$$\hat{d} = d^T U_k \Sigma_k^{-1} \quad (k \times p) \neq (p \times m) \quad (m \times k) \quad (k \times k)$$



关联度矩阵Z (160*160)

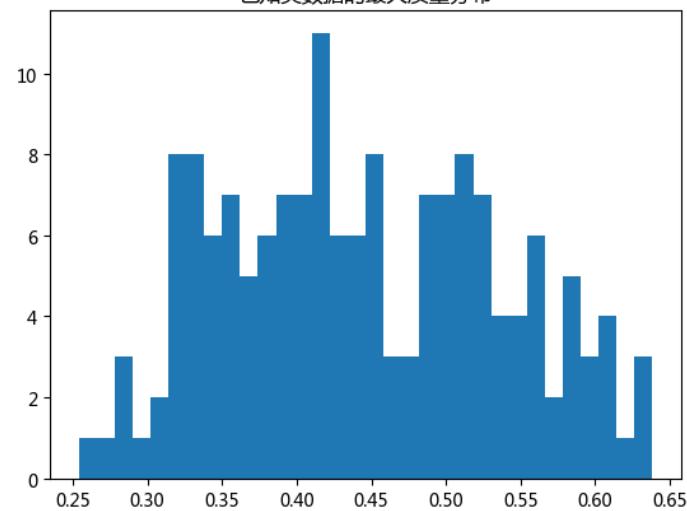
行归一化



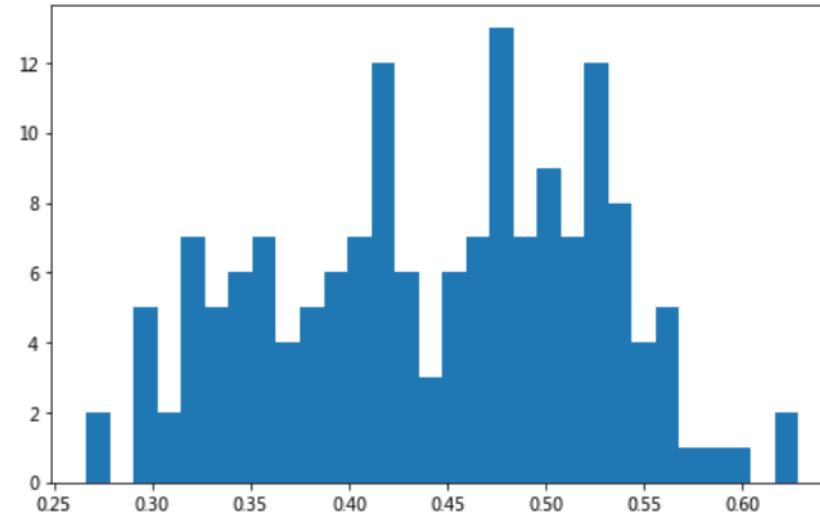




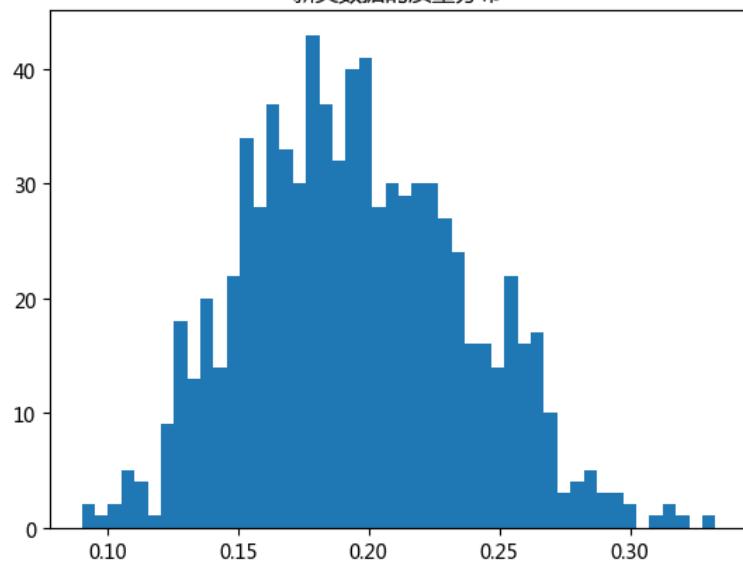
已知类数据的最大质量分布



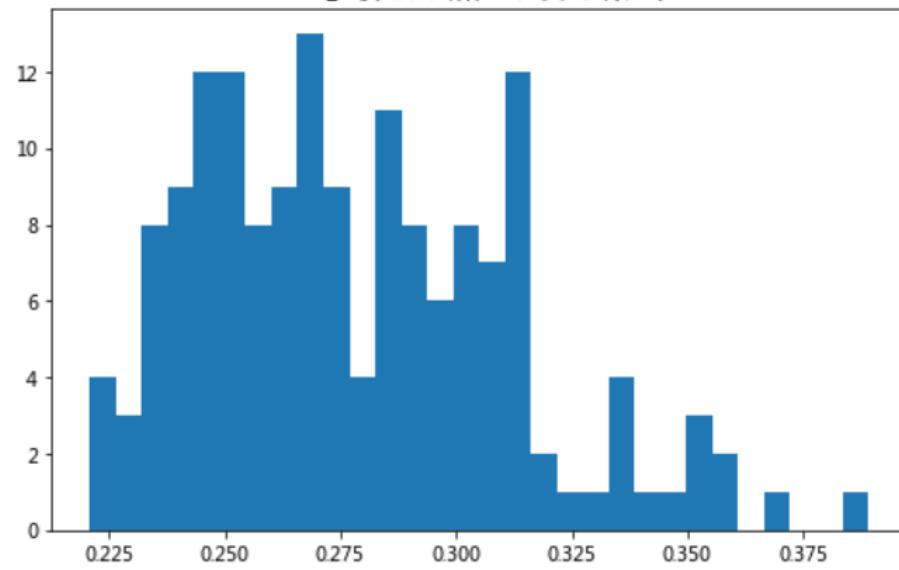
fold_in快速预测所得已知类Z统计分布



新类数据的质量分布



fold_in快速预测所得已知类Z统计分布

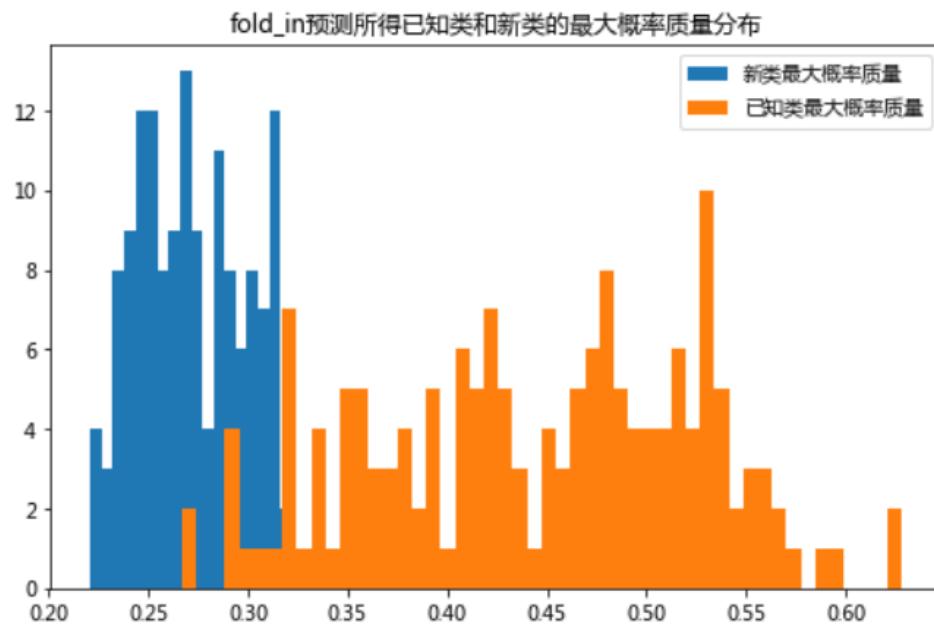




delta = 0.32

acc_known = 0.925

acc_new = 0.89375

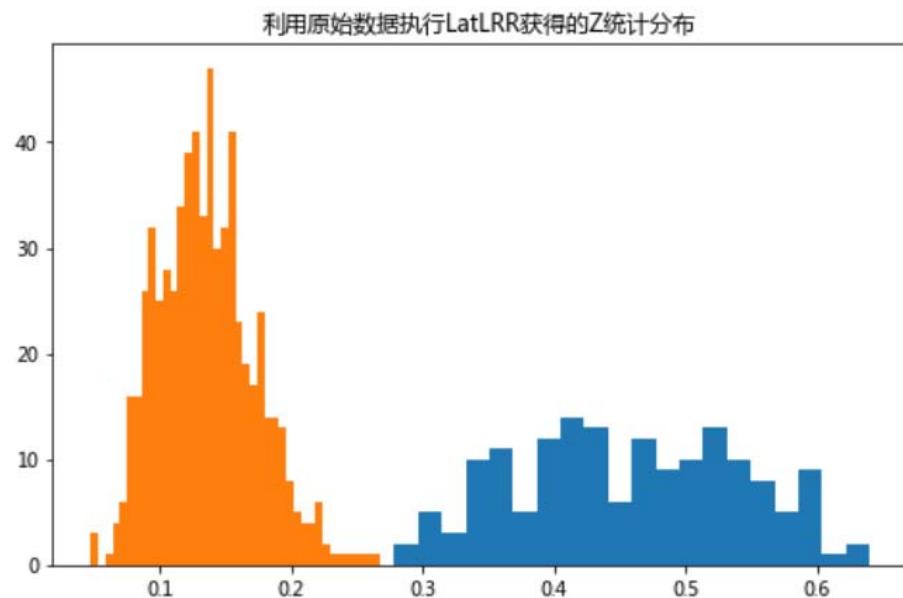


不同特征的比较

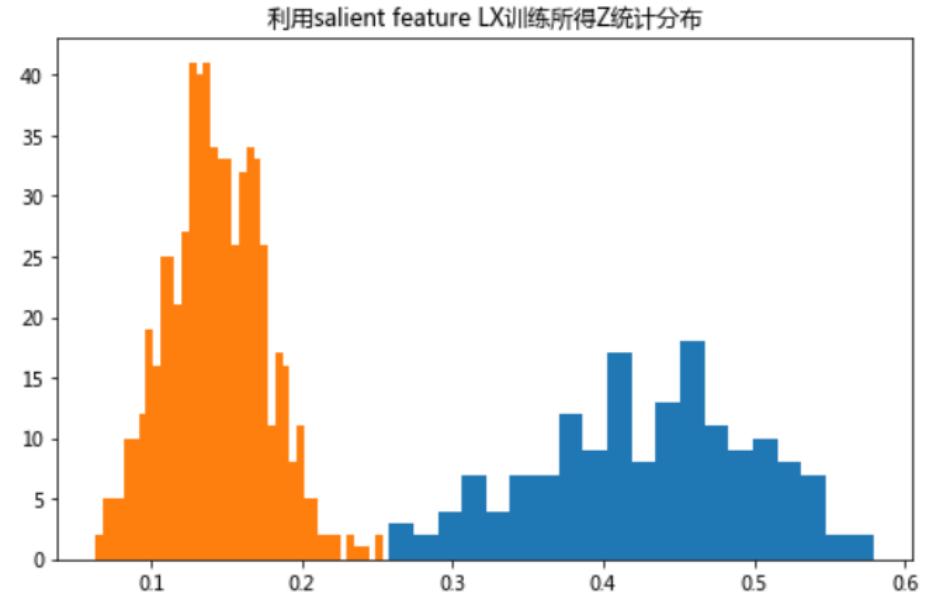


p_1 p_2 p_3 p_4 p_5

raw data



LX



$$Accuracy = \frac{A_{new} + A_{known}}{m}$$

AAAI 2017



Table 1: Comparisons of different methods on simulated streams.

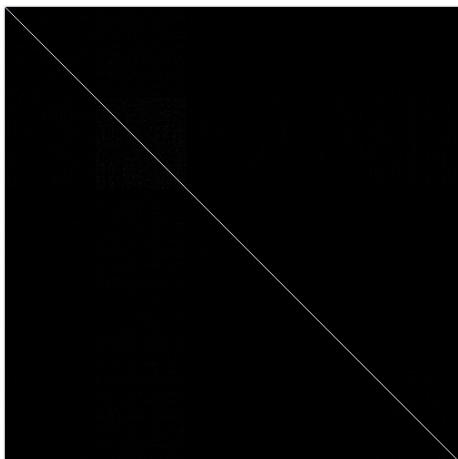
Algorithm	KDD Cup 99		Forest Cover		MNIST	
	Accuracy	F-measure	Accuracy	F-measure	Accuracy	F-measure
iForest+KNN	0.867±0.01	0.882±0.04	0.707± 0.02	0.742± 0.08	0.720 ± 0.06	0.593 ± 0.05
LACU-SVM	0.853±0.05	0.827± 0.02	0.702± 0.07	0.752± 0.11	0.752 ± 0.01	0.697 ± 0.04
SAND-F	0.880±0.03	0.892± 0.03	0.799± 0.02	0.771± 0.03	0.725 ± 0.04	0.622 ± 0.03
ECSMiner	0.857± 0.03	0.852±0.06	0.823± 0.05	0.794± 0.02	0.745 ± 0.07	0.641 ± 0.03
SENC-non-MaS	0.792± 0.08	0.722±0.13	0.633± 0.02	0.651± 0.05	0.701 ± 0.07	0.652 ± 0.06
SENC-MaS	0.897± 0.03	0.902±0.02	0.792± 0.04	0.752± 0.07	0.817 ± 0.05	0.710 ± 0.09

Table 1: F1, Precesion and Recall for seen classes 2,3,5 in MNIST dataset (NIPC means number of instances per class)

	Measure	NIPC	OC-SVM	MOC-SVM	1-vs-Set	OVR-SVM	NNO	ASG-SVM
Seen Class	F1	100	.398±.033	.446±.028	.488±.046	.552±.021	.424±.013	.570±.029
		1000	.389±.026	.437±.027	.542±.043	.612±.013	.421±.010	.624±.024
	Precision	100	.330±.037	.414±.033	.336±.051	.398±.019	.367±.012	.539±.027
		1000	.314±.027	.374±.031	.388±.048	.534±.017	.379±.011	.566±.022
	Recall	100	.502±.031	.484±.030	.882±.046	.898±.024	.501±.014	.605±.031
		1000	.511±.029	.525±.027	.897±.044	.716±.014	.474±.012	.697±.025
Unseen Class	F1	100	.645±.035	.918±.031	.882±.048	.895±.023	.702±.012	.933±.030
		1000	.617±.031	.905±.029	.897±.044	.930±.016	.722±.011	.935±.026
	Precision	100	.736±.036	.941±.034	.983±.049	.987±.020	.763±.014	.957±.028
		1000	.726±.027	.944±.033	.986±.043	.968±.018	.763±.012	.966±.024
	Recall	100	.577±.032	.897±.032	.752±.053	.818±.025	.650±.013	.911±.034
		1000	.538±.030	.870±.028	.789±.048	.896±.013	.685±.01	.907±.026

IJCAI 2017

compare with mnist



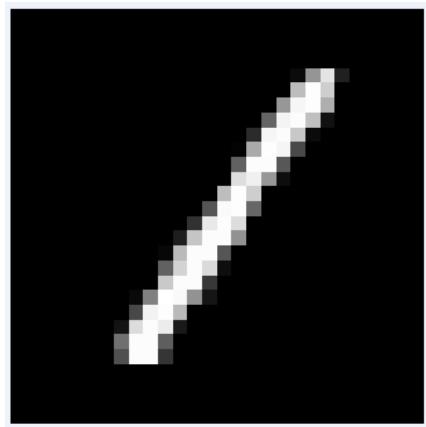
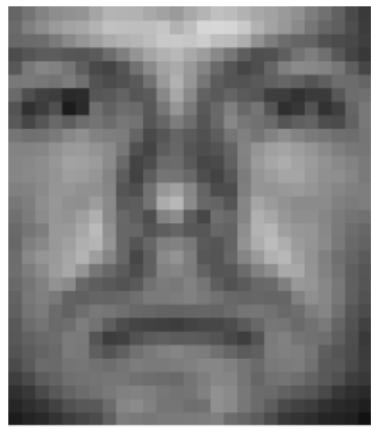
$\lambda \nearrow$ ← → $\lambda \searrow$

Algorithm 1 Solving Problem (6) by Inexact ALM

Initialize: $Z = J = 0, L = S = 0, E = 0, Y_1 = 0, Y_2 = 0, Y_3 = 0, \mu = 10^{-6}, max_u = 10^6, \rho = 1.1$, and $\varepsilon = 10^{-6}$.

while not converged **do**

1. Fix the others and update J by setting $J = \arg \min_J \frac{1}{\mu} \|J\|_* + \frac{1}{2} \|J - (Z + Y_2/\mu)\|_F^2$.
 2. Fix the others and update S by setting $S = \arg \min_S \frac{1}{\mu} \|S\|_* + \frac{1}{2} \|S - (L + Y_3/\mu)\|_F^2$.
 3. Fix the others and update Z by setting $Z = (\mathbf{I} + X^T X)^{-1}(X^T(X - LX - E) + J + (X^T Y_1 - Y_2)/\mu)$.
 4. Fix the others and update L by setting $L = ((X - XZ - E)X^T + S + (Y_1 X^T - Y_3)/\mu)(\mathbf{I} + XX^T)^{-1}$.
 5. Fix the others and update E by setting $E = \arg \min_E \frac{\lambda/\mu}{\mu} \|E\|_1 + 0.5 \|E - (X - XZ - LX + Y_1)/\mu\|_F^2$
 6. Update the multipliers by $Y_1 = Y_1 + \mu(X - XZ - LX - E)$, $Y_2 = Y_2 + \mu(Z - J)$, $Y_3 = Y_3 + \mu(L - S)$.
 7. Update the parameter μ by $\mu = \min(\rho\mu, max_u)$.
 8. Check the convergence conditions: $\|X - XZ - LX - E\|_\infty < \varepsilon$, $\|Z - J\|_\infty < \varepsilon$, and $\|L - S\|_\infty < \varepsilon$.
- end while**
-



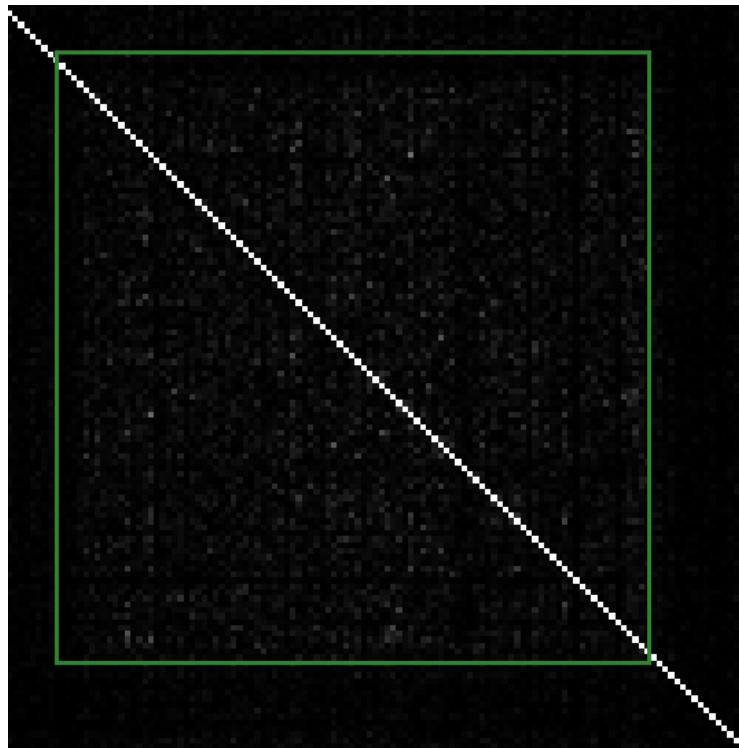
$$\min_{Z,L} \|Z\|_* + \|L\|_* + \|E\|_1 \quad s.t. X = XZ + LX + E$$



$$\min_{Z,L} \|Z\|_* + \|L\|_* \quad s.t. X = XZ + LX$$

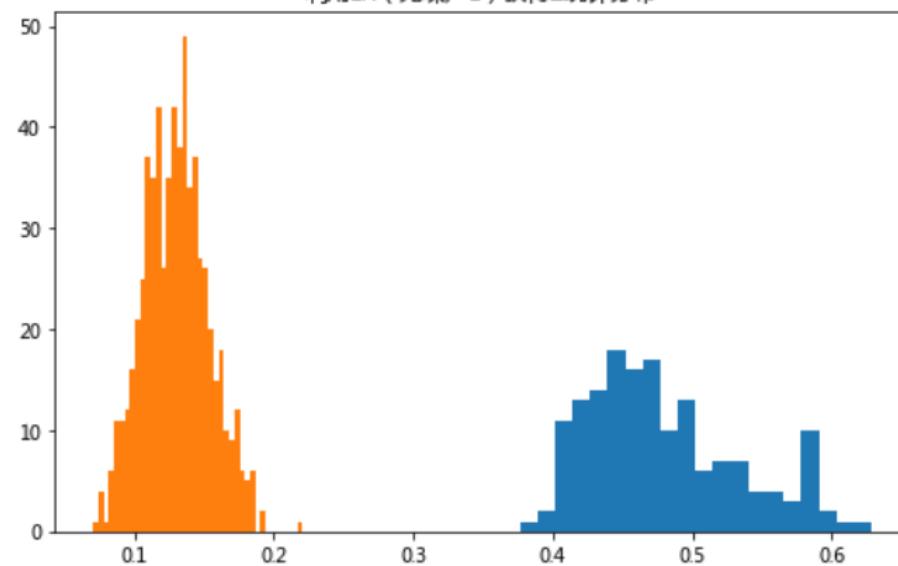


$Z_{ii} = 0/1e - 5$

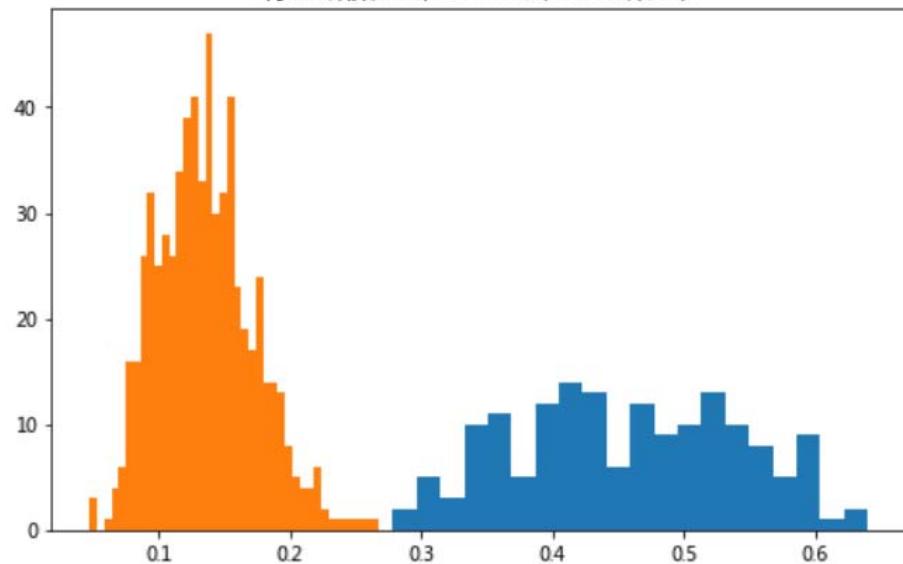




利用LX (无噪声E) 获得Z统计分布



利用原始数据执行LatLRR获得的Z统计分布



利用salient feature LX训练所得Z统计分布

